Affirmative Action and Racial Segregation*

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Abstract: A number of states have recently prohibited the use of affirmative action in admissions to public universities statewide. A growing body of research suggests that these affirmative action bans reduce minority enrollment at selective colleges while leaving overall minority college enrollment rates unchanged. The effect of the bans on segregation across colleges is theoretically ambiguous and has not yet been directly estimated. This paper uses variation in the timing of affirmative action bans across states to estimate their effects on racial segregation, as measured by exposure and dissimilarity indexes. The results suggest that affirmative action bans have in some cases increased segregation across colleges but in others cases have actually reduced segregation across colleges.

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I. 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] However, in recent years, several states have discontinued affirmative action in admissions to public universities statewide. This has 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. There is a growing body of research on the effects of these affirmative action bans on enrollment, and the typical finding is that they reduce minority enrollment at selective colleges (Arcidiacono 2005, Arcidiacono et al. 2014, Backes 2012, Hinrichs 2012, Howell 2010, Long 2004b).[2]

Meanwhile, the Supreme Court has considered the issue of whether affirmative action in college admissions is constitutional, as well as the related issue of whether it is constitutional for the voters of a state to ban affirmative action.[3] While the Supreme Court is set to soon decide on the issue again in a case involving the University of Texas, its rulings thus far have held that it is permissible to ban affirmative action but also that it is permissible to practice affirmative action on the grounds that there are educational benefits to racial diversity. The decisions in these cases cite a variety of evidence from other social sciences that support the benefits of college racial diversity, although the evidence from economics is more mixed.[4]

But even apart from the question of whether there are educational benefits to diversity, a more fundamental question is whether there will actually be more interaction between members

[1] For more on the history of affirmative action, see Bowen and Bok (1998) or Stulberg and Chen (2011).
[2] See Arcidiacono and Lovenheim (forthcoming) for a review 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), and *Fisher v. University of Texas* (2013). The case on the constitutionality of affirmative action bans by voters is *Schuette v. Coalition to Defend Affirmative Action* (2014).
[4] See Arcidiacono and Vigdor (2010); Daniel, Black, and Smith (2001); and Hinrichs (2011).

of different racial groups with affirmative action than without it. One issue, which has been highlighted by Arcidiacono et al. (2013) and Arcidiacono, Khan, and Vigdor (2011), is that students may be more likely to interact with college peers who have an academic background that is similar to their own. If affirmative action leads to a wider disparity in academic backgrounds between white students and minority students within colleges, then the use of affirmative action may actually results in less interaction between students of different races.

A second issue is that the effect of affirmative action on racial segregation across colleges is theoretically ambiguous. From the vantage point of an individual college that is selective in its admissions and holding the behavior of other colleges fixed, it seems likely that the college will have higher minority representation if it uses affirmative action than if it does not.[5] However, if the practice of affirmative action were suddenly prohibited for all colleges in a state, there could be complex interactions and responses by students and colleges. One possibility is that affirmative action bans could result in an increase in segregation across colleges by lowering minority representation at elite colleges in which minorities are already underrepresented, leading to minority students being more isolated at a particular set of colleges that are less selective. Another possibility, however, is that affirmative action bans may only affect highly selective colleges and that minority students who are displaced from the most selective institutions attend slightly less selective institutions that would have had very low minority enrollment in the absence of an affirmative action ban. This second possibility could lead to a reduction in measured racial segregation and is plausible given the U-shaped relationship between measures of college selectivity and the share of students who are black found by

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

Arcidiacono, Khan, and Vigdor (2011); Arcidiacono, Aucejo, and Hotz (forthcoming); and Reardon, Baker, and Klasik (2012). Depending on the exact way students would be matched to colleges with and without an affirmative action ban, an affirmative action ban could increase or decrease racial segregation across colleges, or it may even have no net effect on segregation.

This paper examines the impact of affirmative action bans on racial segregation empirically. I measure segregation using standard exposure and dissimilarity indexes, and I estimate generalized difference-in-differences models that exploit variation in the timing of affirmative action bans across states. I also estimate the effects separately for states that banned affirmative action earlier and more recently. I find that the more recent affirmative action bans have led to greater segregation across colleges on average, despite the fact that most of these bans have not had much effect on the demographic composition of universities. On the other hand, regression results suggest that affirmative action bans are associated with less racial segregation in the earlier time period.

Section II of this paper discusses the data, including the construction of the segregation indexes. Section III outlines the empirical methods used in the paper and assesses the exogeneity of affirmative action bans. Section IV briefly discusses the impact of more recent affirmative action bans on the overall demographic composition of universities, and then Section V presents the main empirical results on affirmative action and racial segregation. Section VI concludes.

II. Data

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. This coding is consistent with the coding of affirmative action bans in earlier research, such as

Antman and Duncan (2015). I drop from the regressions the following states that were in jurisdictions that had important affirmative action litigation but did not have outright bans: Alabama, Georgia, Louisiana, and Mississippi. 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 alternative treatments of these cases.

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. IPEDS covers information on program offerings, enrollment, cost of attendance, institutional finances, staff, and other characteristics of surveyed institutions. Most importantly for the purposes of this study, IPEDS contains information on enrollment by race. Although many of the estimations include only a subset of the years and institutions, I utilize data from four-year colleges on the number of full-time, first-time, degree-seeking undergraduates by race in the fall of 1986, 1988, and 1990-2013. I use these data 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. The first two of these are measures of potential interaction between members of different racial groups. The index of white exposure to blacks measures the percentage of students at the average white student's institution who are black, and the index of black exposure to whites measures the percentage of students at the average black student's institution who are white. The dissimilarity index 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 be racially balanced. 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 these three indexes mathematically, use N to denote the total number of colleges, 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 $100 \times \frac{1}{W} \sum_{i=1}^{N} w_i \frac{b_i}{w_i + b_i + h_i + a_i + n_i}$, the exposure index of blacks to whites is calculated as $100 \times \frac{1}{B} \sum_{i=1}^{N} b_i \frac{w_i}{w_i + b_i + h_i + a_i + n_i}$, and 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 exposure indexes use the count of members of all races in the denominator. However, although not shown in this paper, the general pattern of results is unchanged when limiting the denominator to whites and blacks.

III. Methods

I estimate regression models of the following form:

$$segregation_{st} = ban_{st}\alpha + \mu_s + \delta_t + \eta_s t + \varepsilon_{st} .$$

Here $segregation_{st}$ is a segregation index for state s in year t, ban_{st} is a dummy variable for 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. All standard errors I use are robust to clustering at the state level. 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 white enrollment and black enrollment.

Before estimating the models for segregation at the state level, I estimate models of the effects of affirmative action bans on enrollment shares by race at universities of varying selectivity levels. These are similar to models estimated by Hinrichs (2012), which uses data for 1995-2003. Here I use data from 2004-2013 to estimate the effects of more recent bans. The models I estimate take the form

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

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), μ_i refers to institution dummies, and the rest of the notation is similar to before. These regressions are weighted by total enrollment, and I show standard errors that are robust to clustering at the state level.

In addition to regression estimates for enrollment shares, I also show results from using the synthetic control method developed in Abadie, Diamond, and Hainmueller (2010) and Abadie and Gardeazabal (2003). This method has been used in a number of papers, including Hinrichs (2012) on affirmative action, Moser (2005) on patent laws and innovation, and Kleven, Landais, and Saez (2013) on taxation and migration. The method can be used for comparative case studies in which a treatment goes into effect at some point in time for a treatment unit but not in a set of potential control units. A researcher chooses a set of variables for matching, and the method selects a convex combination of the potential control units that is the closest to the treatment unit based on the matching variables and a particular criterion for "closeness." Studying how the outcome evolves in the treatment unit relative to this synthetic control provides an estimate of treatment effects over time. More formally, let the variables used for matching be stacked into the vector X_1 for the treated unit and assembled into the matrix X_0 for the potential control units. I choose the weights W^* for the synthetic control by minimizing $\sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$ over W, where V weights the variables used in the matching and is chosen to minimize the mean squared prediction error over the pre-treatment period. Letting Y_1 refer to a vector of outcomes for the treated unit and Y_0 refer to a matrix of outcomes for the potential control units, the synthetic control estimate for the effect of the treatment on these outcomes is $Y_1 - Y_0W^*$. The synthetic control method is useful because it provides a quantitative method for conducting case studies and allows the data to play some role in selecting the control group.[6] In the setting in this paper, the donor pool consists of public universities in states that did not have an affirmative action ban and are not located in the four aforementioned states that are dropped from all the analysis due to facing an ambiguous or uncertain legal situation regarding affirmative action. I perform the matching based on the level of the outcome variable in each of the pre-treatment years.

A number of papers have estimated difference-in-differences models similar to the ones in this paper in order to study the effects of affirmative action bans, including Antman and

[6] For more information on the synthetic control method, see Abadie, Diamond, and Hainmueller (2010, 2015).

Duncan (2015), Backes (2012), Blume and Long (2014), and Hinrichs (2012, 2014). The identifying assumption for these models when including state-specific time trends in that segregation levels in treated states and control states would follow a common time path in the absence of the treatment after accounting for state-specific linear time trends. This assumption is not directly testable, but some earlier papers on affirmative action have provided indirect tests of this assumption.[7] These earlier tests generally support the exogeneity of affirmative action bans, but I consider the issue further in Table 2. This table shows results from estimating models at the institution level that are similar to those above but that use on the left-hand side a set of variables on which affirmative action bans should likely have no effect. Finding an effect is thus potential evidence of misspecification. The results from Table 2 suggest that these variables are generally unassociated with affirmative action bans, although there may be some evidence to suggest that affirmative action bans are associated with lower tuition at selective institutions.

IV. Effects of Recent Affirmative Action Bans on Demographic Composition of Universities

A large portion of the research on affirmative action bans has focused on California, Florida, Texas, and Washington, which are all large states that were early to ban affirmative action. However, several other states have banned affirmative action in college admissions more recently. Before turning to the main results on racial segregation in the next section, this section briefly considers the impact of these more recent bans on the demographic composition of universities in the states that banned affirmative action.

[7] 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) argues for the importance of using state-specific time trends due to different pre-existing trends in different states. He also 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 the outcomes they consider.

Table 3 shows summary statistics. This table shows that more selective institutions have higher Asian representation than less selective institutions. For other racial groups, however, the results generally point to a U-shaped relationship between selectivity and representation. For example, the percentage of students at all four-year colleges in the sample who are black is roughly 11.8%. The percentage at the subset of 115 institutions in the top two tiers of the 1995 *U.S. News & World Report* college rankings who are black is roughly 5.8%, but the percentage in the smaller subset in the top 50 of the 1995 *U.S. News* rankings is 6.3%. When confining attention solely to public institutions, this pattern does not appear for blacks and there is instead slightly lower representation in the top 50 than in the 115 institutions in the top two tiers, although this could potentially be an effect of affirmative action bans. For Native Americans, the pattern is the same as for blacks. For Hispanics, the U shape is present both when considering all institutions and also when confining attention to public universities. For whites, the pattern is an inverted U shape: white representation is higher at the subset of 115 institutions in the top two tiers of the *U.S. News* rankings than in the more selective top 50, regardless of whether public and private universities are considered together or attention is confined just to publics. Finally, in most of the samples somewhere between 20% and 35% of students are attending institutions in states with an affirmative action ban, but when considering the public universities in the top 50 of the *U.S. News* rankings over half of the students attending these institutions are in a state that has an affirmative action ban. However, most of these bans were already in place before the sample period began.

Table 4 shows regression results. The results in the first four columns show little impact of the affirmative action bans overall. The results in the final two columns do suggest an impact at institutions that were rated in the top 50 of the 1995 *U.S. News & World Report* college rankings. The results in the final column, for example, suggest that affirmative action bans are associated with a decrease in black representation of about 1.2 percentage points, a decrease in Hispanic representation of about 1.0 percentage points, a decrease in Native American representation of about .35 percentage points, and an increase in white representation of about 2.8 percentage points at public universities in the top 50 of the *U.S. News* rankings. However, there are only two states that had an affirmative action ban first go into effect between 2004 and 2013 that had a university in the top 50 of the 1995 *U.S. News* rankings: New Hampshire (Dartmouth College, which is a private college that was not covered by New Hampshire's ban) and Michigan (University of Michigan). This suggests that there may be value in explicitly estimating the effects of affirmative action bans on particular colleges.

Figure 1 shows synthetic control results for eight major public universities in states with affirmative action bans. The outcome variable is the percentage of students who are black, Hispanic, or Native American. In general, the synthetic controls appear to be close matches to the treated units in the pre-treatment periods and also continue along similar paths to the treated units in the post-treatment periods. The main exception to this is the two universities in Michigan, the University of Michigan and Michigan State University. At the University of Michigan there was a declining trend in underrepresented minority enrollment even before the affirmative action was in place, and this continued into the post-ban period. However, this trend does not continue in the post-ban period at the synthetic University of Michigan, suggesting that the affirmative action ban led to lower underrepresented minority at the University of Michigan than there would have been otherwise. The same can possibly also be said of Michigan State University. There is not a clear trend in underrepresented minority enrollment at Michigan State University, but the synthetic Michigan State University shows an increase in underrepresented minority enrollment in the years after Michigan's affirmative action ban, again pointing to a possible negative effect of the affirmative action bans on minority representation. The results for the Michigan universities are thus similar to the results in Hinrichs (2012) for the early affirmative action ban states of California, Florida, Texas, and Washington. One common feature between all of these states is that they all are home to selective public universities.

V. Effects on Racial Segregation

Table 5 shows summary statistics for the samples used in the racial segregation regressions. The observations are at the state-by-year level, and the sample size differs across columns due to the fact that not every state contains universities that are rated highly in the *U.S. News* rankings. The summary statistics, like the later regressions, are shown for the entire sample period and are also broken down by the earlier and later parts of this time period. There are at least three reasons for breaking down the results in this manner. First, the earlier period is the focus of earlier work, and it may be useful to compare results over a common time period. Second, the Supreme Court cases of 2003 may have changed the allowable behavior in the control states that do not have an affirmative action ban. Third, when comparing the results in Section IV of this paper to results of earlier papers studying an earlier time period, it seems that the earlier affirmative action bans may have more potential to affect segregation across colleges. In any case, Table 5 shows that the exposure of whites to blacks is lower in the "top two tiers" samples than in the "top 50" samples, while the opposite is true for black exposure to whites. This is somewhat consistent with the U-shaped relationship found earlier. Moreover, black-white dissimilarity is lower in the samples that are limited to more selective institutions, but it is worth noting that these samples cover fewer institutions.

Table 6 shows regression results for the impact of affirmative action bans on segregation across colleges. The top panel shows results for the full time period, the middle panel shows results in the earlier part of the sample, and the bottom panel shows results in the later part of the sample. For completeness, I show results in the four rightmost columns that limit the sample to selective institutions. However, these results are difficult to interpret in light of the fact that research such as Hinrichs (2012) and the results in Section IV of this paper show that there can be selection into these samples by whites and selection out of these samples by underrepresented minority students as a result of affirmative action bans. Thus, I focus on the leftmost two columns of Table 6, as Hinrichs (2012) and the results of Section IV show that affirmative action bans generally do not affect the demographic composition of universities overall.

The two leftmost columns of the top panel of Table 6 suggest that there is not much of an effect of affirmative action bans on average. However, the middle and bottom panels in Table 6 suggest that there are effects but that these effects were different for the bans going into effect in the two different time periods. The middle panel, which shows results for 1995-2003, suggests that affirmative action bans are associated with an increase in black exposure to whites of about 3.8 percentage points, which means that there is a decline in segregation. The results for black-white dissimilarity also point to a decline in segregation. In the 2004-2013 time period, however, which is shown in the bottom panel, the results for black exposure to whites and black-white dissimilarity are the opposite of the 1995-2003 period. In this period affirmative action bans are associated with lower exposure of blacks to white and higher black-white dissimilarity, both of which point to higher segregation.

To further study this issue, Figures 2 and 3 plot black exposure to whites and black-white dissimilarity across California universities over a long time period. Both of these graphs show a notable change in 1998, the first year of California's affirmative action ban. Moreover, Table 7 shows summary statistics and Table 8 shows regression results for Hispanic-white segregation. The regression results are similar to the results in Table 5 for black-white segregation.

How could affirmative action bans lead to less segregation across colleges? Two results from recent research papers may provide an explanation for this finding. First, research on the enrollment effects of affirmative action bans, including Hinrichs (2012), finds that affirmative action bans redistribute blacks from the most selective colleges to slightly less selective ones. Second, Arcidiacono, Khan, and Vigdor (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, Aucejo, and Hotz (forthcoming) also show this for the case of California. Reardon, Baker, and Klasik (2012) find similar results as Arcidiacono, Khan, and Vigdor (2011) but using Barron's rankings rather than SAT scores.[8] In light of these two results, it is plausible that an affirmative action ban could decrease measured racial segregation as this U shape is flattened.

This possibility is supported by Figures 4 and 5, which show the percentage white and the percentage black at California public universities in 1997 and 1998. These are plotted against a test score measure derived from the College Board's Annual Survey of Colleges: the sum of the average of the 25th and 75th percentiles of SAT verbal scores and the average of the 25th and 75th percentiles of SAT math scores. This measure is likely approximately equal to the mean and median SAT score at the institution. Figures 4 and 5 plot the raw data as well as a quadratic fit. Consistent with earlier work, there is a clear U-shaped relationship between percentage black and the test score measure. Moreover, there is an inverted U-shaped relationship between percentage

[8] It is also interesting to note that this U shape between percent minority and average SAT score 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.

white and the test score measure. However, both of these relationships are flatter in 1998, the first year of the affirmative action ban, than in 1997. A flattening of these relationships is consistent with lower black-white segregation.

But what is the reason for the U-shaped relationship between college quality and minority share? One possibility is that affirmative action used by the most selective institutions takes away minority students from moderately selective institutions, and the spaces at moderately selective institutions are not filled by students from less selective institutions. This could be either because moderately selective institutions do not want to admit minority students who would have otherwise attended less selective institutions or because the students may not want to attend such institutions. As pointed out by Arcidiacono and Lovenheim (forthcoming), students from less selective institutions may not consider moderately selective institutions due to a lack of information about these schools being a good fit. Another possibility pointed out by Arcidiacono and Lovenheim (forthcoming) is that moderately selective institutions may have low minority shares because they do not use affirmative action very heavily. This may be because the top institutions have taken such a large share of well-qualified minority students that would be successful at moderately selective institutions that moderately selective institutions feel as though they do not have any to choose from or would have to reach too far, or it could be that they are not under as much pressure as highly selective institutions to use affirmative action. Whatever the reason may be for low minority shares at moderately selective institutions, low minority shares at these schools may then compound if future minority students are further deterred from attending by the already low minority shares at these schools.[9]

[9] This 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 affirmative action bans or efforts to circumvent them. For example, policies in place in some states that result in automatic admission for students at the top of their high school class not result in as much minority representation at

VI. Conclusion

The Supreme Court has ruled that affirmative action is constitutional on the grounds that there are educational benefits to racial diversity. The presumption seems to be that there will be more diversity if colleges are allowed to use affirmative action. However, it is not clear that there will be more interaction between members of different racial groups with affirmative action than without it. Arcidiacono et al. (2013) and Arcidiacono, Khan, and Vigdor (2011) have addressed the issue of interaction within colleges and found that affirmative action may actually lead to less interaction. There is also the issue of segregation across colleges. At selective colleges, evidence suggests that an affirmative action ban will lower minority representation at those colleges. But there is a question of what happens to students who are displaced from particular colleges due to affirmative action bans. These students could potentially attend some other college that would have had very low minority representation if other colleges were allowed to practice affirmative action. In this paper, I have addressed the issue of segregation across colleges and found that there may actually be more segregation across colleges with affirmative action than without it. In other words, the regression results suggest that the affirmative action bans could actually reduce racial segregation. I have given a possible explanation for this finding having to do with the U-shaped relationship between measures of college quality and the percentage of the student body that is black at colleges.

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highly selective schools as with explicit race-based affirmative action, but there is likely higher minority representation at highly selective schools with these policies than without them. Moreover, Antonovics and Backes (2014) also present evidence suggesting that campuses of the University of California changed the weight given in admissions decisions to various characteristics of applicants in a way that increased minority admissions rates relative to what they would have been otherwise, and Luppino (2013) and Yagan (2014) find that admissions advantages for minority students did not disappear at the University of California after the affirmative action ban.

However, even if affirmative action increases racial segregation, this is only one a variety of considerations that should be taken into account when evaluating the desirability of affirmative action as a policy. The simple argument that diversity is beneficial may not be enough, since one college's gain in diversity as a result of using affirmative action is likely another college's loss. But affirmative action may still be justified if, for example, there are complementarities between diversity and student quality, since affirmative action does result in higher minority representation in highly selective colleges.[10] Moreover, 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, Black, and Smith (2001) and Dale and Krueger (2014)). If this is true, then 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, Hinrichs 2012, Howell 2010, Long 2004b), pre-college human capital investment (Antonovics and Backes 2014b, Hickman 2013), major choice (Arcidiacono, Aucejo, and Hotz forthcoming; Arcidiacono, Aucejo, and Spenner 2012), longer-run outcomes such as educational attainment and earnings (Arcidiacono 2005, Arcidiacono, Aucejo, and Hotz forthcoming; Arcidiacono et al. 2014, Hinrichs 2014), and cross-racial interaction (Arcidiacono et al. 2013 and Arcidiacono, Khan, and Vigdor 2011); the effects of cross-racial interaction on attitudes and on friendship groups (Boisjoly et al. 2006; Baker, Mayer, and Puller 2011; Camargo, Stinebrickner, and Stinebrickner 2010); and the effects of overall college racial diversity on earnings and other outcomes (Arcidiacono and Vigdor 2010; Daniel,

[10] See Arcidiacono 2005, Arcidiacono et al. 2014, Backes 2012, Hinrichs 2012, Howell 2010, and Long 2004b.

Black, and Smith 2001; Hinrichs 2011).[11] However, despite these other issues, the rationale the Supreme Court has given for the constitutionality of affirmative action is that there are educational benefits to racial diversity. But, as shown by this paper, the effects of affirmative action are unclear, and in some cases segregation across colleges can be reduced by banning affirmative action. However, even if reducing segregation is a desirable goal, a case could be made that a better way to do this is to bring black students from the bottom to the middle rather than, as affirmative action sometimes does, from the top to the middle.

[11] Additional areas of research that are relevant to the affirmative action debate include research on college quality (Black and Smith 2004, 2006; Dale and Krueger 2002, 2011; Hoekstra 2009; Long 2008, 2010) and the more general body of research on peer effects in college (Foster 2006; Sacerdote 2001; Stinebrickner and Stinebrickner 2006; Zimmerman 2003).

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Table 1: Timing of Affirmative Action Bans

State	First Year Ban in Place for Fall Admissions Cycle
Texas	1997 (last year: 2004)
California	1998
Washington	1999
Florida	2001
Michigan	2007
Nebraska	2009
Arizona	2011
New Hampshire	2012
Oklahoma	2013

Table 2: Falsification Tests

	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
ln(Endowment)	0.0034	0.1270	-0.1208	-0.0316	-0.2714	0.0292
	(0.1147)	(0.1058)	(0.1133)	(0.0884)	(0.2432)	(0.0822)
ln(Instruction Expenditure)	-0.0082	0.0568***	0.0209	0.0034	-0.0180	-0.0089
	(0.0207)	(0.0195)	(0.0172)	(0.0181)	(0.0444)	(0.0557)
ln(Research Expenditure)	-0.0919	-0.0671	0.0325	-0.0081	-0.0027	0.0133
	(0.0558)	(0.0644)	(0.0347)	(0.0344)	(0.0520)	(0.0553)
ln(Total Current Expenditure)	0.0122	0.0841***	0.0350	0.0129	-0.0204	-0.0309
	(0.0367)	(0.0276)	(0.0242)	(0.0171)	(0.0287)	(0.0436)
ln(Total Assets)	0.0319	0.0093	0.0816	0.0404	-0.1817*	-0.0415
	(0.2034)	(0.0318)	(0.0505)	(0.0346)	(0.0953)	(0.0265)
ln(Tuition and Fee Revenue)	-0.0289	0.0400	-0.0198	-0.0248	-0.1629***	-0.1559**
	(0.0703)	(0.0477)	(0.0632)	(0.0629)	(0.0536)	(0.0655)
ln(Federal Appropriations)	-0.0358	0.1222	0.0820	-0.1326	0.1110	0.1110
	(0.3735)	(0.1988)	(0.4165)	(0.2537)	(0.0698)	(0.0819)
ln(State Appropriations)	-0.1478	0.0925*	-0.4557	0.0636***	0.0775	0.0556
	(0.1877)	(0.0515)	(0.4772)	(0.0118)	(0.0726)	(0.0324)
ln(In-State Tuition and Fees)	-0.0365	-0.0450	-0.0476	-0.0560	-0.1041**	-0.1532*
	(0.0386)	(0.0647)	(0.0601)	(0.0757)	(0.0371)	(0.0680)
ln(Out-of-State Tuition and Fees)	0.0090	-0.0024	-0.0125	-0.0163	-0.0074	-0.0290
	(0.0298)	(0.0347)	(0.0296)	(0.0399)	(0.0214)	(0.0410)

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.

Table 3: Summary Statistics for Racial Composition Regressions, 2004-2013

	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
% Asian	7.123	7.789	14.45	14.29	22.51	24.89
% Black	11.84	10.90	5.776	5.605	6.280	5.504
% Hispanic	11.55	12.42	9.588	9.434	10.43	10.59
% Native American	0.885	0.952	0.458	0.431	0.484	0.408
% White	68.61	67.93	69.72	70.24	60.30	58.61
Affirmative Action Ban	0.203	0.228	0.231	0.275	0.346	0.510
N	22255	5585	1100	550	470	150

Notes: The table shows means at the college level that are weighted by total enrollment.

Table 4: Effects of Affirmative Action Bans on Representation by Race, 2004-2013

	Type of Institution					
				Public		Public
		Public	*U.S. News*	*U.S. News*	*U.S. News*	*U.S. News*
Racial Group	Four-Year	Four-Year	Top Two Tiers	Top Two Tiers	Top 50	Top 50
% Asian	-0.2121**	-0.1692**	0.1758	0.1241	-0.8770*	-0.2478
	(0.0960)	(0.0668)	(0.5211)	(0.4706)	(0.5029)	(0.6593)
% Black	0.2870	-0.1209	-0.1839	-0.2886	-0.8779***	-1.2181**
	(0.3214)	(0.3347)	(0.2308)	(0.2282)	(0.2959)	(0.4024)
% Hispanic	-0.6330	0.4293	-0.0385	-0.0121	-0.9609**	-1.0073**
	(0.4589)	(0.3360)	(0.1131)	(0.1192)	(0.4115)	(0.3976)
% Native American	-0.0228	0.0169	-0.0071	0.0172	-0.3532***	-0.3501***
	(0.0698)	(0.0675)	(0.0848)	(0.0903)	(0.0435)	(0.0950)
% White	0.5809	-0.1561	0.0536	0.1595	3.0690***	2.8232**
	(0.5108)	(0.2466)	(0.8603)	(0.8348)	(0.3143)	(0.9283)
N	22112	5583	1100	550	470	150

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.

Table 5: Summary Statistics for Effects of Affirmative Action Bans on Black-White Segregation

		Type of Institution					
					Public		Public
			Public	*U.S. News*	*U.S. News*	*U.S. News*	*U.S. News*
Time Period	*Variable*	Four-Year	Four-Year	Top Two Tiers	Top Two Tiers	Top 50	Top 50
A. 1995-2013							
	W Exposure to B	7.617	7.422	5.721	5.736	6.495	6.198
	B Exposure to W	49.33	50.01	70.98	72.64	64.72	65.15
	B-W Dissimilarity	40.78	35.61	13.14	9.18	9.28	3.87
	Affirmative Action Ban	0.1331	0.1442	0.1504	0.1684	0.1989	0.2938
	N	893	893	608	551	418	190
B. 1995-2003							
	W Exposure to B	6.596	6.771	5.734	5.837	6.519	6.538
	B Exposure to W	50.11	50.82	73.47	74.84	67.81	67.71
	B-W Dissimilarity	40.59	36.34	13.45	9.74	9.45	5.61
	Affirmative Action Ban	0.0951	0.1024	0.1215	0.1267	0.1283	0.1772
	N	423	423	288	261	198	90
C. 2004-2013							
	W Exposure to B	8.430	7.941	5.710	5.648	6.474	5.904
	B Exposure to W	48.86	49.48	68.93	70.78	62.16	62.87
	B-W Dissimilarity	40.92	35.04	12.87	8.69	9.12	2.36
	Affirmative Action Ban	0.1623	0.1767	0.1755	0.2042	0.2619	0.3947
	N	470	470	320	290	220	100

Notes: The table shows means at the state level. The means for white exposure to blacks are weighted by the number of whites, the means for black exposure to whites are weighted by the number of blacks, and 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 1995-2013 and 2004-2013 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 6: Effects of Affirmative Action Bans on Black-White Segregation

		Type of Institution					
					Public		Public
			Public	*U.S. News*	*U.S. News*	*U.S. News*	*U.S. News*
Time Period	*Variable*	Four-Year	Four-Year	Top Two Tiers	Top Two Tiers	Top 50	Top 50
A. 1995-2013							
	W Exposure to B	-0.4605	-0.2076	-0.4908*	-0.5677*	-0.6370***	-0.9418**
		(0.3614)	(0.1539)	(0.2510)	(0.3096)	(0.1959)	(0.3480)
	B Exposure to W	0.2801	-0.1236	1.9964**	1.4823	2.9554***	2.1534**
		(0.9213)	(1.3590)	(0.7770)	(0.9270)	(1.0013)	(0.8906)
	B-W Dissimilarity	0.5356	0.5106	2.0747*	1.0650	0.4869	-1.4356
		(0.9017)	(1.1671)	(1.0204)	(1.4069)	(0.6250)	(1.4163)
	N	893	893	608	551	418	190
B. 1995-2003							
	W Exposure to B	-0.1251	-0.4068**	-1.0050***	-1.2419***	-1.7558*	-2.0408*
		(0.0992)	(0.1702)	(0.3360)	(0.3476)	(0.9823)	(1.0834)
	B Exposure to W	3.8154**	3.1614**	2.3232***	1.9684***	4.8717***	3.7478***
		(1.5136)	(1.3980)	(0.7465)	(0.4075)	(0.2815)	(1.0320)
	B-W Dissimilarity	-3.2161***	-2.5886**	2.1835	-0.5438	-3.9752*	-3.7749
		(1.0316)	(0.9664)	(3.9948)	(3.8118)	(2.0660)	(2.9158)
	N	423	423	288	261	198	90
C. 2004-2013							
	W Exposure to B	-0.4243	-0.1119	-0.1857	-0.3020	-0.8551***	-1.2455**
		(0.4761)	(0.2057)	(0.2246)	(0.2226)	(0.2976)	(0.4747)
	B Exposure to W	-3.2152***	-4.8354***	0.7541	0.5036	3.2561***	2.4002
		(1.0322)	(0.7934)	(0.8045)	(0.6905)	(0.2846)	(1.4152)
	B-W Dissimilarity	3.4151***	3.6469**	0.1709	-0.5060	0.4023	2.1540
		(0.9154)	(1.6214)	(0.5407)	(0.7970)	(1.0426)	(2.0218)
	N	470	470	320	290	220	100

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 1995-2013 and 2004-2013 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 7: Summary Statistics for Effects of Affirmative Action Bans on Hispanic-White Segregation

		Type of Institution					
					Public		Public
			Public	*U.S. News*	*U.S. News*	*U.S. News*	*U.S. News*
Time Period	*Variable*	Four-Year	Four-Year	Top Two Tiers	Top Two Tiers	Top 50	Top 50
A. 1995-2013							
	W Exposure to H	6.721	6.779	6.950	6.548	7.907	7.724
	H Exposure to W	49.98	47.11	61.90	60.31	55.89	51.83
	H-W Dissimilarity	29.87	26.19	14.53	8.71	9.54	3.46
	Affirmative Action Ban	0.1566	0.1741	0.1697	0.1924	0.2235	0.3295
	N	893	893	608	551	418	190
B. 1995-2003							
	W Exposure to H	5.039	4.971	5.517	5.132	6.367	6.275
	H Exposure to W	54.76	52.35	66.20	65.23	59.84	55.92
	H-W Dissimilarity	31.35	27.07	15.70	9.12	10.62	3.78
	Affirmative Action Ban	0.1115	0.1224	0.1352	0.1436	0.1426	0.1982
	N	423	423	288	261	198	90
C. 2004-2013							
	W Exposure to H	8.061	8.219	8.200	7.767	9.293	8.974
	H Exposure to W	47.90	44.95	59.63	57.82	53.71	49.64
	H-W Dissimilarity	28.77	25.53	13.57	8.38	8.62	3.19
	Affirmative Action Ban	0.1902	0.2121	0.1983	0.2323	0.2921	0.4362
	N	470	470	320	290	220	100

Notes: The table shows means at the state level. The means for white exposure to Hispanics are weighted by the number of whites, the means for Hispanic exposure to whites are weighted by the number of Hispanics, and 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 1995-2013 and 2004-2013 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 8 Effects of Affirmative Action Bans on Hispanic-White Segregation

		Type of Institution					
					Public		Public
			Public	*U.S. News*	*U.S. News*	*U.S. News*	*U.S. News*
Time Period	*Variable*	Four-Year	Four-Year	Top Two Tiers	Top Two Tiers	Top 50	Top 50
A. 1995-2013							
	W Exposure to H	-0.9683	-1.2893**	-1.5336**	-1.6978**	-2.4671***	-2.8881**
		(0.5927)	(0.6041)	(0.5803)	(0.7622)	(0.7238)	(0.9634)
	H Exposure to W	-0.2149	-1.4826	1.1616	0.5032	2.4756**	1.9669
		(1.6754)	(2.2019)	(1.0687)	(1.2443)	(1.0114)	(1.0753)
	H-W Dissimilarity	0.8487	2.5311	-2.4723	-1.3771	-3.7837	-2.5190
		(1.2186)	(2.0544)	(2.7430)	(2.9206)	(2.5809)	(2.2528)
	N	893	893	608	551	418	190
B. 1995-2003							
	W Exposure to H	-0.6654	-0.6583	-0.9501	-1.1244	-1.4480**	-1.6609*
		(0.4844)	(0.5600)	(0.7285)	(0.9215)	(0.6157)	(0.8508)
	H Exposure to W	1.0430	0.5595	1.8443***	1.4825**	3.5699***	2.8715**
		(0.9647)	(1.3724)	(0.2149)	(0.5700)	(0.5499)	(0.8898)
	H-W Dissimilarity	-0.7034	-0.1138	-2.0356	-0.7892	-2.2285	-1.3982
		(1.0684)	(1.6077)	(1.9201)	(2.4620)	(1.5342)	(1.3855)
	N	423	423	288	261	198	90
C. 2004-2013							
	W Exposure to H	0.4670	0.2441	0.0967	0.0758	-1.0037**	-1.2735**
		(0.2789)	(0.1671)	(0.1262)	(0.1298)	(0.3783)	(0.4608)
	H Exposure to W	0.6127	0.7589**	-0.5874	-0.7481	3.0211***	2.5882**
		(0.7768)	(0.3750)	(1.1196)	(1.1474)	(0.2886)	(1.0175)
	H-W Dissimilarity	-0.9284	-0.7114	-3.1563**	-1.8071	0.3441	0.4379
		(0.6375)	(0.9638)	(1.1896)	(1.4065)	(1.1544)	(0.7370)
	N	470	470	320	290	220	100

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 white enrollment and Hispanic 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 1995-2013 and 2004-2013 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.

Figure 1: Synthetic Control Estimates for Recent Bans

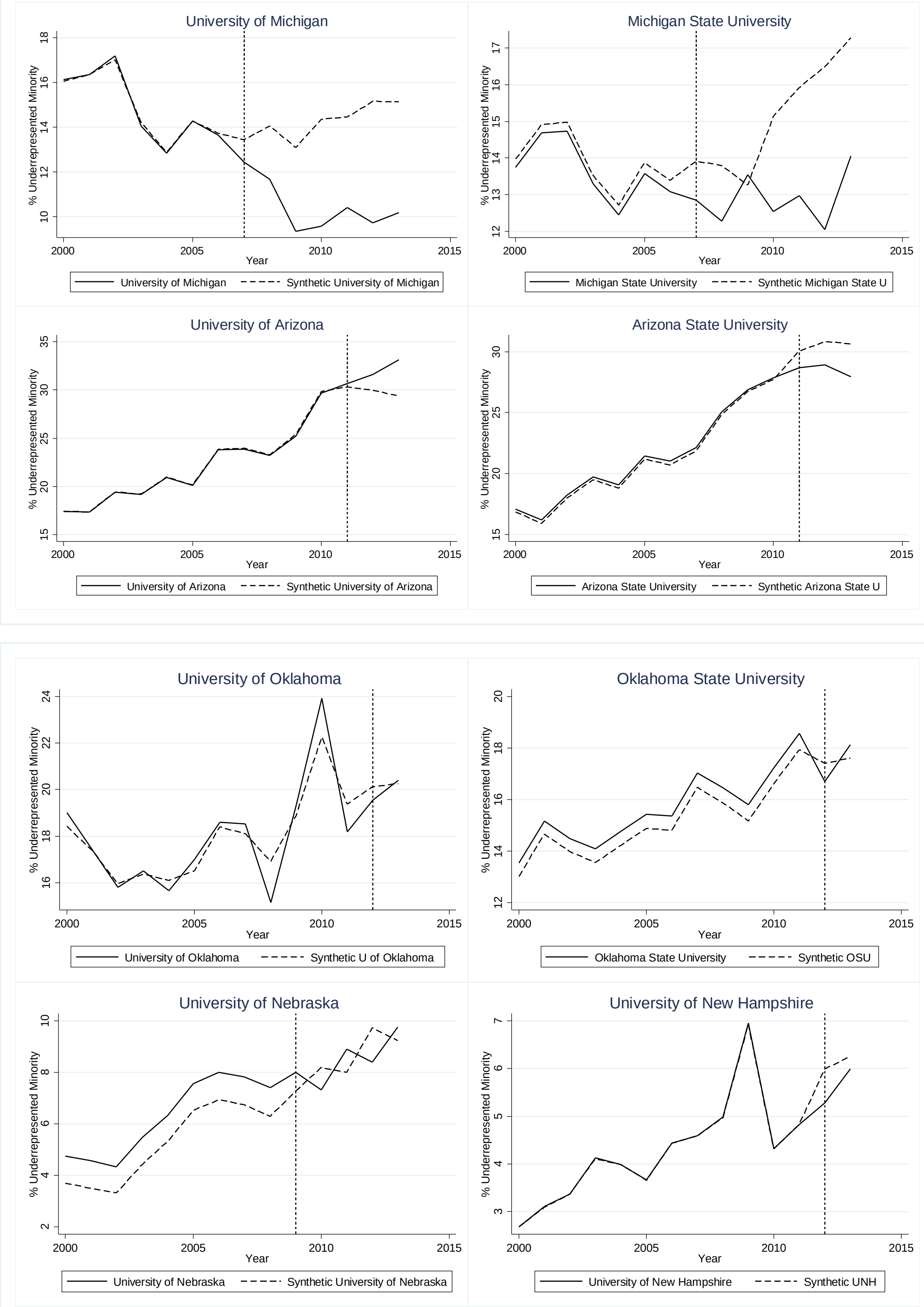

Figure 2: Black Exposure to Whites for California Universities

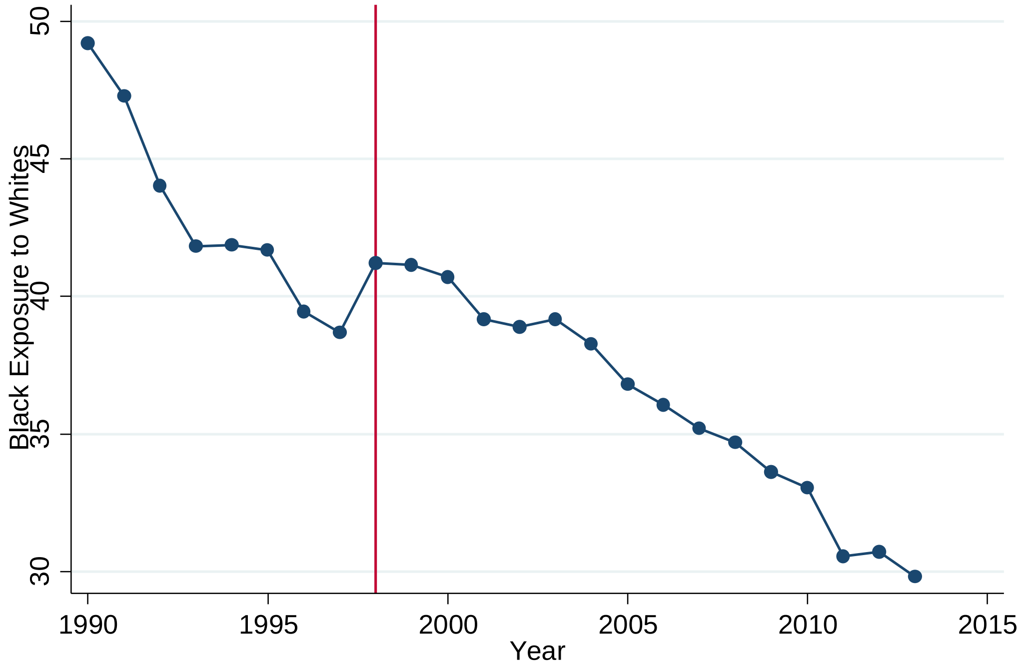

Figure 3: Black-White Dissimilarity for California Universities

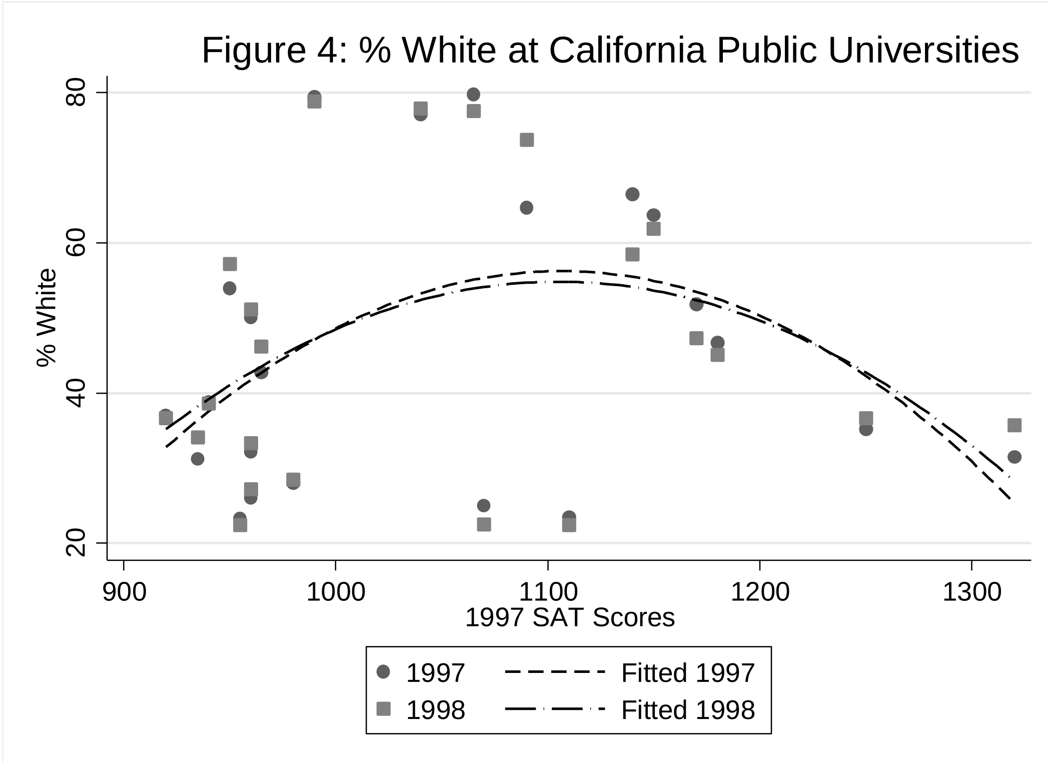

Figure 4: % White at California Public Universities
% White
20
40
60
80
900
1000
1100
1200
1300
1997 SAT Scores
1997
1998
Fitted 1997
Fitted 1998

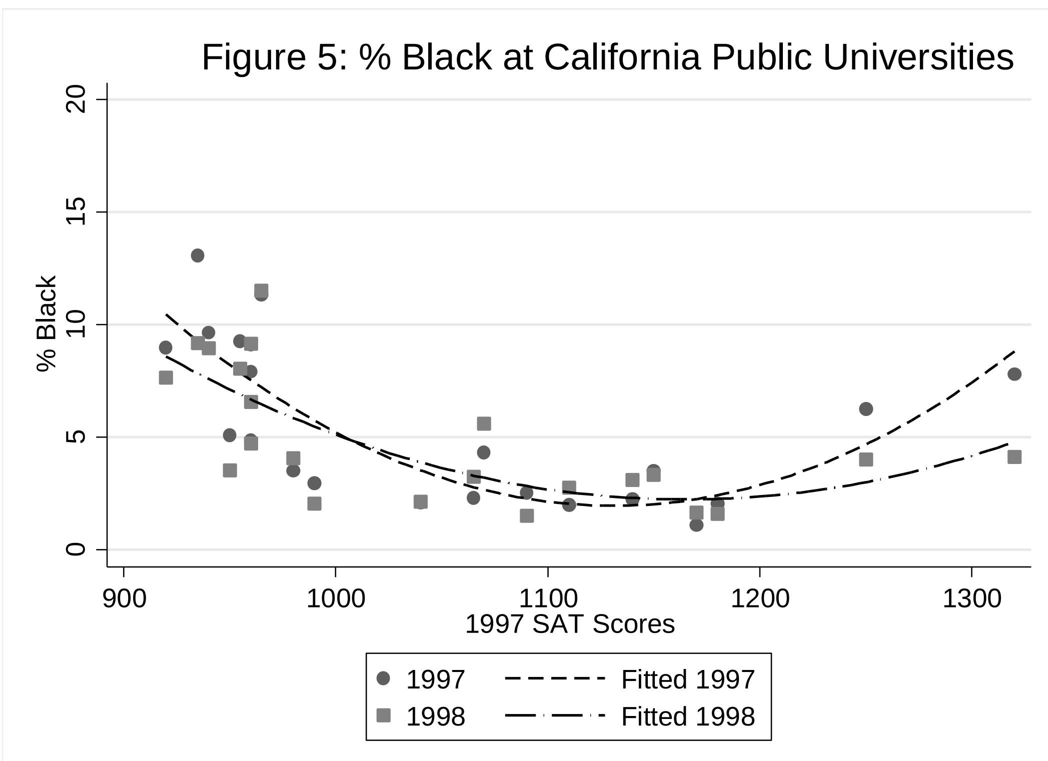

Figure 5: % Black at California Public Universities
% Black
0
5
10
15
20
900
1000
1100
1200
1300
1997 SAT Scores
1997
1998
Fitted 1997
Fitted 1998