working paper

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FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 16-36R October 2019*

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Prior research suggests that statewide affirmative action bans reduce minority enrollment at selective colleges while leaving overall minority college enrollment unchanged. However, the effect of these bans on across-college racial segregation has not yet been estimated. This effect is theoretically ambiguous due to a U-shaped relationship across colleges between minority enrollment and college selectivity. This paper uses variation in the timing of affirmative action bans across states to estimate their effects on racial segregation as measured by standard exposure and dissimilarity indexes, finding that affirmative action bans have increased segregation across colleges in some cases but reduced it in others. In particular, early affirmative action bans in states with highly selective public universities appear to be associated with less segregation, whereas more recent affirmative action bans appear to be associated with more segregation.

Keywords: affirmative action, college admissions, higher education, segregation.
JEL Classification: I24, I28, J15.

Suggested citation: Hinrichs, Peter. 2019. "Affirmative Action and Racial Segregation." Federal Reserve Bank of Cleveland, Working Paper no. 16-36R. https://doi.org/10.26509/frbc-wp-201636r.

Peter Hinrichs is at the Federal Reserve Bank of Cleveland (peter.hinrichs@clev.frb.org). The author thanks Joseph Altonji, Andrew Barr, Michael Dinerstein, Will Dobbie, Jonathan Guryan, Andrew Hill, Pawel Krolikowski, Mark Long, Michael Lovenheim, Byron Lutz, Martin Orland, Monica Reusser, Jonah Rockoff, Jenny Schuetz, Christopher Taber, Jacob Vigdor, Danny Yagan, the editor, and an anonymous referee for helpful discussions and comments. He also thanks participants at the 2019 Society of Labor Economists conference, the 2018 Western Economic Association International conference, the 2018 Cleveland Fed/University of Kentucky Workshop on the Economics of Education, the 2017 Federal Reserve System Committee on Applied Microeconomics conference, the 2016 American Economic Association conference, the 2015 Association for Public Policy Analysis and Management conference, and the 2015 Association for Education Finance and Policy conference, as well as seminar participants at the Federal Reserve Bank of New York/New York University, Oberlin College, Ohio State University, the University of California–Riverside, the University of Connecticut, and the University of Washington. He thanks Emily Dohrman for valuable research assistance.

*First version December 2016.

1 Introduction

Affirmative action went into widespread use at American colleges and universities in the 1960s and 1970s in an effort to raise minority enrollment.[1] In recent years, several states have discontinued affirmative action in admissions to public universities. These affirmative action bans have come through direct decisions of voters in Arizona, California, Michigan, Nebraska, Oklahoma, and Washington state; executive order in Florida; legislative action in New Hampshire; and, for a time, a federal court ruling in Texas. The growing body of research on affirmative action bans finds that that they reduce minority enrollment at selective colleges but do not affect overall minority college attendance (Arcidiacono, 2005; Arcidiacono et al., 2014; Backes, 2012; Hinrichs, 2012; Howell, 2010; Long, 2004b; Naven, 2017).[2] Affirmative action has been in the headlines again recently, with a lawsuit against Harvard University alleging discrimination against Asian American applicants having gone to trial in 2018.

The Supreme Court has ruled that affirmative action in college admissions is constitutional on the grounds that there are educational benefits to racial diversity.[3,4,5] However, a more fundamental question is whether there will actually be more cross-racial interaction with affirmative action than without it. If affirmative action bans lead to lower minority enrollment at selective colleges, students who are displaced may cascade down to institutions that already have high minority enrollment. Alternatively, they may cascade down to institutions that would have otherwise had low minority enrollment. The two scenarios have differing implications for the impact of affirmative action bans on segregation. Additionally, each of these scenarios is a distinct possibility, given the U-shaped

[1]For more on the history of affirmative action, see Bowen and Bok (1998) or Stulberg and Chen (2011).

[2]See Arcidiacono and Lovenheim (2016) for a recent review of research on affirmative action. This article examines a number of issues but frames much of the discussion around the "minority mismatch hypothesis," an important part of the affirmative action debate but a separate question from the issue of segregation across colleges that I study here. See Arcidiacono et al. (2015) for an additional review of affirmative action research.

[3]The means employed must also be "narrowly tailored" to achieve the benefits of diversity. For example, colleges cannot use explicit racial quotas.

[4]Justice Sandra Day O'Connor's majority opinion from 2003 in the *Grutter v. Bollinger* case cites some evidence in support of the claim that there are educational benefits to racial diversity. However, the evidence from economics on the effects of diversity at the institution level is more mixed (Arcidiacono and Vigdor, 2010; Daniel et al., 2001; Hinrichs, 2011). Studies by economists based on randomly assigned roommates or peer groups generally find positive effects of cross-racial interaction (Baker et al., 2011; Boisjoly et al., 2006; Camargo et al., 2010; Carrell et al., 2016), although it is unclear whether this result has external validity for predicting the effects of changing the level of diversity of an entire student body.

[5]The key cases on the constitutionality of affirmative action are *Regents of the University of California v. Bakke* (1978), *Gratz v. Bollinger* (2003), *Grutter v. Bollinger* (2003), *Fisher v. University of Texas* (2013), and *Fisher v. University of Texas* (2016). In *Schuette v. Coalition to Defend Affirmative Action* (2014), the Supreme Court ruled that it is constitutional for the voters of a state to ban affirmative action. In addition to lawsuits that have been recently filed by private citizens against Harvard and the University of North Carolina over affirmative action, there is speculation that the U.S. Department of Justice will begin to take action against universities whose affirmative action admissions policies are deemed to discriminate against whites (Savage, 2017).

relationship across colleges between percent minority and measures of college quality documented by Arcidiacono et al. (2011), Arcidiacono et al. (2016), and Reardon et al. (2012).[6]

The Supreme Court affirmative action decisions focus on the academic freedom and First Amendment rights of particular universities, and the Court has deferred to the judgment of universities such as the University of California, Davis and the University of Michigan, which argued that their students benefit from the increased racial diversity that results from affirmative action. However, from the point of view of social welfare, the extent to which these benefits occur in higher education more broadly is arguably more important than the extent to which they occur at any particular university. This distinction is a meaningful one because, as one institution diversifies its student body through the use of affirmative action, it might do so by drawing in students who would have otherwise attended other institutions, resulting in a loss of diversity at those institutions. The reshuffling of students from one institution to another suggests that the way to measure the impact of affirmative action on cross-racial interaction is not to focus on minority representation at any one particular institution but rather to study cross-racial interaction in higher education as a whole. In light of the U-shaped relationship across colleges between percent minority and measures of college quality mentioned earlier, this reshuffling could result in either less segregation, more segregation, or no change in the amount of segregation across colleges. If banning affirmative action flattens out this U shape by decreasing minority representation at the most selective institutions and increasing it at slightly less selective institutions, thereby making the racial compositions of different institutions more similar to each other, the result could be a decline in segregation.[7] In contrast, banning affirmative action may increase segregation if it shifts minority students from less selective institutions with high minority representation to even less selective institutions with even higher existing minority representation.

This paper is the first to directly estimate the impacts of affirmative action bans on racial segregation.[8] I measure segregation using standard exposure and dissimilarity indexes at the state

[6]Arcidiacono et al. (2011) show that there is a U-shaped relationship across colleges between average SAT score and percent black, with the minimum black share coming at an SAT score of 1090 out of 1600. Arcidiacono et al. (2016) show that there is a U-shaped relationship between percent minority and a measure of academic preparation that depends on SAT scores and high school grade point averages across campuses of the University of California system. Reardon et al. (2012) find a similar U shape for both blacks and Hispanics when using *Barron's* rankings rather than SAT scores. Interestingly, the U shape found in all of this research exists despite the fact that a higher minority share may mechanically pull down the average SAT score at the places with the highest average SAT score.

[7]One caveat is that if there are benefits from diversity and these benefits are larger or more important at more selective colleges, this would in itself be a point in favor of affirmative action. On the other hand, the benefits could potentially be larger at less selective colleges. I return to this point in Section 6.

[8]As I explain in more detail in Section 4.1, the existing research on the enrollment effects of affirmative action bans by broad selectivity tier, such as Backes (2012), Hinrichs (2012), and Naven (2017), is insufficient for determining the effects on segregation because it does not provide information on the reshuffling of students between particular universities within a broad selectivity tier.

level. The exposure indexes measure the potential exposure of the average member of one group to the members of another group across an entire state (rather than at one particular college), and the dissimilarity index measures how unevenly members of two groups are distributed across colleges. These segregation indexes can take into account the fact that a gain in diversity at one college may come at the expense of diversity at another.[9] I use these segregation indexes to estimate generalized difference-in-differences models that exploit variation in the timing of affirmative action bans across states. I find little effect of affirmative action bans on racial segregation on average, showing that an affirmative action ban need not be accompanied by an increase in segregation.

I also estimate the effects separately for states that banned affirmative action earlier and more recently. Unlike more recent affirmative action bans, earlier affirmative action bans occurred in states like California and Texas that are home to highly selective public universities. Early affirmative action bans have been studied in prior work, such as Backes (2012) and Hinrichs (2012), whereas more recent affirmative action bans have not yet been the subject of much study.[10] Estimating effects separately for earlier and more recent bans allows for comparison to earlier work while also providing new estimates of the effects of more recent affirmative action bans. I find that recent affirmative action bans are associated with greater segregation across colleges on average, while earlier affirmative action bans that occurred in states that are home to highly selective public universities are associated with less segregation.

The rest of the paper proceeds as follows: Section 2 of this paper discusses the data, including the construction of the segregation indexes. Section 3 briefly discusses the impact of more recent affirmative action bans on the overall demographic composition of universities. Section 4 presents the main empirical results on affirmative action and racial segregation. Section 5 is a case study of California that illustrates how it is possible for an affirmative action ban to *increase* segregation. Section 6 concludes.

2 Data

The main data in this study come from the Integrated Postsecondary Education Data System (IPEDS), a college-level data set compiled every year by the United States Department of Edu-

[9] There is relatively little research on segregation in higher education, although Hinrichs (2015) describes trends in segregation across colleges in the United States since the 1960s. The effects of higher education segregation are unknown, but segregation is a useful outcome to study in the context of affirmative action because claims are often made about the effects of affirmative action on cross-racial interaction. Segregation indexes such as exposure indexes and dissimilarity indexes are useful summary measures of potential cross-racial interaction. There is much more research on K–12 segregation, and the segregation indexes I use in this paper are standard measures used to study segregation in that context. Much of the K–12 research, such as Guryan's (2004) work on black dropout rates, finds deleterious effects of segregation. See Rivkin and Welch (2006) for a review.

[10] However, see Naven (2017), who studies more recent affirmative action bans.

cation's National Center for Education Statistics. Institutions that participate in federal financial aid programs are required to complete IPEDS surveys, providing information on program offerings, enrollment, cost of attendance, institutional finances, staff, and other institutional characteristics. Most importantly for the purposes of this study, IPEDS contains information on enrollment by race. I utilize data from four-year colleges on the number of full-time, first-time, degree-seeking undergraduates by race in the fall of each year between 1995 and 2016 to construct segregation indexes at the state-by-year level.[11]

I use three standard segregation indexes: the index of white exposure to blacks, the index of black exposure to whites, and the black-white dissimilarity index. The two exposure indexes measure potential interaction between members of different racial groups. White exposure to blacks measures the percentage of students who are black at the institution of the average white student, while black exposure to whites measures the percentage of students who are white at the institution of the average black student. Dissimilarity is a measure of unevenness that calculates the percentage of students of one race who would need to be reassigned to a different institution in order for institutions to have the same racial composition as each other. These segregation indexes provide a useful means of summarizing the potential for cross-racial interaction — as well as how unevenly different groups are distributed — *across all colleges*, rather than at a particular college.

To define the three segregation indexes mathematically, use N to denote the total number of colleges in a state in a particular year, W to denote the combined number of white students across these colleges, and B to denote the total number of black students across these colleges. Further, suppose that college i enrolls w_i white students, b_i black students, h_i Hispanic students, a_i Asian students, and n_i Native American students. Then the exposure index of whites to blacks is calculated as $100 \times \frac{1}{W} \sum_{i=1}^{N} \frac{b_i}{w_i+b_i+h_i+a_i+n_i} w_i$, and the exposure index of blacks to whites is calculated as $100 \times \frac{1}{B} \sum_{i=1}^{N} \frac{w_i}{w_i+b_i+h_i+a_i+n_i} b_i$.[12] The scale of the exposure indexes is 0–100, with a higher value indicating that students are more exposed to other races. The white-black dissimilarity index is calculated as $100 \times \frac{1}{2} \sum_{i=1}^{N} \left| \frac{b_i}{B} - \frac{w_i}{W} \right|$. The scale of the dissimilarity index is 0–100, with a lower value indicating that students are distributed across colleges more evenly.

Consistent with earlier work, such as Antman and Duncan (2015), I code the timing of affirmative action bans based on the year an affirmative action ban first applied to public universities statewide. Table 1 shows the timing of these bans. I drop observations from Alabama, Georgia, Louisiana, and Mississippi. These states do not have outright affirmative action bans but have been subject to important litigation that has resulted in an uncertain legal situation surrounding

[11] A "first-time" student is one who is attending college for the first time. Loosely, these are college freshmen. Transfer students are not included in this category.

[12] The exposure indexes use the count of members of all races in the denominator. Although not shown in this paper, the general pattern of results is unchanged when limiting the denominator to whites and blacks.

Table 1: Timing of Affirmative Action Bans

State	Years with Ban for Fall Admission Cycle
Texas	1997-2004
California	1998-
Washington	1999-
Florida	2001-
Michigan	2007-
Nebraska	2009-
Arizona	2011-
New Hampshire	2012-
Oklahoma	2013-

affirmative action.[13]

3 Effects on Demographic Compositions of Universities

Before turning to the main segregation results in the next section, I consider the effects of affirmative action bans on the demographic composition of universities of various selectivity levels between 1995 and 2016. A large portion of the research on affirmative action bans has focused on California, Florida, Texas, and Washington, all of which banned affirmative action early. However, several other states have banned affirmative action more recently, including Arizona, Michigan, Nebraska, New Hampshire, and Oklahoma. The effects on college demographics of these more recent bans may differ from the effects of the earlier bans studied in earlier research. Moreover, understanding the effects of these recent affirmative action bans on the demographic composition of universities may aid in interpreting the segregation results I present later.

The demographic composition models I estimate take the form

$$enrollmentshare_{ist} = ban_{st}\alpha + \mu_i + \delta_t + \eta_s t + \epsilon_{ist}. \tag{1}$$

Here $enrollmentshare_{ist}$ denotes the percentage of students at institution i in state s in year t who are of a particular race (such as Asian, black, or white), ban_{st} is a dummy variable for whether state s has an affirmative action ban in effect in year t, μ_i refers to a full set of institution dummies, δ_t refers to a full set of year dummies, $\eta_s t$ denotes a full set of state-specific linear time trends, ϵ_{ist} is the error term, and α is the parameter of interest. The regressions are weighted by total

[13] There are also some cases of particular universities voluntarily discontinuing affirmative action before a statewide affirmative action ban went into place. For example, Florida State University discontinued affirmative action one year before the University of Florida did, and Texas A&M University discontinued affirmative action one year before the University of Texas did. The results are robust to changing the timing of the bans in Florida and Texas.

enrollment across all racial groups at the institution-by-year level, and I show standard errors that are robust to clustering at the state level. The models are similar to those in Hinrichs (2012), which used data only from 1995–2003. Here I expand the sample to 1995–2016. In addition to showing results for the full sample of four-year institutions, I show results for various subsamples, including public institutions, the 115 institutions in the top two tiers of the 1995 *U.S. News & World Report* college ranking, and the top 50 institutions in the *U.S. News* ranking.[14]

The top panel of Table 2 shows results for the entire 1995–2016 time period. According to these results, affirmative action bans are associated with declining black, Hispanic, and Native American representation and increasing Asian and white representation, especially at the most selective institutions. For example, over this time period, affirmative action bans were associated with a 0.79 percentage point decline in the black share of the first-year class, a 3.82 percentage point decline in the Hispanic share, a 0.40 percentage point decline in the Native American share, a 3.67 percentage point increase in the Asian share, and a 1.34 percentage point increase in the white share at public universities that were ranked within the top 50 of the 1995 *U.S. News & World Report* college ranking.

Comparing the middle panel of Table 2, which shows results for 1995–2003, to the bottom panel, which shows results for 2004–2016, reveals some similarities and some differences over time.[15] The results are similar in showing that affirmative action bans have statistically significant effects on the racial composition of institutions within the top 50 of the *U.S. News* ranking. For example, more recent affirmative action bans are associated with a highly statistically significant 1.29 percentage point reduction in the share of students who are black and a highly statistically significant 1.79 percentage point reduction in the share of students who are Hispanic at public universities within the top 50, which are similar to the corresponding statistically significant reductions of 1.83 and 2.01 percentage points in the earlier time period. However, the results in the two time periods differ in that statistically significant effects appear in the "top two tiers" subsample only in the earlier time period, a result that suggests there may be treatment effect heterogeneity even within this subsample. For example, I find that affirmative action bans are associated with statistically insignificant declines of 0.42 percentage points in black enrollment and 0.33 percentage points in Hispanic enrollment in the later time period, compared to larger and statistically significant declines of 1.22 percentage points in black enrollment and 1.26 percentage points in Hispanic enrollment in the earlier time period.[16]

[14] Table A1 in the appendix shows summary statistics.

[15] The results for 1995–2003 are similar, although not exactly identical, to the results presented in Hinrichs (2012). Hinrichs (2012) used a balanced panel of colleges and also excluded colleges in Michigan from the analysis.

[16] I have conducted two additional analyses that are not shown here. First, I have estimated effects on the universities that are in the top two tiers of the *U.S. News* ranking but not in the top 50. I find little effect on these

Table 2: Effects of Affirmative Action Bans on Representation by Race

	Type of Institution					
Variable	Four-Year	Public Four-Year	*U.S. News* Top Two Tiers	Public *U.S. News* Top Two Tiers	*U.S. News* Top 50	Public *U.S. News* Top 50
			A. 1995-2016			
% Asian	0.29	0.47	1.28	1.57	3.04**	3.67*
	(0.31)	(0.43)	(0.76)	(0.94)	(1.26)	(1.67)
% Black	0.29	0.09	−0.40	−0.47	−0.58	−0.79
	(0.21)	(0.14)	(0.27)	(0.35)	(0.45)	(0.60)
% Hispanic	−1.47	−1.57	−2.15***	−2.27**	−3.52***	−3.82**
	(0.92)	(1.13)	(0.77)	(0.96)	(1.19)	(1.43)
% Native Am.	−0.18	−0.23	−0.11**	−0.14*	−0.33***	−0.40***
	(0.13)	(0.16)	(0.05)	(0.08)	(0.08)	(0.10)
% White	1.06	1.24	1.39*	1.31	1.39	1.34
	(0.64)	(0.79)	(0.79)	(0.98)	(1.07)	(1.38)
N	45,534	11,971	2,417	1,210	1,034	330
			B. 1995-2003			
% Asian	0.31	0.50	0.50**	0.87**	0.76*	1.35
	(0.26)	(0.41)	(0.21)	(0.43)	(0.41)	(0.76)
% Black	−0.31	−0.38	−1.03***	−1.22***	−1.71**	−1.83*
	(0.29)	(0.40)	(0.24)	(0.31)	(0.71)	(0.86)
% Hispanic	−0.70	−0.62	−1.12**	−1.26*	−1.81***	−2.01**
	(0.44)	(0.47)	(0.53)	(0.69)	(0.56)	(0.71)
% Native Am.	−0.08	−0.11*	−0.12	−0.14	−0.39**	−0.48***
	(0.05)	(0.06)	(0.09)	(0.11)	(0.14)	(0.12)
% White	0.77*	0.60*	1.77***	1.74**	3.14***	2.97**
	(0.40)	(0.33)	(0.39)	(0.67)	(0.69)	(0.96)
N	16,583	4,551	990	495	423	135
			C. 2004-2016			
% Asian	−0.23**	−0.23**	0.07	0.09	−1.37***	−1.07
	(0.11)	(0.10)	(0.64)	(0.58)	(0.39)	(0.73)
% Black	0.27	−0.12	−0.37	−0.42	−1.03***	−1.29***
	(0.44)	(0.44)	(0.29)	(0.30)	(0.26)	(0.34)
% Hispanic	0.06	0.24	−0.35	−0.33	−1.81***	−1.79***
	(0.20)	(0.22)	(0.36)	(0.43)	(0.25)	(0.46)
% Native Am.	−0.04	−0.04	−0.08	−0.07	−0.41***	−0.44***
	(0.08)	(0.07)	(0.07)	(0.07)	(0.06)	(0.09)
% White	−0.06	0.15	0.73	0.72	4.62***	4.59***
	(0.36)	(0.20)	(1.23)	(1.24)	(0.36)	(0.92)
N	28,951	7,420	1,427	715	611	195

Notes: The table shows estimates of equation 1 at the institution-by-year level. Regressions weight by total enrollment. Each cell corresponds to a separate regression and shows the coefficient on the affirmative action ban dummy variable, along with (in parentheses) standard errors that are robust to clustering at the state level. A single asterisk denotes statistical significance at the 10% level, a double asterisk at the 5% level, and a triple asterisk at the 1% level.

4 Effects on Racial Segregation

4.1 Theoretical Considerations

The effect of affirmative action on racial segregation across colleges is theoretically ambiguous. Holding the behavior of other colleges fixed, it is reasonable to assume that minority representation will be lower at a selective college if that college does not use affirmative action.[17] However, if affirmative action were prohibited for all colleges in a state, there might be complex responses by students and colleges that influence segregation in differing directions but that cannot be predicted *ex ante*.

One possibility is that affirmative action bans could lead to an increase in segregation across colleges as a result of minority students being displaced from selective institutions. A second possibility, though, is that minority students who are displaced as a result of affirmative action bans cascade down to mid-level institutions that would have had very low minority representation if affirmative action were in place, resulting in a reduction in racial segregation.[18] A third possibility is that there is no overall effect of affirmative action bans on racial segregation. This could happen if, for example, movements of students from one college to another that increase segregation are offset by other movements that decrease segregation. All in all, depending on the exact way students are matched to colleges with and without an affirmative action ban, an affirmative action ban could increase, decrease, or have no net effect on racial segregation across colleges. It is ultimately an empirical issue.

Moreover, the effects of affirmative action bans on racial segregation are not implied by the results of earlier research on the effects of affirmative action bans on the racial composition of colleges by broad selectivity tier, such as Backes (2012), Hinrichs (2012), Naven (2017), and Section 3 of this paper. One way to see that the two analyses are different is to see that studying segregation inherently has stronger data requirements than studying racial composition. Calculat-

institutions on average, although it is worth noting that the synthetic control case study in Hinrichs (2012) found an increase in underrepresented minority enrollment at UC Irvine, and UC Riverside, UC Santa Barbara, and UC Santa Cruz after California's affirmative action ban. Second, I have estimated effects on private institutions. The empirical results are somewhat unclear. Underrepresented minority students displaced from public universities as a result of affirmative action bans may attend private universities instead, but those who would have attended a private institution may leave the state entirely because they perceive a hostile atmosphere. It is even possible that some underrepresented minority students shift from a private to a public institution because attending a public institution that does not use affirmative action sends a stronger signal of ability.

[17] One complication is that discontinuing affirmative action may lead to behavioral responses from students that impact colleges' application quantities or admissions yields. Research on affirmative action and application behavior finds mixed results (Antonovics and Backes, 2013; Card and Krueger, 2005; Long, 2004a). Antonovics and Sander (2013) find that California's affirmative action ban actually increased the yield for minority students.

[18] This second possibility is plausible given the U-shaped relationship between college selectivity and underrepresented minority share found by Arcidiacono et al. (2011), Arcidiacono et al. (2016), and Reardon et al. (2012).

ing segregation indexes between blacks and whites requires knowing how many blacks and whites attend each college. Knowing the overall percentage of students at selective institutions who are black is not sufficient. In contrast, knowing the black share at selective institutions is sufficient for estimating the impact on demographic composition. One could simply estimate a model with this variable on the left-hand side and an affirmative action ban dummy variable on the right-hand side. Notably, this averaging of racial compositions across institutions could potentially obscure even a high degree of segregation.[19] A second way to see that studying segregation is different from studying demographic composition is to consider hypothetical scenarios in which the two analyses would give differing results. For example, if affirmative action bans reshuffle students within a broad selectivity tier (e.g., the top 50 institutions in the *U.S. News* ranking) but do not cause much movement across tiers, there could be large segregation impacts despite only a minimal effect on demographic composition by broad selectivity tier.

4.2 Empirical Methods

In order to study the effects of affirmative action bans on racial segregation across colleges empirically, I estimate regression models of the following form:

$$segregation_{st} = ban_{st}\alpha + \mu_s + \delta_t + \eta_s t + \epsilon_{st}. \tag{2}$$

Here $segregation_{st}$ is a segregation index for state s in year t, ban_{st} is a dummy variable indicating whether state s has an affirmative action ban in effect in year t, μ_s refers to a full set of state dummies, δ_t refers to a full set of year dummies, $\eta_s t$ denotes a full set of state-specific linear time trends, ϵ_{st} is the error term, and α is the parameter of interest. The regressions for white exposure to blacks are weighted by the number of whites, the regressions for black exposure to whites are weighted by the number of blacks, the regressions for black-white dissimilarity are weighted by the sum of white enrollment and black enrollment, and I show standard errors that are robust to clustering at the state level. The models I estimate are similar to those estimated in earlier research on affimative action bans, including Antman and Duncan (2015), Backes (2012), Blume and Long (2014), Hill (2017), Hinrichs (2012, 2014), and Naven (2017).

The inclusion of state-specific linear time trends may help reduce bias from different states having different underlying segregation trajectories due to differing demographics or other reasons.[20] The identifying assumption is that, after accounting for state-specific linear time trends,

[19] To consider an extreme example, suppose that there are only two institutions, one of which enrolls 1000 blacks and 0 whites and the other of which enrolls 0 blacks and 1000 whites. Under this scenario, overall black representation is fairly high (50%), even though the colleges are completely segregated.

[20] Some graphical evidence in support of including time trends comes from Figure 2 later in the paper, which shows

segregation levels in treated and untreated states would follow parallel time paths in the absence of the treatment. This assumption is not directly verifiable, but earlier research has generally found support for the exogeneity of affirmative action bans.[21] As a further test of whether there are pre-existing differential trends that imperil the identification strategy, I show "event study" estimates that replace the single affirmative action ban variable with a set of variables indicating whether a ban was enacted a specified number of years in the past or whether one will be enacted a specified number of years in the future. Examining the coefficients on the variables indicating a future affirmative action ban provides some information about whether states that ban affirmative action show a similar pre-ban segregation trajectory as those that do not.

Three additional points about the data and models are in order. First, when estimating impacts on racial segregation, I do not disaggregate by selectivity. Segregation indexes are calculated across universities, and most states are home to only a few — in many cases 0 or 1 — selective institutions. Calculating segregation indexes across such a small number of institutions is of limited value.[22] Second, I show results for four-year institutions rather than including two-year or less-than-two-year institutions, with the goal of focusing on institutions that are potentially affected — either directly or indirectly — by affirmative action bans.[23] Third, I treat states as their own markets and generally ignore cross-state effects.[24] The estimates give impacts for colleges in a state and do not directly show impacts on residents (e.g., recent high school graduates) of a state.

Table 3 shows summary statistics for the samples used in the racial segregation regressions.[25]

a fairly smooth linear trend in black exposure to whites for California. However, the inclusion of time trends may induce bias if the treatment variable induces a dynamic adjustment process (Wolfers, 2006). Also, there is a risk that including time trends will lead to unstable or imprecise results, especially in regressions that use only a subset of the available years.

[21] Blume and Long (2014) find that the SAT/ACT and National Assessment of Educational Progress (NAEP) test score gaps between underrepresented minority students and others evolve similarly in ban states and nonban states. Backes (2012) finds that bans coming several years in the future are not predictive of minority enrollment at public universities, especially when time trends are included. Antman and Duncan (2015) also generally find that future affirmative action bans are not predictive of future outcomes. Naven (2017) shows the results of falsification tests using two types of institutions that arguably should not be impacted very heavily by affirmative action bans (for-profit universities and public community colleges) and generally finds that there is not much of an effect on these institutions.

[22] However, even in a state with only one selective institution, it may be of interest to estimate the effects of the demographic composition of that institution. This is why I estimated results separately by selectivity in Section 3.

[23] Although not shown here, I do estimate segregation models that expand the sample to include two-year institutions and less-than-two-year institutions. The results are broadly similar when expanding the sample. However, point estimates are generally smaller with the expanded sample, especially when including less-than-two-year institutions.

[24] In results not shown here, I use data from the census and the American Community Survey to study whether affirmative action bans are associated with the propensity to attend an out-of-state college. I find little evidence of migration across state lines for blacks, Hispanics, or whites in response to affirmative action bans, which suggests that treating states as their own markets is a good first approximation when studying affirmative action bans.

[25] Table A1 shows that the overall percentage black for 1995–2016 is about 11% and the overall percentage white is about 70%. In contrast, Table 3 shows that white exposure to blacks is on the order of 8% and black exposure to whites is on the order of 49%. The disparity between the exposure indexes and the overall representation shows that students are not evenly distributed by race across colleges.

Table 3: Summary Statistics for Black-White Segregation Regressions

		Type of Institution	
Time Period	Variable	Four-Year	Public Four-Year
A. 1995-2016			
	W Exposure to B	7.75	7.55
		(3.53)	(3.83)
	B Exposure to W	49.13	49.80
		(16.84)	(18.59)
	B-W Dissimilarity	40.47	35.31
		(11.51)	(14.28)
	Affirmative Action Ban	0.14	0.16
		(0.35)	(0.36)
	N	1,034	1,034
B. 1995-2003			
	W Exposure to B	6.60	6.77
		(3.07)	(3.59)
	B Exposure to W	50.11	50.82
		(18.32)	(19.31)
	B-W Dissimilarity	40.59	36.34
		(12.54)	(14.95)
	Affirmative Action Ban	0.10	0.10
		(0.29)	(0.30)
	N	423	423
C. 2004-2016			
	W Exposure to B	8.47	8.02
		(3.60)	(3.90)
	B Exposure to W	48.67	49.29
		(16.10)	(18.22)
	B-W Dissimilarity	40.40	34.70
		(10.85)	(13.84)
	Affirmative Action Ban	0.17	0.19
		(0.38)	(0.39)
	N	611	611

Notes: The table shows means and standard deviations at the state-by-year level. Summary statistics for white exposure to blacks weight by the number of whites, summary statistics for black exposure to whites weight by the number of blacks, and summary statistics for the other variables weight by the sum of black enrollment and white enrollment. The variable measuring white exposure to blacks has one fewer observation in the 1995–2016 and 2004–2016 public four-year samples than the other variables due to there being no whites who were full-time, first-time, degree-seeking undergraduates in public universities in the District of Columbia in 2010.

The unit of observation is a state-year pair. The summary statistics, like the later regressions, are shown for the entire sample period and are also shown separately for 1995–2003 and 2004–2016. There are at least four reasons for separating the results by time period. First, the earlier period is the focus of prior work that examined other outcomes, and it may be useful to compare results across different outcomes over a common time period. Second, some might interpret the Supreme Court cases of 2003 as having changed or clarified the permissible behavior in the control states that do not have an affirmative action ban. Third, the states that banned affirmative action in 1995–2003 tend to be home to more highly selective public universities than those that banned affirmative action in 2004–2016, which suggests that there may be differeing impacts when affirmative action is banned. Fourth, the results in Section 3 show that effects on racial compositions of colleges may actually be different in the two time periods, and so it is plausible that effects on segregation may differ as well.

4.3 Results

Table 4 shows regression results for the effects of affirmative action bans on segregation between blacks and whites as measured by the index of white exposure to blacks, the index of black exposure to whites, and the black-white dissimilarity index. I show results with and without time trends and for different time periods. I also show segregation results for the full set of four-year institutions, as well as for the public subset.

Consider first the results for 1995–2016. According to the -0.37 coefficient for white exposure to blacks when excluding time trends, affirmative action bans are associated with the average white student attending a college that is 0.37 percentage points less black. For purposes of comparison, Table 3 shows that the average percentage black at the colleges of white students is 7.75. The coefficient increases in magnitude to -0.56 in the regression that includes time trends, which would correspond to the average white student attending a college that is 0.56 percentage points less black, but the coefficient is still statistically insignificant.

The 0.19 and -0.02 estimates for black exposure to whites are statistically insignificant and very small relative to the mean of 49.13, suggesting that black students are attending colleges with similar white shares regardless of whether an affirmative action ban is in place.[26]

[26]The results for white exposure to blacks sometimes differ in sign or statistical significance from the results for black exposure to whites. This is interesting in light of the fact that the formulas for the two indexes are quite similar to one another. One way in which they could change in opposite directions as a result of an affirmative action ban, though, would be if the affirmative action ban caused the total number of white students or the total number of black students to change. However, results from earlier research, including Hinrichs (2012), suggest that affirmative action bans do not affect overall college attendance rates. Moreover, the results discussed in footnote 24 do not give much evidence that affirmative action bans cause out-of-state migration either. But even with all of this in mind, it is not literally true that the number of white or black students in a state is completely unchanged from one year

Table 4: Effects of Affirmative Action Bans on Black-White Segregation

		Without Time Trends		With Time Trends	
			Public		Public
Time Period	Variable	Four-Year	Four-Year	Four-Year	Four-Year
A. 1995-2016					
	W Exposure to B	−0.37	−0.48**	−0.56	−0.14*
		(0.33)	(0.23)	(0.62)	(0.08)
	B Exposure to W	0.19	0.01	−0.02	−0.22
		(1.61)	(1.34)	(0.99)	(1.47)
	B-W Dissimilarity	2.12	2.43	0.80	0.91
		(2.10)	(1.75)	(1.04)	(1.16)
	N	1,034	1,034	1,034	1,034
B. 1995-2003					
	W Exposure to B	−0.10	−0.18	−0.13	−0.41**
		(0.34)	(0.29)	(0.10)	(0.17)
	B Exposure to W	1.60**	1.42	3.82**	3.16**
		(0.74)	(0.91)	(1.51)	(1.40)
	B-W Dissimilarity	−1.28	−0.85	−3.22***	−2.59**
		(0.82)	(1.19)	(1.03)	(0.97)
	N	423	423	423	423
C. 2004-2016					
	W Exposure to B	−0.97	−0.23	−0.35	−0.23
		(0.68)	(0.15)	(0.32)	(0.18)
	B Exposure to W	−2.56	−1.29	−3.55***	−4.39***
		(2.33)	(1.52)	(1.12)	(1.26)
	B-W Dissimilarity	3.26	2.05	4.31***	3.79***
		(2.53)	(1.64)	(0.83)	(1.36)
	N	611	611	611	611

Notes: The table shows regression estimates of equation 2 at the state-by-year level. Regressions for white exposure to blacks weight by the number of whites, regressions for black exposure to whites weight by the number of blacks, and regressions for black-white dissimilarity weight by the sum of black enrollment and white enrollment. Each cell corresponds to a separate regression and shows the coefficient on the affirmative action ban dummy variable, along with (in parentheses) standard errors that are robust to clustering at the state level. A single asterisk denotes statistical significance at the 10% level, a double asterisk at the 5% level, and a triple asterisk at the 1% level. Regressions involving white exposure to blacks have one fewer observation in the 1995–2016 and 2004–2016 public four-year samples than the other regressions in those samples due to there being no whites who were full-time, first-time, degree-seeking undergraduates in public universities in the District of Columbia in 2010.

The average black-white dissimilarity shown in Table 3 is 40.47, meaning that 40.47% of whites (or 40.47% of blacks) would need to move to a new college in order to achieve racial balance. The 2.12 coefficient for black-white dissimilarity in Table 4 suggests that the number of students who would need to move to a new college in order to achieve racial balance is about 2 percentage points higher with an affirmative action ban than without one. However, this coefficient is roughly equal to its standard error, and including time trends lowers the coefficient to 0.80.

All in all, the results in Table 4 suggest that there is not much evidence that affirmative action bans affect segregation on average. The results when focusing only on public institutions are similar to those for all institutions, although the −0.48 estimated effect for white exposure to blacks is significant at the 5% level.

A null segregation result is noteworthy: despite the consequences affirmative action bans may have on other outcomes, they will not necessarily result in greater segregation across colleges. However, a zero average effect could come about from a zero effect in every single state, or it could come about as an average of positive effects in some states but negative effects in others. Indeed, although the results in panel A of Table 4 point to a zero effect on average, the results in panels B and C suggest that there is heterogeneity. In particular, the results for black exposure to whites and for black-white dissimilarity suggest that the affirmative action bans of 1995–2003 are associated with less segregation, whereas the bans of 2004–2016 are associated with more segregation. The results without time trends are generally not statistically significant at conventional levels, even though the magnitudes point in this general direction. The 1995-2003 results suggest that affirmative action bans in that time period were associated with an increase in black exposure to whites of 1.60 percentage points (mean of 50.11) and a decline in black-white dissimilarity of 1.28 points (mean of 40.59). In contrast, the 2004–2016 results suggest a decrease in black exposure to whites of 2.56 (mean of 48.67) and an increase in black-white dissimilarity of 3.26 (mean of 40.40).[27] The inclusion

to the next, which raises the possibility that changes in the number of white college students in a state (or black college students in a state) still might be part of the reason for the difference in the results between black exposure to whites and white exposure to blacks. However, simulations suggest that it is possible for regression results to give differing results for these two indexes even if the number of white students and the number of black students are both completely unchanged, and even if every college retains the same number of students overall. If there are heterogeneous effects across states, this can result in one of the indexes rising while the other is falling.

[27] Although this paper primarily focuses on segregation between blacks and whites, Table A2 in the appendix shows summary statistics and Table A3 shows regression results for segregation between Hispanics and whites. Table A4 shows summary statistics and Table A5 shows regression results for segregation between underrepresented minority (black, Hispanic, or Native American) and other (Asian or white) students. The results in Table A3 for Hispanic-white segregation are broadly consistent with the results for black-white segregation in Table 4, although there are some differences. For example, fewer of the results for Hispanic-white segregation are statistically significant than the results for black-white segregation, and many of the magnitudes are smaller. There is also one case (exposure to whites at public four-year institutions with time trends included) in which the black-white and Hispanic-white results are both statistically significant but of opposite signs. The results in Table A5 are broadly consistent with the segregation results from Table 4. Although there are some cases in which a coefficient in Table A5 is statistically significant and the corresponding coefficient in Table 4 is not (or vice versa), there are no situations in which the two

of linear state-specific time trends makes the results larger in magnitude and highly statistically significant, but it is worth noting that the states that have banned affirmative action more recently generally have low black populations. In this situation, movements of a small number of students from one college to another can have large influences on the dissimilarity index.[28] One final point to make is that, in light of the fact that Table 2 shows little impact on the overall racial composition in both the four-year university and public four-year university samples, the changes in exposure observed in Table 4 are likely due to a reshuffling of students among colleges rather than a change in the overall demographic composition of college-going students in a state.

Figure 1 shows results from event studies that exclude the state-specific linear time trends and replace the single affirmative action ban dummy variable with a set of variables indicating whether an affirmative action ban went into effect in the current year, whether one will go into effect a particular number of years in the future, and whether one went into effect a particular number of years in the past. Specifically, I include eight variables that indicate 2, 3, or 4 years before a ban; the year of a ban; and 1, 2, 3, or 4 or more years after a ban. The excluded category is one year before a ban. In addition to showing how the effects of a policy evolve over time, estimating these models gives an indication of whether there are pre-existing differential time trends between treated and nontreated states.

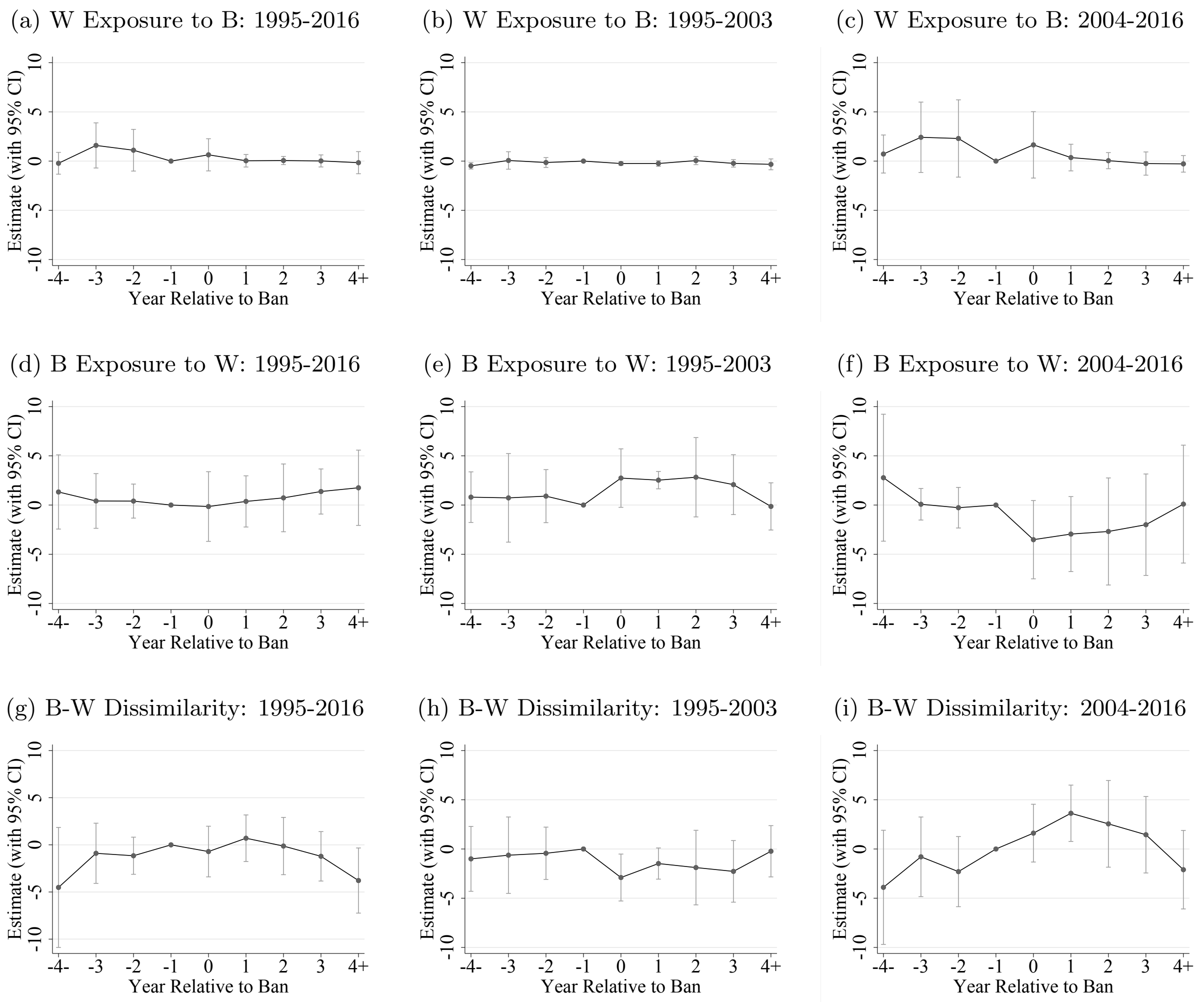
The three panels on the left of Figure 1, which show results for 1995–2016, do not show any dramatic changes from one year to the next. On these three panels, the coefficients on the variables representing two years before a ban (−2), three years before a ban (−3), and four or more years before a ban (−4−) are generally close to 0, and the confidence intervals all cover 0. Thus, there is not much evidence of pre-existing differential trends between ban states and nonban states. In addition, in these three panels, the coefficients on the year of a ban (0) and indicators for one, two, three, and four or more years after a ban are generally statistically insignificant and close to 0 as well. These results are consistent with the finding from Table 4 that affirmative action bans do not affect segregation on average.

The 1995–2003 and 2004–2016 results are noteworthy, however. The 1995–2003 results do not show much evidence of pre-existing differential trends, but they suggest a sharp increase in black exposure to whites and a sharp decline in black-white dissimilarity in the year of a ban. The exposure result is statistically significant at the 5% level, although the dissimilarity result is not.

coefficients are statistically significant with opposite signs.

[28] To consider one extreme hypothetical example, suppose there are only two colleges and only two black students. If the white students are evenly split between the two colleges and one black student attends each college, then the dissimilarity index is 0. But if one black student switches colleges, the dissimilarity index would be 50. Provided there are a large number of white students, though, the exposure indexes would not change as dramatically as the dissimilarity index does.

Figure 1: Segregation Event Studies



(a) W Exposure to B: 1995-2016

(b) W Exposure to B: 1995-2003

(c) W Exposure to B: 2004-2016

(d) B Exposure to W: 1995-2016

(e) B Exposure to W: 1995-2003

(f) B Exposure to W: 2004-2016

(g) B-W Dissimilarity: 1995-2016

(h) B-W Dissimilarity: 1995-2003

(i) B-W Dissimilarity: 2004-2016

The 2004–2016 results suggest a decline in black exposure to whites at the time of an affirmative action ban, although this is not statistically significant. The black-white dissimilarity results for 2004–2016 suggest an increase at the time of the ban, although in this case it appears to be the continuation of a trend that begins two years before the ban.

5 How Could Banning Affirmative Action Increase Segregation? A Case Study of California

The results of Section 4 suggest that it is possible for an affirmative action ban to actually reduce segregation. How could this happen? Two results from recent research, which I have alluded to earlier, provide a possible explanation. First, research on the enrollment effects of affirmative action bans finds that affirmative action bans redistribute black students from the most selective colleges to slightly less selective ones. Second, there is a U-shaped relationship between college quality and minority representation. In light of these two results, it is plausible that an affirmative action ban could decrease measured racial segregation as the U shape is flattened and the racial compositions of different universities become more similar to one another. However, it is not a foregone conclusion that the result will be less segregation even with the U shape. For example, segregation could rise if black students on the downward-sloping part of the U are pushed further to the left.

To explore the relationship between affirmative action bans and racial segregation in greater depth, I turn to a case study of California. I select California for this case study because it is a large and diverse state, is home to a variety of universities of varying selectivity levels, and is subject to an affirmative action ban. With these issues in mind, Figures 2 and 3 plot black exposure to whites and black-white dissimilarity across California universities from 1990 through 2016. Both of these graphs show a notable break in 1998, the first year of California's affirmative action ban. In the case of black exposure to whites, there is a clear downward trend over time but a large increase in 1998. In the case of black-white dissimilarity, there is not a clear trend over time, but the largest change from one year to the next is the decline from 1997 to 1998, the first year of California's affirmative action ban.

Figure 4 shows that California's public universities fit the U-shaped pattern described earlier. This figure plots the percentage black at California public universities in 1997 and 1998 against an SAT test score measure derived from the College Board's Annual Survey of Colleges, along with a quadratic fit.[29] There is a U shape in both years, but the U is flatter in 1998, the first year

[29] The data set provides the 25th and 75th percentiles of SAT verbal scores, as well as the 25th and 75th percentiles of SAT math scores. I average the 25th and 75th percentiles within each section and then take the sum. I match 1997 test scores with both the 1997 and 1998 race data, so the 1998 observation for a university falls either directly

Figure 2: Black Exposure to Whites for California Universities

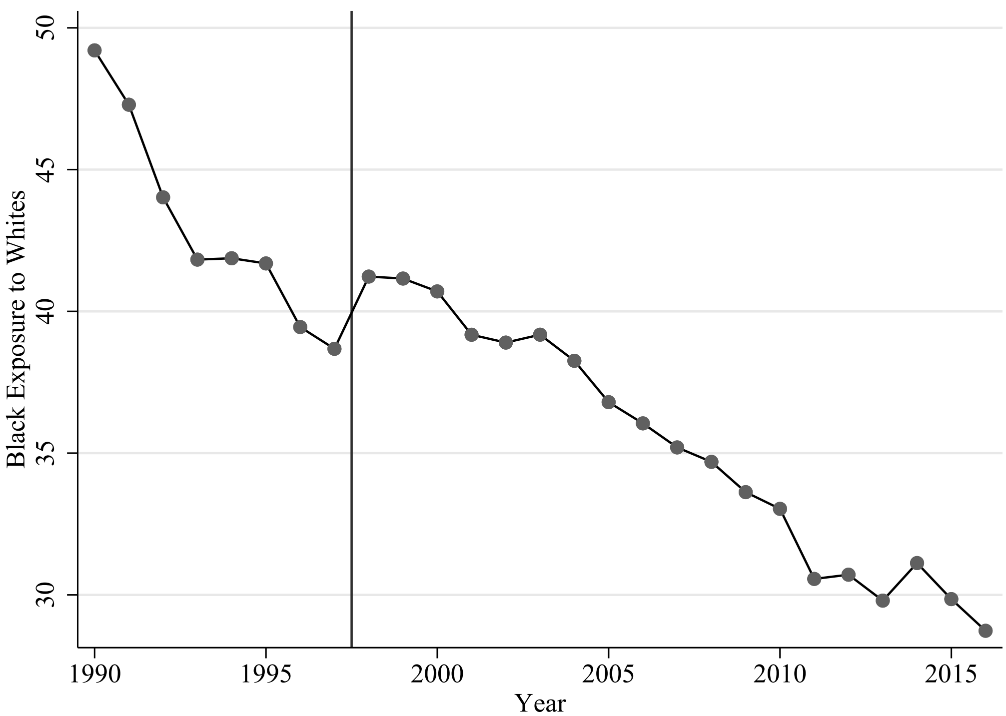


Figure 3: Black-White Dissimilarity for California Universities

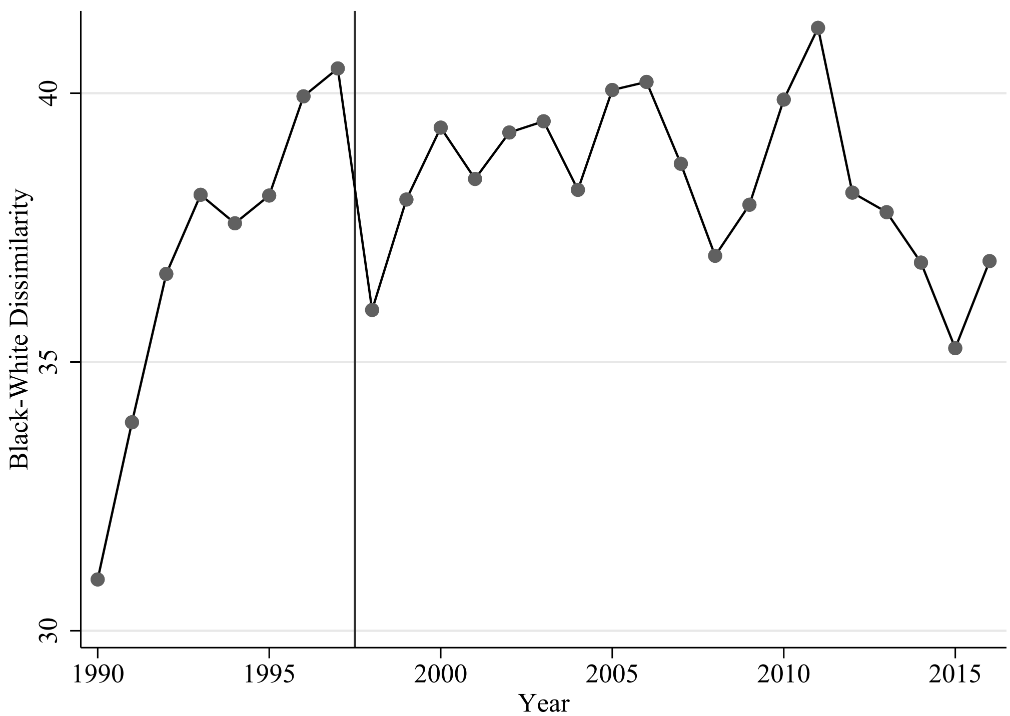
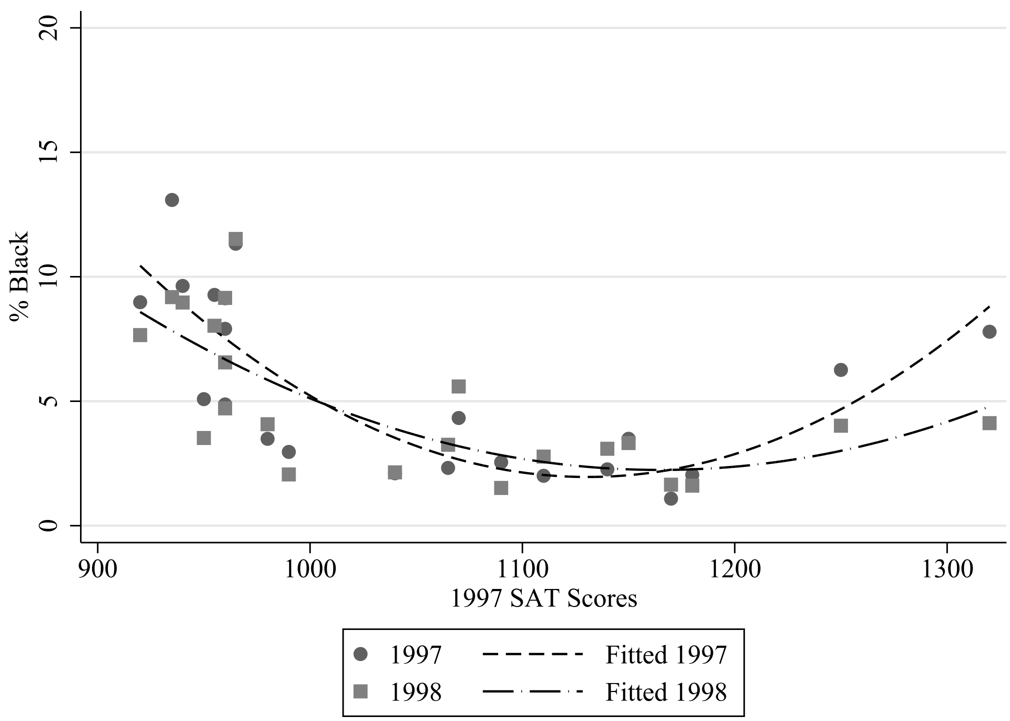


Figure 4: Percent Black at California Public Universities



of the affirmative action ban, than in 1997. A flattening of this U shape is consistent with lower black-white segregation.

What is the reason for the U-shaped relationship between college quality and minority share? One likely part of the explanation is that the affirmative action policies, and possibly the financial aid policies, used by the most selective institutions draw in minority students who would have otherwise attended moderately selective institutions.[30] Another likely part of the explanation is that the ensuing openings at moderately selective institutions are not filled by students from less selective institutions. On the institution side, Arcidiacono and Lovenheim (2016) point out that moderately selective institutions may have low minority shares because they do not use affirmative action very heavily. This could be because they are not under as much pressure to do so as highly selective institutions are, or it could be because moderately selective institutions are averse to reaching deeper and deeper into the ability distribution in order to recruit minority students. On the student side, Arcidiacono and Lovenheim (2016) point out that students from less selective institutions may not consider the possibility of attending moderately selective institutions due to a lack of information about these schools being a good fit.[31] Students may also believe, and perhaps incorrectly, that moderately selective institutions are more expensive to attend than less selective ones.[32] Whatever the reasons may be for low minority shares at moderately selective institutions, minority shares at these schools may then fall even further if future minority students are deterred from attending by the already low minority shares.

6 Conclusion

This paper provides the first estimates of the impact of affirmative action bans on racial segregation across colleges. The results suggest that affirmative action bans may increase segregation in some cases but reduce it in others. This result is noteworthy because it shows that increasing representation of disadvantaged groups and reducing segregation are not equivalent and may

above or directly below the 1997 observation in Figure 4.

[30] The overrepresentation of minority students at the very top compared to the middle could occur to some extent even with an affirmative action ban in place if, for example, there is either imperfect compliance with the ban or an effort to circumvent it. For example, policies in place in some states that result in automatic admission for students at the top of their high school class might result in a U shape between college quality and minority representation. In addition, Antonovics and Backes (2014a) present evidence suggesting that campuses of the University of California changed the weight given in admissions decisions to applicant characteristics in a way that increased minority admissions rates. Moreover, Luppino (2013) and Yagan (2016) find that admissions advantages for minority students did not disappear at the University of California after the affirmative action ban.

[31] Also see Hoxby and Avery (2013), who show that students of high ability but with low family incomes often do not apply to selective colleges.

[32] Although the relationship is not monotonic, Table 1 of Hoxby and Avery (2013) shows that out-of-pocket costs for students at the 20th percentile of family income are often lower at more selective institutions than at less selective ones.

actually sometimes be in conflict.[33] One explanation for why affirmative action bans can reduce segregation is related to the U-shaped relationship between college quality and percent minority, and the evidence discussed in Section 5 of this paper bolsters this interpretation in the case of California.

A full cost-benefit analysis of affirmative action is beyond the scope of this paper. However, the results of this paper have shown that, even if there are benefits to diversity at one college, this alone is not necessarily a point in favor of affirmative action because one college's gain in diversity may be another college's loss. In order to make a compelling case one way or the other, it would be necessary to know the impacts of diversity as well as the impact of affirmative action on diversity across colleges, which can be measured by segregation indexes. One caveat, though, is that the impacts of diversity may vary by college quality. On the one hand, if there are beneficial effects to diversity and these benefits are larger at more selective colleges, this in itself could be a point in favor of affirmative action. This could be true if, for example, selective institutions are a training ground for future leaders and it is especially important to expose such individuals to a diverse group of peers while in college. On the other hand, there may be beneficial effects of diversity, but these benefits may be larger at less selective colleges. For example, racial diversity may reduce prejudicial attitudes about race, but students at more selective institutions may already have less prejudicial attitudes than those at less selective institutions, or they may have access to other opportunities to reduce these prejudicial attitudes. Ultimately, I know of no existing research that estimates effects of the interaction between diversity and college quality on social outcomes for nonminorities.[34]

There are a number of other considerations that would need to be taken into account in a full cost-benefit analysis. One additional consideration is that affirmative action bans displace minorities from highly selective universities, and there is evidence suggesting that the return to attending a selective college is higher for members of minority groups (e.g., Daniel et al. (2001) or Dale and Krueger (2014)). If this is true, it may be socially valuable to ration the scarce slots

[33] Some additional evidence on this general point comes from research on the impact of affirmative action on cross-racial interaction within colleges. Arcidiacono et al. (2013) and Arcidiacono et al. (2011) have found that students are more likely to interact with college peers who have an academic background that is similar to their own. The use of affirmative action may thus result in less cross-racial interaction if it widens the disparity in academic backgrounds between white students and minority students within colleges. Also see Carrell et al. (2016), who find that white male students at the U.S. Air Force Academy are more likely to be roommates with black students in the future when the black students in their squadron score higher on an academic composite index.

[34] There are large challenges even in estimating the main effect of diversity at the college level. Arcidiacono and Vigdor (2010), Daniel et al. (2001), and Hinrichs (2011) have all done so and have found mixed results, although there may be concern about selection bias. Affirmative action bans may be useful for identifying the effects of diversity, but they likely also change the ability level of the student body and so cannot necessarily be used to identify the effects of diversity net of ability. Studies based on random roommate assignments have strong internal validity for estimating the effects of roommates, but they do not necessarily have strong external validity for estimating the effects of changing the diversity level of an entire college.

in selective colleges in favor of minority groups. On the other hand, other evidence suggests that there is "minority mismatch," meaning that some minority students would be better off attending a less selective college compared to a more selective one (Arcidiacono and Lovenheim, 2016). Other important issues to consider include the effects of affirmative action on minority enrollment (Arcidiacono, 2005; Arcidiacono et al., 2014; Backes, 2012; Hinrichs, 2012; Howell, 2010; Long, 2004b; Naven, 2017), pre-college human capital investment (Antonovics and Backes, 2014b; Hickman, 2013), major choice (Arcidiacono et al., 2016, 2012; Hill, 2017), longer-run outcomes such as educational attainment and earnings (Arcidiacono, 2005; Arcidiacono et al., 2016, 2014; Hinrichs, 2014), and cross-racial interaction (Arcidiacono et al., 2013, 2011). Also relevant are the effects of cross-racial interaction on attitudes and on friendship groups (Baker et al., 2011; Boisjoly et al., 2006; Camargo et al., 2010; Carrell et al., 2016).[35]

Finally, even if banning affirmative action can reduce racial segregation, this is not to say that such a ban would be the preferred means of doing so. If there is a goal to reduce segregation across colleges, arguably a better way to do this is to reduce the overrepresentation of minority students at the bottom of the college quality spectrum by increasing application flows to moderately selective colleges, perhaps through an information intervention like the one in Hoxby and Turner (2013). In contrast, affirmative action bans sometimes displace minority students from the top of the college quality spectrum. Regardless, banning affirmative action is a policy that a number of states have already implemented, and it is conceivable that there will be more affirmative action bans in the future. Although at first glance it may seem clear that banning affirmative action will exacerbate segregation, the results of this paper suggest that the effects of these bans are not always as they may initially seem.

[35] Additional areas of research that are relevant to the affirmative action debate include the more general bodies of research on college quality (Black and Smith, 2004, 2006; Dale and Krueger, 2002, 2014; Hoekstra, 2009; Long, 2008, 2010; Zimmerman, 2014) and on peer effects in college (Foster, 2006; Sacerdote, 2001; Stinebrickner and Stinebrickner, 2006; Zimmerman, 2003).

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A Appendix Tables

Table A1: Summary Statistics for Representation by Race

	Type of Institution					
Variable	Four-Year	Public Four-Year	*U.S. News* Top Two Tiers	Public *U.S. News* Top Two Tiers	*U.S. News* Top 50	Public *U.S. News* Top 50
			A. 1995-2016			
% Asian	7.03	7.58	13.87	13.69	21.50	23.73
	(9.81)	(10.75)	(13.45)	(14.80)	(14.57)	(17.40)
% Black	11.10	10.53	5.77	5.66	6.27	5.67
	(16.28)	(15.63)	(3.16)	(3.23)	(3.02)	(3.25)
% Hispanic	10.70	11.49	8.88	8.71	9.80	10.10
	(14.37)	(15.82)	(7.14)	(7.76)	(5.78)	(6.60)
% Native Am.	0.84	0.93	0.46	0.44	0.48	0.42
	(3.29)	(3.61)	(0.47)	(0.41)	(0.52)	(0.38)
% White	70.33	69.48	71.01	71.49	61.96	60.08
	(23.98)	(24.80)	(17.99)	(19.41)	(17.60)	(20.49)
N	45,534	11,971	2,417	1,210	1,034	330
N (colleges)	3,083	653	110	55	47	15
			B. 1995-2003			
% Asian	6.43	6.80	12.43	12.20	19.27	21.41
	(9.55)	(10.53)	(13.18)	(14.59)	(14.35)	(17.41)
% Black	9.97	10.00	5.85	5.88	6.41	6.24
	(16.42)	(16.26)	(3.33)	(3.50)	(3.03)	(3.48)
% Hispanic	6.97	7.13	6.25	5.94	7.09	7.25
	(10.82)	(11.58)	(4.88)	(4.99)	(3.89)	(4.28)
% Native Am.	0.87	1.01	0.54	0.54	0.55	0.54
	(3.08)	(3.51)	(0.48)	(0.44)	(0.49)	(0.37)
% White	75.75	75.06	74.94	75.44	66.67	64.57
	(22.58)	(23.15)	(16.25)	(17.49)	(16.32)	(19.10)
N	16,583	4,551	990	495	423	135
N (colleges)	2,269	533	110	55	47	15
			C. 2004-2016			
% Asian	7.35	8.00	14.76	14.60	22.87	25.11
	(9.93)	(10.85)	(13.54)	(14.85)	(14.55)	(17.28)
% Black	11.72	10.81	5.73	5.53	6.18	5.33
	(16.16)	(15.27)	(3.04)	(3.04)	(3.01)	(3.06)
% Hispanic	12.75	13.86	10.51	10.40	11.47	11.79
	(15.61)	(17.24)	(7.80)	(8.62)	(6.11)	(7.15)
% Native Am.	0.83	0.88	0.41	0.38	0.43	0.36
	(3.40)	(3.66)	(0.45)	(0.38)	(0.52)	(0.37)
% White	67.35	66.45	68.59	69.09	59.05	57.41
	(24.21)	(25.14)	(18.58)	(20.12)	(17.74)	(20.86)
N	28,951	7,420	1,427	715	611	195
N (colleges)	2,806	643	110	55	47	15

Notes: The table shows means and standard deviations at the institution-by-year level. Summary statistics weight by total enrollment.

Table A2: Summary Statistics for Hispanic-White Segregation Regressions

		Type of Institution	
Time Period	Variable	Four-Year	Public Four-Year
A. 1995-2016			
	W Exposure to H	7.41	7.56
		(6.74)	(7.70)
	H Exposure to W	48.73	45.69
		(18.18)	(19.82)
	H-W Dissimilarity	29.49	25.88
		(10.70)	(13.12)
	Affirmative Action Ban	0.17	0.19
		(0.38)	(0.39)
	N	1,034	1,034
B. 1995-2003			
	W Exposure to H	5.04	4.97
		(4.80)	(5.36)
	H Exposure to W	54.76	52.35
		(16.53)	(18.30)
	H-W Dissimilarity	31.35	27.07
		(10.68)	(12.80)
	Affirmative Action Ban	0.11	0.12
		(0.32)	(0.33)
	N	423	423
C. 2004-2016			
	W Exposure to H	8.88	9.14
		(7.32)	(8.46)
	H Exposure to W	46.92	43.84
		(18.27)	(19.84)
	H-W Dissimilarity	28.43	25.22
		(10.57)	(13.25)
	Affirmative Action Ban	0.21	0.23
		(0.40)	(0.42)
	N	611	611

Notes: The table shows means and standard deviations at the state-by-year level. Summary statistics for white exposure to Hispanics weight by the number of whites, summary statistics for Hispanic exposure to whites weight by the number of Hispanics, and summary statistics for the other variables weight by the sum of Hispanic enrollment and white enrollment. The variable measuring white exposure to Hispanics has one fewer observation in the 1995–2016 and 2004–2016 public four-year samples than the other variables due to there being no whites who were full-time, first-time, degree-seeking undergraduates in public universities in the District of Columbia in 2010.

Table A3: Effects of Affirmative Action Bans on Hispanic-White Segregation

		Without Time Trends		With Time Trends	
			Public		Public
Time Period	Variable	Four-Year	Four-Year	Four-Year	Four-Year
A. 1995-2016					
	W Exposure to H	−0.51	−0.83	−0.79	−1.28*
		(1.52)	(1.69)	(0.68)	(0.65)
	H Exposure to W	−1.03	−1.35	−0.25	−1.27
		(1.82)	(1.60)	(2.39)	(2.94)
	H-W Dissimilarity	1.84	3.01	0.87	2.55
		(2.10)	(2.78)	(1.62)	(2.54)
	N	1,034	1,034	1,034	1,034
B. 1995-2003					
	W Exposure to H	0.18	0.10	−0.67	−0.66
		(0.30)	(0.42)	(0.48)	(0.56)
	H Exposure to W	−1.56	−2.37	1.04	0.56
		(1.90)	(2.28)	(0.97)	(1.37)
	H-W Dissimilarity	2.92**	4.10***	−0.70	−0.11
		(1.17)	(1.51)	(1.07)	(1.61)
	N	423	423	423	423
C. 2004-2016					
	W Exposure to H	−0.16	−0.77	0.09	−0.03
		(1.60)	(1.43)	(0.31)	(0.16)
	H Exposure to W	−0.02	−1.06	0.75	0.95**
		(0.79)	(1.16)	(0.86)	(0.42)
	H-W Dissimilarity	0.01	0.76	−0.94	−1.31
		(1.28)	(2.11)	(0.56)	(1.15)
	N	611	611	611	611

Notes: The table shows regression estimates of equation 2 at the state-by-year level. Regressions for white exposure to Hispanics weight by the number of whites, regressions for Hispanic exposure to whites weight by the number of Hispanics, and regressions for Hispanic-white dissimilarity weight by the sum of Hispanic enrollment and white enrollment. Each cell corresponds to a separate regression and shows the coefficient on the affirmative action ban dummy variable, along with (in parentheses) standard errors that are robust to clustering at the state level. A single asterisk denotes statistical significance at the 10% level, a double asterisk at the 5% level, and a triple asterisk at the 1% level. Regressions involving white exposure to Hispanics have one fewer observation in the 1995–2016 and 2004–2016 public four-year samples than the other regressions in those samples due to there being no whites who were full-time, first-time, degree-seeking undergraduates in public universities in the District of Columbia in 2010.

Table A4: Summary Statistics for Asian/White-Black/Hispanic/Native American Segregation Regressions

		Type of Institution	
Time Period	Variable	Four-Year	Public Four-Year
A. 1995-2016			
	A/W Exposure to B/H/NA	16.64	16.85
		(8.33)	(9.13)
	B/H/NA Exposure to A/W	56.86	56.60
		(15.65)	(16.94)
	B/H/NA-A/W Dissimilarity	33.57	30.35
		(11.12)	(13.13)
	Affirmative Action Ban	0.18	0.21
		(0.39)	(0.41)
	N	1,034	1,034
B. 1995-2003			
	A/W Exposure to B/H/NA	13.00	13.33
		(6.21)	(6.86)
	B/H/NA Exposure to A/W	60.00	60.17
		(16.37)	(17.02)
	B/H/NA-A/W Dissimilarity	34.56	31.37
		(12.30)	(14.19)
	Affirmative Action Ban	0.12	0.14
		(0.33)	(0.34)
	N	423	423
C. 2004-2016			
	A/W Exposure to B/H/NA	18.85	18.96
		(8.67)	(9.66)
	B/H/NA Exposure to A/W	55.65	55.23
		(15.19)	(16.71)
	B/H/NA-A/W Dissimilarity	33.03	29.80
		(10.39)	(12.50)
	Affirmative Action Ban	0.22	0.25
		(0.41)	(0.43)
	N	611	611

Notes: The table shows means and standard deviations at the state-by-year level. Summary statistics for Asian/white exposure to blacks/Hispanics/Native Americans weight by the number of Asians/whites, summary statistics for black/Hispanic/Native American exposure to Asians/whites weight by the number of blacks/Hispanics/Native Americans, and summary statistics for the other variables weight by total enrollment. The variable measuring Asian/white exposure to blacks/Hispanics/Native Americans has one fewer observation in the 1995–2016 and 2004–2016 public four-year samples than the other variables due to there being no Asians or whites who were full-time, first-time, degree-seeking undergraduates in public universities in the District of Columbia in 2010.

Table A5: Effects of Affirmative Action Bans on Asian/White-Black/Hispanic/Native American Segregation

		Without Time Trends		With Time Trends	
			Public		Public
Time Period	Variable	Four-Year	Four-Year	Four-Year	Four-Year
A. 1995-2016					
	A/W Exposure to B/H/NA	−1.20	−1.66	−1.83***	−2.11**
		(1.51)	(1.65)	(0.66)	(0.90)
	B/H/NA Exposure to A/W	−1.03	−1.43	0.79	0.44
		(1.69)	(1.64)	(1.33)	(1.90)
	B/H/NA-A/W Dissimilarity	2.45***	3.75***	1.06	1.88*
		(0.74)	(0.66)	(0.70)	(1.03)
	N	1,034	1,034	1,034	1,034
B. 1995-2003					
	A/W Exposure to B/H/NA	−0.31	−0.66	−1.01**	−1.41***
		(0.74)	(0.91)	(0.48)	(0.45)
	B/H/NA Exposure to A/W	−0.34	−0.63	2.71***	2.35**
		(0.63)	(1.16)	(0.92)	(1.10)
	B/H/NA-A/W Dissimilarity	0.76	1.40*	−1.12	−0.49
		(0.63)	(0.73)	(1.03)	(1.39)
	N	423	423	423	423
C. 2004-2016					
	A/W Exposure to B/H/NA	−1.79*	−1.84	−0.44**	−0.42
		(1.05)	(1.37)	(0.20)	(0.26)
	B/H/NA Exposure to A/W	−0.85	−0.90	−1.59***	−1.40***
		(1.55)	(1.66)	(0.48)	(0.43)
	B/H/NA-A/W Dissimilarity	2.06*	2.47*	2.94***	2.87**
		(1.07)	(1.30)	(0.65)	(1.15)
	N	611	611	611	611

Notes: The table shows regression estimates of equation 2 at the state-by-year level. Regressions for Asian/white exposure to blacks/Hispanics/Native Americans weight by the number of Asians/whites, regressions for black/Hispanic/Native American exposure to Asians/whites weight by the number of blacks/Hispanics/Native Americans, and regressions for the other variables weight by total enrollment. Each cell corresponds to a separate regression and shows the coefficient on the affirmative action ban dummy variable, along with (in parentheses) standard errors that are robust to clustering at the state level. A single asterisk denotes statistical significance at the 10% level, a double asterisk at the 5% level, and a triple asterisk at the 1% level. Regressions involving white exposure to blacks have one fewer observation in the 1995–2016 and 2004–2016 public four-year samples than the other regressions in those samples due to there being no whites who were full-time, first-time, degree-seeking undergraduates in public universities in the District of Columbia in 2010.