Affirmative Action and Racial Segregation

Peter Hinrichs *

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Abstract: Prior research suggests that statewide affirmative action bans reduce minority representation at selective colleges while leaving overall minority college enrollment unchanged. The effect of these bans on racial segregation across colleges, as measured by standard exposure and dissimilarity indexes, has not yet been estimated directly and is theoretically ambiguous due to a U-shaped relationship 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, finding that affirmative action bans have in some cases increased segregation across colleges but in other cases have actually reduced it. 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
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*Federal Reserve Bank of Cleveland. Mailing Address: PO Box 6387, Cleveland OH, 44101. E-mail: peter.hinrichs@clev.frb.org

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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).[2]

Meanwhile, the Supreme Court has ruled that colleges may practice affirmative action on the grounds that there are educational benefits to racial diversity.[3,4] 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, the Supreme Court has also referred to general societal benefits of diversity in a broader way that abstracts away from whether that diversity occurs at any specific higher education institution. For example, in reference to benefits from diversity, Justice O'Connor's 2003 majority opinion in *Grutter v. Bollinger* states, "These benefits are not theoretical but real, as major American businesses have made clear that the skills needed in today's increasingly global marketplace can only be developed through exposure to widely diverse people, cultures, ideas, and viewpoints."

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

[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) and Arcidiacono et al. (2015) for two recent reviews of research on affirmative action.

[3] 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. There have recently been lawsuits filed against Harvard and the University of North Carolina over affirmative action, and 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).

[4] Justice Sandra Day O'Connor's majority opinion from 2003 in the *Grutter v. Bollinger* case cites some evidence in support of this claim. 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.

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 documented by Arcidiacono et al. (2011), Arcidiacono et al. (2016), and Reardon et al. (2012), 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 slighly less selective institutions, thereby making the racial compositions of different institutions more similar to each other, the result could be a decline in segregation. 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.[5] I measure segregation using standard exposure and dissimilarity indexes at the state level. The exposure indexes measure potential exposure of the average member of one group to those 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. 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, which is noteworthy because it shows that a ban in affirmative action need not necessarily be accompanied by an increase in segregation.

I also estimate the effects separately for states that banned affirmative action earlier and more recently. 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. 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. Estimating

[5] 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) and Hinrichs (2012), 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.

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 the more recent affirmative action bans are associated with greater segregation across colleges on average. In contrast, affirmative action bans are associated with less segregation in the earlier time period.

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 considers the issue of migration to out-of-state colleges in response to affirmative action bans. Section 7 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 Education'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 2015 in order to construct segregation indexes at the state-by-year level.

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. Exposure indexes measure potential interaction between members of different racial groups: white exposure to blacks measures the percentage of students at the average white student's institution who are black, and black exposure to whites measures the percentage of students at the average black student's institution who are white. 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.

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-

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 $100 \times \frac{1}{B} \sum_{i=1}^{N} \frac{w_i}{w_i+b_i+h_i+a_i+n_i} b_i$.[6] 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 affirmative action.[7]

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 2015. A large portion of the research on affirmative action bans has focused on California, Florida, Texas, and Washington, which were all early to ban affirmative action.

[6] 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.

[7] 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.

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 by Backes (2012) and Hinrichs (2012). 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 time 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 are weighted by total 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 1995-2015. 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.[8]

The top panel of Table 2 shows results for the entire 1995-2015 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 0.88 percentage point decline in the black share of the first-year class, a 3.76 percentage point decline in the Hispanic share, a 0.40 percentage point decline in the Native American share, a 3.49 percentage point increase in the Asian share, and a 1.55 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 2004-2015, reveals some similarities and some differences over time.[9] The results are similar in showing that affirmative action bans have statistically significant effects on

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

[9]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.

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

Variable	Type of Institution 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. 1995-2015			
% Asian	0.26	0.43	1.14*	1.43*	2.85**	3.49**
	(0.28)	(0.40)	(0.65)	(0.84)	(1.13)	(1.54)
% Black	0.29	0.11	−0.41	−0.49	−0.63	−0.88
	(0.21)	(0.13)	(0.27)	(0.35)	(0.40)	(0.54)
% Hispanic	−1.44	−1.56	−2.08***	−2.20**	−3.42***	−3.76**
	(0.91)	(1.11)	(0.73)	(0.92)	(1.08)	(1.31)
% Native Am.	−0.17	−0.22	−0.11**	−0.14*	−0.34***	−0.40***
	(0.12)	(0.16)	(0.05)	(0.07)	(0.08)	(0.09)
% White	1.05	1.24	1.46*	1.40	1.53	1.55
	(0.66)	(0.80)	(0.79)	(0.99)	(1.00)	(1.26)
N	43,377	11,339	2,308	1,155	987	315
			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. 2004-2015			
% Asian	−0.14*	−0.13**	0.24	0.26	−0.96**	−0.58
	(0.08)	(0.06)	(0.56)	(0.49)	(0.35)	(0.73)
% Black	0.23	−0.13	−0.39	−0.46	−1.03***	−1.33***
	(0.43)	(0.43)	(0.30)	(0.30)	(0.28)	(0.38)
% Hispanic	0.10	0.27	−0.33	−0.30	−1.48***	−1.39***
	(0.23)	(0.26)	(0.23)	(0.28)	(0.30)	(0.41)
% Native Am.	−0.06	−0.04	−0.06	−0.05	−0.40***	−0.44***
	(0.09)	(0.09)	(0.08)	(0.08)	(0.06)	(0.10)
% White	−0.13	0.03	0.53	0.55	3.88***	3.74***
	(0.32)	(0.25)	(1.06)	(1.04)	(0.32)	(0.94)
N	26,794	6,788	1,318	660	564	180

Notes: Regressions are weighted by total enrollment. Standard errors that are robust to clustering at the state level are in parentheses. A single asterisk denotes statistical significance at the 10% level, a double asterisk denotes statistical significance at the 5% level, and a triple asterisk denotes statistical significance at the 1% level.

the racial composition of institutions within the top 50 of the *U.S. News* ranking. They differ in that statistically significant effects appear in the "top two tiers" subsample only in the earlier time period, a result which suggests there may be treatment effect heterogeneity even within this subsample.

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.[10] 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 institutions that would have had very low minority representation if affirmative action were in place, resulting in a reduction in racial segregation. 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). 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 racial composition of colleges by broad selectivity tier, such as Backes (2012), Hinrichs (2012), and Section 3 of this paper. One way to see that the two analyses are different is to see that studying segregation inherently

[10] 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.

has stronger data requirements than studying racial composition. Calculating 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.[11] 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 time 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), and Hinrichs (2012, 2014).

The inclusion of state-specific linear time trends may help reduce bias from different states having different underlying segregation trajectories due to demographic or other reasons.[12] The

[11]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.

[12]In contrast, the inclusion of time trends may induce bias if the treatment variable induces a dynamic adjustment

identifying assumption is that, after accounting for state-specific linear time trends, 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.[13] 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.[14] 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. Third, I treat states as their own markets and generally ignore cross-state effects. 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. However, I return to this issue in Section 6, in which I discuss migration across state lines in response to affirmative action bans.

Table 3 shows summary statistics for the samples used in the racial segregation regressions.[15] 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 2004-2015. There are at least three 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

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.

[13] 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 non-ban 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.

[14] 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.

[15] Table A1 shows that the overall percentage black for 1995-2015 is about 11% and the overall percentage white is about 71%. 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 50%. 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. 1995-2015			
	W Exposure to B	7.71	7.51
		(3.53)	(3.82)
	B Exposure to W	49.21	49.92
		(16.91)	(18.65)
	B-W Dissimilarity	40.59	35.39
		(11.58)	(14.39)
	Affirmative Action Ban	0.14	0.15
		(0.35)	(0.36)
	N	987	987
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. 2004-2015			
	W Exposure to B	8.46	8.00
		(3.62)	(3.90)
	B Exposure to W	48.75	49.42
		(16.14)	(18.28)
	B-W Dissimilarity	40.58	34.77
		(10.92)	(14.00)
	Affirmative Action Ban	0.17	0.19
		(0.38)	(0.39)
	N	564	564

Notes: The table shows means and standard deviations at the state-by-year level. Summary statistics for white exposure to blacks are weighted by the number of whites, summary statistics for black exposure to whites are weighted by the number of blacks, and summary statistics for the other variables are weighted by the sum of black enrollment and white enrollment. The variable measuring white exposure to blacks has one fewer observation in the 1995-2015 and 2004-2015 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.

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 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 1995-2015. These estimates are generally small in magnitude and statistically insignificant. For example, according to the estimates that exclude time trends, affirmative action bans are associated with the average white student attending a college that is 0.31 percentage points less black. This result for white exposure to blacks is statistically insignificant and of a modest size relative to the mean of 7.71 shown in Table 3. The coefficient increases in magnitude to -0.55 in the regression that includes time trends, but it is still statistically insignificant. The 0.15 and 0.01 estimates for black exposure to whites are statistically insignificant and very small relative to the mean of 49.21. The 2.02 coefficient on black-white dissimilarity is of a modest magnitude relative to the mean of 40.59, but it is equal to its standard error. Moreover, the inclusion of time trends lowers the coefficient to 0.78, and it is still not significant at conventional levels. The results when focusing only on public institutions are similar to those for all institutions, although the -0.47 estimated effect for white exposure to blacks manages to be significant at the 10% 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 may be 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 2004-2015 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

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. 1995-2015					
	W Exposure to B	−0.31	−0.47*	−0.55	−0.15
		(0.35)	(0.23)	(0.58)	(0.09)
	B Exposure to W	0.15	−0.03	0.01	−0.24
		(1.58)	(1.35)	(0.98)	(1.50)
	B-W Dissimilarity	2.02	2.28	0.78	0.87
		(2.02)	(1.75)	(1.03)	(1.21)
	N	987	987	987	987
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. 2004-2015					
	W Exposure to B	−0.87	−0.23	−0.37	−0.24
		(0.57)	(0.14)	(0.38)	(0.23)
	B Exposure to W	−2.59	−1.45	−3.72***	−4.91***
		(2.24)	(1.54)	(1.10)	(1.16)
	B-W Dissimilarity	3.16	1.89	4.52***	4.35***
		(2.43)	(1.63)	(0.79)	(1.45)
	N	564	564	564	564

Notes: 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, and the regressions for black-white dissimilarity are weighted by the sum of black enrollment and white enrollment. Standard errors that are robust to clustering at the state level are in parentheses. A single asterisk denotes statistical significance at the 10% level, a double asterisk denotes statistical significance at the 5% level, and a triple asterisk denotes statistical significance at the 1% level. Regressions involving white exposure to blacks have one fewer observation in the 1995-2015 and 2004-2015 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.

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 2004-2015 results suggest a decrease in black exposure to whites of 2.59 (mean of 48.75) and an increase in black-white dissimilarity of 3.16 (mean of 40.58).[16] The inclusion 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 segregation indexes.[17]

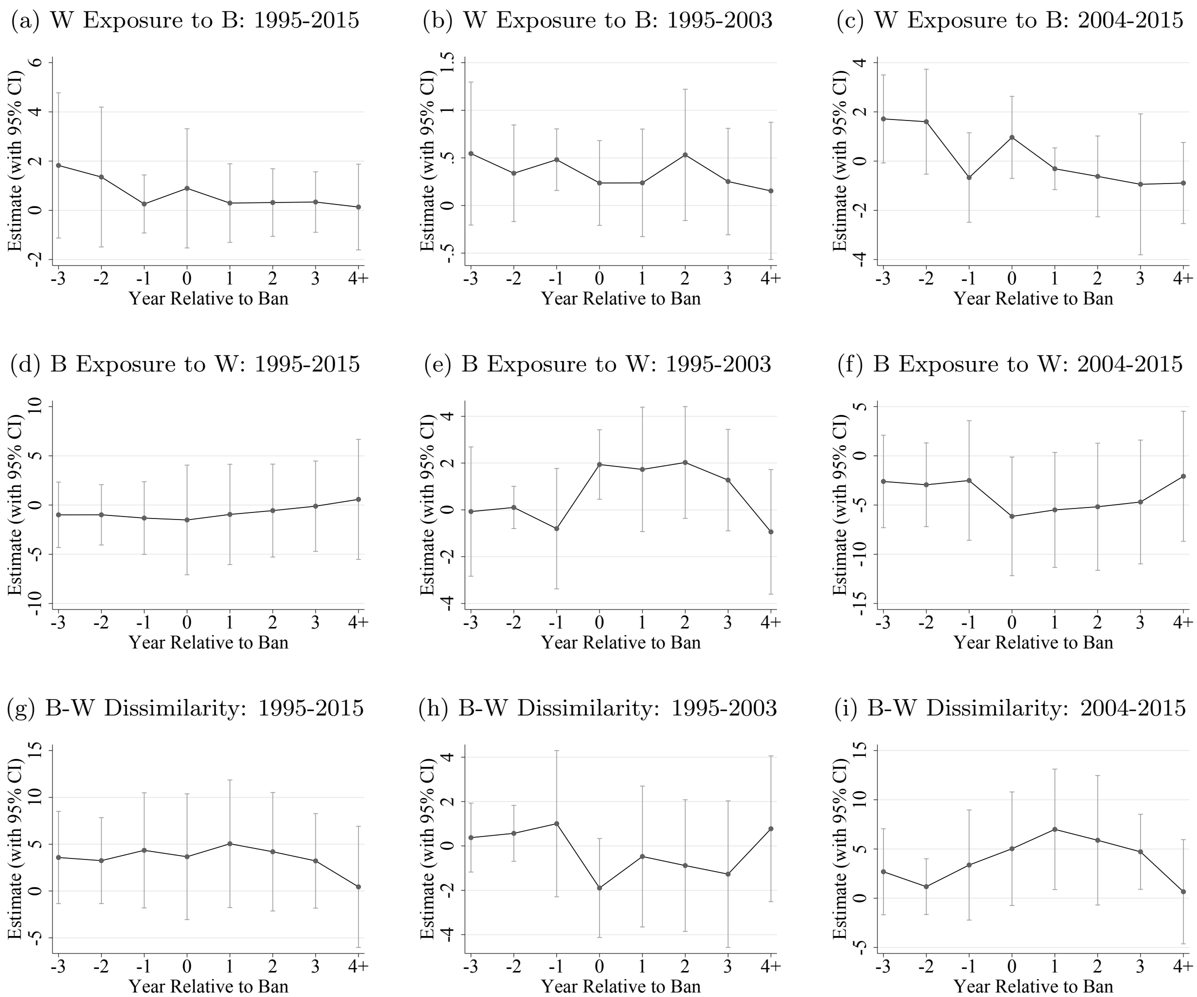
Figure 1 shows results from event studies that exclude the state-specific linear time trends and replace the single affirmative action ban dummy variable with a set of variables indicating whether an affirmative action ban went into effect in the current year, whether one will go into effect a particular 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 which indicate 1, 2, or 3 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 4 or more years 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 1995-2015, do not show any dramatic changes from one year to the next. There is not much evidence of pre-existing differential trends, but there is not much evidence of an effect after affirmative action bans are enacted either. The 1995-2003 and 2004-2015 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 manages to be statistically significant at the 5% level, although the dissimilarity result does not. The 2004-2015 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

[16] Although this paper primarily focuses on segregation between blacks and whites, Table A3 in the appendix shows summary statistics and Table A4 shows regression results for segregation between Hispanics and whites. The results are similar to the results for segregation between blacks and whites, although in the earlier time period, the results for black-white segregation and Hispanic-white segregation are in opposite directions if time trends are not used. If time trends are used, the results for Hispanic-white segregation change signs so that they are in the same direction as the results for black-white segregation, although the Hispanic-white results are generally of lower magnitude than the black-white results. In the later time period, the Hispanic-white results with time trends are in the opposite direction of the black-white results.

[17] 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.

Figure 1: Segregation Event Studies



(a) W Exposure to B: 1995-2015

(b) W Exposure to B: 1995-2003

(c) W Exposure to B: 2004-2015

(d) B Exposure to W: 1995-2015

(e) B Exposure to W: 1995-2003

(f) B Exposure to W: 2004-2015

(g) B-W Dissimilarity: 1995-2015

(h) B-W Dissimilarity: 1995-2003

(i) B-W Dissimilarity: 2004-2015

2004-2015 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.[18] 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 2015. 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

[18] 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 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* ranking 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.

Figure 2: Black Exposure to Whites for California Universities

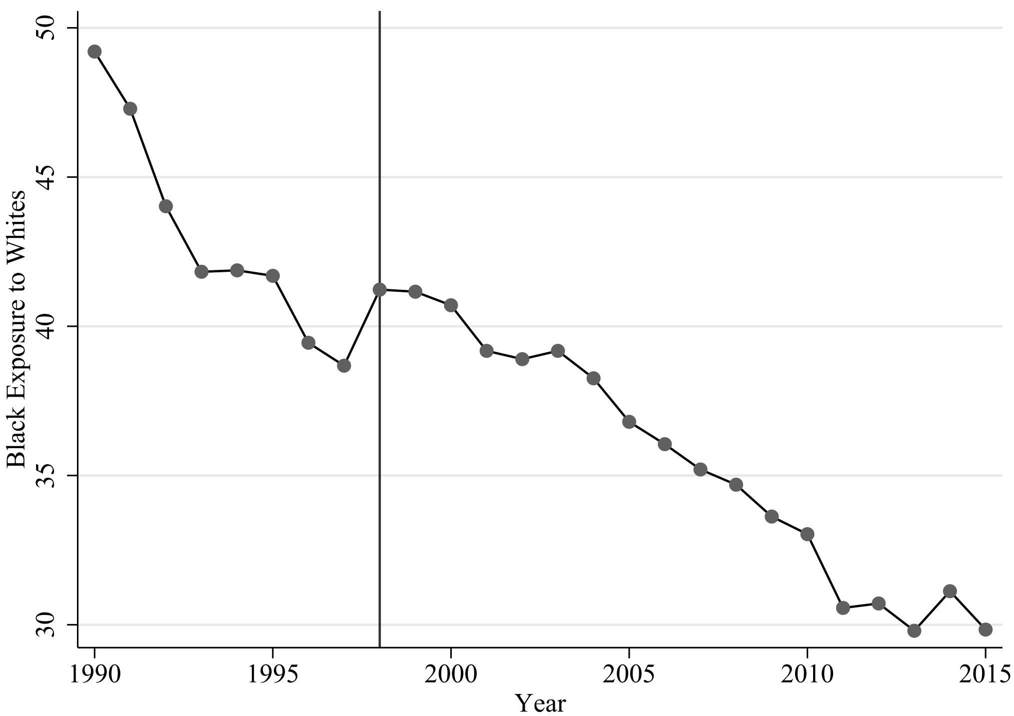


Figure 3: Black-White Dissimilarity for California Universities

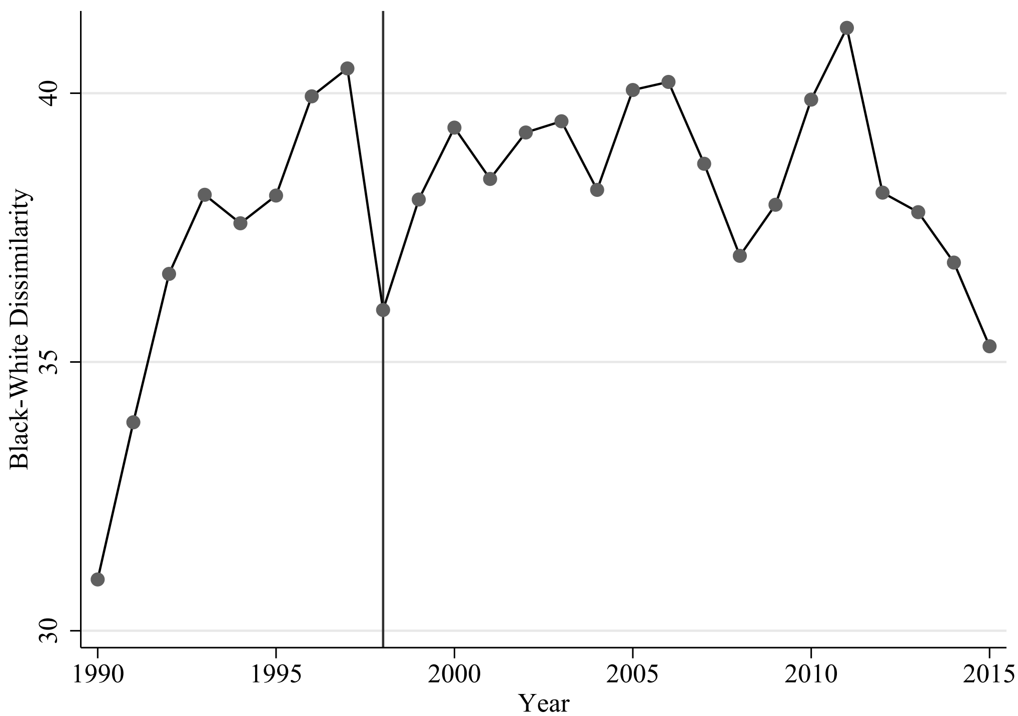
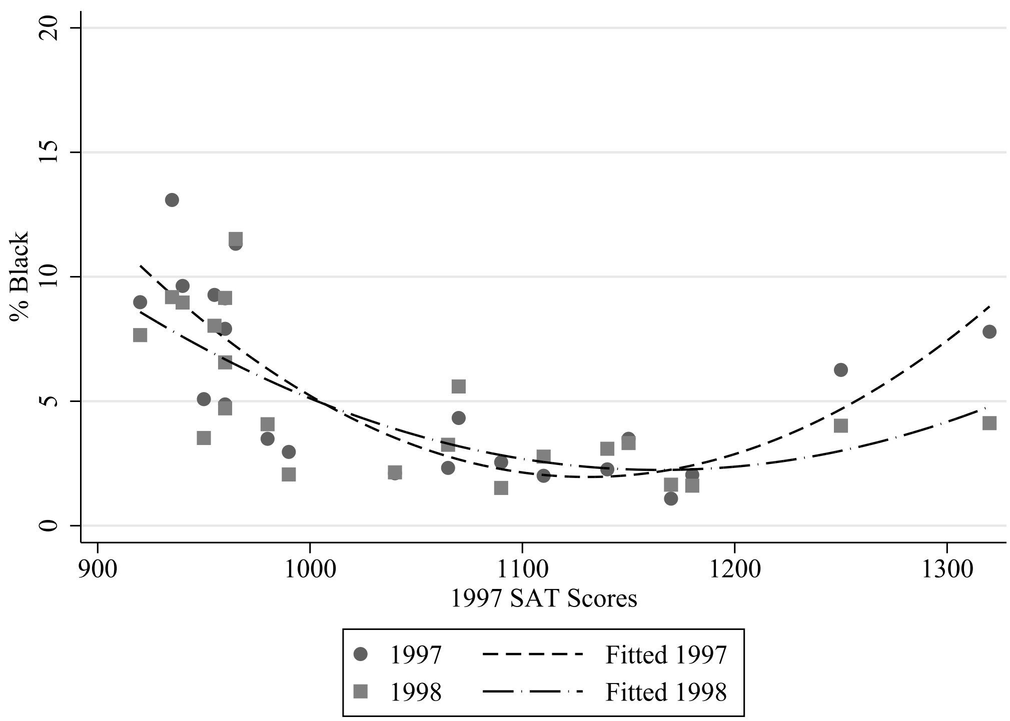


Figure 4: Percent Black at California Public Universities



a quadratic fit.[19] There is a U shape in both years, but the U is flatter in 1998, the first year 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.[20] 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.[21] Students may also believe, and perhaps incorrectly, that moderately selective institutions are more expensive to attend than less selective ones.[22] 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.

Although it is difficult to know the reason for the U-shaped relationship between percent minority and college quality, one piece of information that may provide support for some explanations and cast doubt on others is how the within-institution test score gap between blacks and whites varies across the college quality spectrum. Data breaking down standardized test scores by race for

[19] 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 above or directly below the 1997 observation in Figure 4.

[20] 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.

[21] 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.

[22] 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.

students at particular institutions are difficult to come by, although the limited evidence that exists suggests that the racial test score gap is smaller at the most selective institutions than at slightly less selective institutions.[23] Although there may be varying explanations for this phenomenon, it is consistent with the most selective institutions admitting a disproportionate share of minority students and then slightly less selective institutions reaching further and further down in the ability distribution to attract minority students.

6 What about Migration?

The segregation regressions in this paper show effects of affirmative action bans for the colleges within a state and the students attending those colleges. Racial segregation across a state's colleges may matter for later residential segregation, friendship group segregation, or political economy outcomes. But another issue that may be of interest is the effect of affirmative action bans on a state's current residents, such as high school seniors who are applying to college. In principle, it would be possible to estimate exposure effects for state residents with individual-level data on own race, state of residence, and college racial composition or with college-level data on race by state of residence.[24]

In the absence of a data set that include the necessary variables collected with the right timing to be able to credibly estimate impacts of affirmative action bans for current state residents, I instead turn to data from the decennial census (covering 1990 and 2000) and the American Community Survey (covering each year between 2001 and 2014) to estimate the impacts of affirmative action bans on migration to attend college in a different state. In addition to being of interest in their own right as estimates for an important outcome (migration) that has not yet been studied in the context of affirmative action, these estimates can give some indication of how much the effects of an affirmative action ban on state residents are likely to differ from the effects on students attending

[23] Herrnstein and Murray (1994) report data from the Consortium on Financing Higher Education, a consortium of selective institutions, showing SAT score gaps between blacks and whites for 24 selective private institutions for the entering classes of 1991 and 1992. The test score gap is generally lower at the most selective institutions on this list. For example, the lowest gap is at Harvard. Institutions such as MIT, Princeton, and the University of Pennsylvania also have relatively low gaps. The highest gaps are at institutions such as Rice, Rochester, Wesleyan, and Oberlin. Arcidiacono et al. (2014) show an academic index by race at the campuses of the University of California, and in that case the gap is the highest at the most selective and the least selective campuses. Arcidiacono et al. (2011) find a slightly higher SAT gap at the relatively less selective institutions in the College and Beyond Database, which includes a small set of selective institutions. But with all of this evidence in mind, one caveat is that SAT score gaps may give a misleading impression of racial achievement gaps at very selective institutions because they censor the true achievement level of high scoring students.

[24] In estimating effects of affirmative action bans on white exposure to blacks, for example, the outcome variable would be the average percent black at the colleges attended by a state's residents, regardless of whether the college is actually located in the state. Estimating dissimilarity effects on a state's residents would not be as straightforward due to the complication of defining dissimilarity among just a state's residents.

college in a state. For example, if affirmative action bans do not cause people to move to a new state for college, then studying impacts on segregation within the colleges in a state should be a good approximation for the impacts on state residents.[25] In contrast, if affirmative action bans do cause out-of-state migration, then effects on residents may differ from effects on those attending college in a state.

In using the American Community Survey (ACS) and census data, I am able to estimate migration effects separately by racial group. This is important because affirmative action bans could potentially cause inflows of one group but outflows of another that would not be detected in a migration analysis that combined students of different races.[26] In particular, blacks, Hispanics, and Native Americans might leave a ban state for another state that has more favorable admissions circumstances, and they might be replaced by white or Asian students. Another strength of the data is that they include information on the state each respondent lived in one year ago (ACS) or five years ago (census). Furthermore, college students are surveyed in the state of their college rather than their initial state of residence.[27]

I estimate impacts of affirmative action bans on migration by studying whether the bans are related to moving to a new state in the past year or in the past five years. In doing so, I treat the state of residence one year ago or the state of residence five years ago as a proxy for what state a person is actually from. I code the affirmative action ban variable based on whether there is a ban in place in that state at the current time.[28] I limit the sample to people who are 18 years old and attending college, which I define as being enrolled in school but having already completed 12th grade, in order to focus on the population that is arguably of the most interest.[29] I estimate

[25] One complication is that affirmative action bans may also cause some residents of a state to shift from one out-of-state college to a different out-of-state college. While this may happen in certain instances, I assume that this effect is negligible.

[26] Hinrichs (2012) used data from the IPEDS Residence and Migration survey to estimate impacts of affirmative action bans on the percentage of college-going students from a state who are attending college within their home state. That paper found no effect, although a major limitation is that the data are not disaggregated by race.

[27] For example, see the 2017 ACS form at `https://www2.census.gov/programs-surveys/acs/methodology/questionnaires/2017/quest17.pdf`, which explicitly mentions to "not include anyone who is living somewhere else for more than 2 months, such as a college student living away." But to be sure, I cannot completely rule out the possibility that misreporting by respondents leads to some college students being erroneously listed on their parents' ACS form even after they have moved away for college.

[28] For example, in estimating models using the 1990-2000 census data, a student attending college in Minnesota in 2000 who lived in California five years prior would be coded as being subject to an affirmative action ban because there was a ban in place in California in 2000. A student attending college in California in 2000 who lived in Minnesota five years prior would not be coded as being subject to an affirmative action ban because there was not a ban in place in Minnesota in 2000. One limitation of the data is that some of these moves may have happened before the affirmative action ban actually went into effect. This is especially a limitation with the census data, which includes information on state of residence five years prior to the survey year.

[29] The decision to limit the sample to college students may raise a concern about sample selection because affirmative action bans could potentially impact whether people attend college. However, Hinrichs (2012) found that affirmative action bans do not affect whether people attend college even though they do affect which colleges people

separate models by race, I include a full set of year dummy variables and a full set of state dummy variables, and I cluster standard errors at the state level. Depending on the time period, the state variable is either the state of residence one year ago or the state of residence five years ago. The outcome variable is either a dummy for moving to a new state or a dummy for moving to a new state that is not an affirmative action ban state. Using the same notation as before, the equations I estimate are of the form

$$migrated_{ist} = ban_{st}\alpha + \mu_s + \delta_t + \epsilon_{ist}. \tag{3}$$

The results in Table 5 show that affirmative action bans are generally not associated with lower outflows of whites or higher outflows of blacks and Hispanics.[30] There are three statistically significant coefficients in the top panel of the table, which shows results for moving to a new state, although two of these are in an unexpected direction, suggesting that in the 1990-2000 data, affirmative action bans are associated with higher outflows of whites and lower outflows of Hispanics. The one statistically significant coefficient with the expected sign suggests that blacks were 2.5 percentage points more likely to move to a new state for college when an affirmative action ban is in place over the time period 2001-2014. The bottom panel of Table 5 shows results for moving to a non-ban state, and these results are very similar to the results for moving to a different state regardless of whether it is a ban state or a nonban state, although the coefficient for Hispanics in 1990-2000 is smaller in magnitude and ceases to be statistically significant in the bottom panel of the table.

All in all, the results in Table 5 do not give much support for the idea that migration can explain the segregation results from Table 4. Due to data availability, the years used in the estimations in the two tables do not completely coincide. The migration results for blacks are significant in Table 5 for 2001-2014, although they are not statistically significant for 2004-2014, a time period that more closely coincides with one of the time periods from Table 4.

But if affirmative action bans actually do cause the share of black students attending an in-state college to drop by 2.5 percentage points, to what extent can this drop explain the segregation results from Table 4? The answer depends on which in-state colleges black students would have attended had they not been induced to move to a new state, as well as whether black outmigrants are replaced at in-state colleges and, if so, the race of the students who are replacing them. But suppose for simplicity that black students left in-state colleges proportionally to their enrollment at those colleges and are replaced by Asian, Hispanic, or Native American students. These assumptions imply that any change in exposure coming about from an increase in white students or a change in

attend.

[30]Table A2 in the appendix shows summary statistics.

Table 5: Effects of Affirmative Action Bans on Migration

		5-Year	1-Year	
		1990-2000	2001-2014	2004-2014
		A. Moved to a New State		
White	Coeff.	0.017**	−0.006	−0.012
	SE	(0.008)	(0.017)	(0.011)
	N	89,017	153,753	142,010
Black	Coeff.	0.004	0.025**	0.010
	SE	(0.017)	(0.009)	(0.015)
	N	13,612	20,684	19,541
Hispanic	Coeff.	−0.029**	0.006	0.008
	SE	(0.013)	(0.008)	(0.008)
	N	6,388	18,801	18,013
		B. Moved to a Non-Ban State		
White	Coeff.	0.018*	−0.006	−0.010
	SE	(0.010)	(0.014)	(0.008)
	N	89,017	153,753	142,010
Black	Coeff.	0.001	0.027**	0.015
	SE	(0.016)	(0.011)	(0.009)
	N	13,612	20,684	19,541
Hispanic	Coeff.	−0.014	0.007	0.001
	SE	(0.013)	(0.008)	(0.010)
	N	6,388	18,801	18,013

Notes: Regressions are weighted using person weights. Standard errors that are robust to clustering at the state level are in parentheses. The table also shows sample sizes. A single asterisk denotes statistical significance at the 10% level, a double asterisk denotes statistical significance at the 5% level, and a triple asterisk denotes statistical significance at the 1% level.

college sizes can be ignored. Under these assumptions, the black-white dissimilarity index would be unchanged. This index depends on the way racial groups sort across colleges rather than on the size of the groups.[31] Black exposure to whites would also be unchanged because the remaining black students would be attending colleges that have the same white percentages as before.[32] However, white exposure to blacks would fall by 2.5 percentage points because there are fewer black students at each college.[33]

Turning back to the regression results from Table 4, if the coefficient for white exposure to blacks were in fact higher by 2.5, it would bring the -0.13 coefficient for white exposure to blacks in 1995-2003 more in line with the 3.12 coefficient for black exposure to whites. However, if the coefficient on white exposure to blacks in 2004-2014 were higher by 2.5, it would bring the -0.37 coefficient for white exposure to blacks further away from the -3.72 coefficient for black exposure to whites. In essence, the migration results do not provide strong evidence that affirmative action bans impact migration. But insofar as they do provide such evidence, they can help explain some of the segregation results.

7 Conclusion

The Supreme Court has ruled that affirmative action is constitutional on the grounds that there are educational benefits to racial diversity, but a more fundamental question is whether there will actually be more cross-racial interaction with affirmative action than without it. Earlier research finds that affirmative action bans lead to lower minority enrollment at selective colleges, but there is a question of what happens to students who are displaced. They may cascade down to institutions that already have high minority enrollment, or 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.

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 in other cases may actually reduce it. This result is noteworthy because it shows that increasing representation of disadvantaged groups and reducing segregation are not equivalent

[31] Returning to the definition of the dissimilarity index in Section 2, the changes to the b_i's are exactly offset by the change to B, while the w_i's and W are unchanged. In principle, dissimilarity does not depend on the overall racial representation of college students in the same way that exposure does. In practice, though, there may be impacts on dissimilarity if students who are migrating out in response to affirmative action bans are disproportionately leaving certain colleges.

[32] The denominator inside the summation of the exposure index is unchanged under the assumption that black students are replaced by other non-white students, and the assumption about proportional changes means that the effect on B in the denominator outside the summation exactly offsets the effect on the b_i's inside the summation.

[33] The denominator inside the summation is unchanged. The only change is the b_i's in the numerator.

and may actually sometimes be in conflict.[34] One explanation for why affirmative action bans can reduce segregation is related to the U-shaped relationship between college quality and percent minority, and I have discussed some evidence that bolsters this interpretation in the case of California.

A full cost-benefit analysis of affirmative action is beyond the scope of this paper. But 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. What is needed is 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 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. However, I know of no existing research that estimates effects of the interaction between diversity and college quality on social outcomes for nonminorities.[35]

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 in selective colleges in favor of minority groups. 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), 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;

[34] 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.

[35] 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.

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).[36]

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. But 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.

[36] 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) 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

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
	Type of Institution					
			A. 1995-2015			
% Asian	6.96	7.51	13.76	13.57	21.34	23.59
	(9.80)	(10.76)	(13.48)	(14.85)	(14.63)	(17.51)
% Black	11.09	10.53	5.78	5.68	6.28	5.71
	(16.36)	(15.73)	(3.16)	(3.24)	(3.03)	(3.28)
% Hispanic	10.32	11.03	8.60	8.41	9.49	9.75
	(14.06)	(15.46)	(6.88)	(7.46)	(5.48)	(6.22)
% Native Am.	0.85	0.94	0.47	0.45	0.49	0.44
	(3.30)	(3.63)	(0.47)	(0.41)	(0.52)	(0.38)
% White	70.77	69.99	71.39	71.89	62.40	60.52
	(23.88)	(24.66)	(17.82)	(19.22)	(17.44)	(20.35)
N	43,377	11,339	2,308	1,155	987	315
N (colleges)	2,998	626	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)	2,246	533	110	55	47	15
			C. 2004-2015			
% Asian	7.28	7.93	14.65	14.47	22.74	25.00
	(9.93)	(10.88)	(13.61)	(14.95)	(14.66)	(17.47)
% Black	11.76	10.84	5.73	5.54	6.20	5.37
	(16.28)	(15.40)	(3.04)	(3.04)	(3.03)	(3.11)
% Hispanic	12.33	13.35	10.19	10.06	11.10	11.37
	(15.34)	(16.93)	(7.55)	(8.32)	(5.80)	(6.74)
% Native Am.	0.84	0.90	0.42	0.39	0.44	0.37
	(3.42)	(3.69)	(0.46)	(0.39)	(0.54)	(0.38)
% White	67.78	66.98	69.02	69.54	59.51	57.89
	(24.13)	(25.03)	(18.42)	(19.96)	(17.59)	(20.75)
N	26,794	6,788	1,318	660	564	180
N (colleges)	2,727	616	110	55	47	15

Notes: Means and standard deviations (in parentheses) weight by total enrollment.

Table A2: Summary Statistics for Migration

	5-Year	1-Year	
	1990-2000	2001-2014	2004-2014
A. Moved to a New State			
White	0.14	0.09	0.10
	(0.35)	(0.29)	(0.30)
	89,017	153,753	142,010
Black	0.11	0.07	0.08
	(0.31)	(0.26)	(0.27)
	13,612	20,684	19,541
Hispanic	0.07	0.04	0.04
	(0.26)	(0.19)	(0.20)
	6,388	18,801	18,013
B. Moved to a Non-Ban State			
White	0.14	0.08	0.09
	(0.34)	(0.27)	(0.29)
	89,017	153,753	142,010
Black	0.11	0.06	0.07
	(0.31)	(0.24)	(0.26)
	13,612	20,684	19,541
Hispanic	0.07	0.03	0.03
	(0.25)	(0.17)	(0.18)
	6,388	18,801	18,013

Notes: Means and standard deviations are weighted with person weights. The table also shows the sample size.

Table A3: Summary Statistics for Hispanic-White Segregation Regressions

Time Period	Variable	Type of Institution	
		Four-Year	Public Four-Year
A. 1995-2015			
	W Exposure to H	7.17	7.29
		(6.54)	(7.46)
	H Exposure to W	49.19	46.22
		(18.05)	(19.71)
	H-W Dissimilarity	29.61	25.98
		(10.72)	(13.17)
	Affirmative Action Ban	0.17	0.19
		(0.37)	(0.39)
	N	987	987
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)
	B-H Dissimilarity	31.35	27.07
		(10.68)	(12.80)
	Affirmative Action Ban	0.11	0.12
		(0.32)	(0.33)
	N	423	423
C. 2004-2015			
	W Exposure to H	8.60	8.82
		(7.14)	(8.23)
	H Exposure to W	47.30	44.28
		(18.17)	(19.76)
	B-H Dissimilarity	28.53	25.31
		(10.61)	(13.36)
	Affirmative Action Ban	0.20	0.23
		(0.40)	(0.42)
	N	564	564

Notes: The table shows means and standard deviations at the state-by-year level. Summary statistics for white exposure to Hispanics are weighted by the number of whites, summary statistics for Hispanic exposure to whites are weighted by the number of Hispanics, and summary statistics for the other variables are weighted by the sum of Hispanic enrollment and white enrollment. The variable measuring white exposure to Hispanics has one fewer observation in the 1995-2015 and 2004-2015 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 A4: 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. 1995-2015					
	W Exposure to H	−0.53	−0.82	−0.79	−1.26*
		(1.45)	(1.62)	(0.67)	(0.63)
	H Exposure to W	−0.99	−1.24	−0.19	−1.30
		(1.92)	(1.74)	(2.15)	(2.72)
	H-W Dissimilarity	1.81	2.91	0.76	2.41
		(2.16)	(2.85)	(1.46)	(2.38)
	N	987	987	987	987
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. 2004-2015					
	W Exposure to H	−0.25	−0.78	0.21	0.04
		(1.51)	(1.38)	(0.29)	(0.15)
	H Exposure to W	0.07	−0.85	0.67	0.85**
		(0.81)	(1.13)	(0.83)	(0.38)
	H-W Dissimilarity	−0.18	0.39	−0.96*	−1.27
		(1.27)	(2.11)	(0.52)	(1.17)
	N	564	564	564	564

Notes: The regressions for white exposure to Hispanics are weighted by the number of whites, the regressions for Hispanic exposure to whites are weighted by the number of Hispanics, and the regressions for Hispanic-white dissimilarity are weighted by the sum of Hispanic enrollment and white enrollment. Standard errors that are robust to clustering at the state level are in parentheses. A single asterisk denotes statistical significance at the 10% level, a double asterisk denotes statistical significance at the 5% level, and a triple asterisk denotes statistical significance at the 1% level. Regressions involving white exposure to Hispanics have one fewer observation in the 1995-2015 and 2004-2015 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.