The Effects of Affirmative Action Bans on Low-Income College Access and Upward Mobility

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Abstract

In recent years, many states in the U.S. have banned race-based affirmative action in college admissions. Public universities in these states have put more weight on socioeconomic factors, such as family income, to ensure a diverse student body without the explicit consideration of race. This paper investigates whether statewide affirmative action bans improve college access for low-income students and subsequently help them climb the economic ladder. Using institution-level data, I find that the elimination of race-based preferences increases the enrollment share of low-income and first-generation students at selective public universities. The positive impact on college access is driven by low-income Asian students. Banning the use of race in admissions also raises the upward mobility rate, which measures the extent to which an institution contributes to intergenerational income mobility.

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1. Introduction

Affirmative action is one of the most widely used programs that aims to correct past instances of discrimination.[1] It gives preferences to historically disadvantaged groups to increase their upward mobility, thereby creating a more inclusive society. However, it is argued that affirmative action policies mostly benefit more affluent members of disadvantaged groups, and thus do little to foster equal opportunity (Bertrand, Hanna, and Mullainathan 2010). For instance, in the United States, more than 85 percent of African American students at elite universities are middle or upper-class.[2] This is particularly controversial because race or ethnicity based affirmative action policies give admissions preferences to underrepresented minority (URM) students from high-income families, but not to low-income white or Asian students.

In recent years, many states in the U.S. have banned race-based affirmative action in college admissions.[3] Public institutions in these states have used a variety of methods to ensure a diverse student body without the explicit consideration of race (Kahlenberg 2014). For instance, they have emphasized socioeconomic factors such as family income because it is correlated with race (e.g., Chan and Eyster 2003; Antonovics and Backes 2014). These "color-blind" alternatives are often called *poverty preference* admissions policies because they target students from low-income families.

This paper investigates whether statewide affirmative action bans improve college access for low-income students and subsequently help them climb the economic ladder. In

[1] Findings in this paper are relevant to affirmative action programs in many other counties including India, Brazil, Israel, New Zealand, and South Africa (Guha and Roy Chowdhury 2017). For instance, India mandates affirmative action policies for certain caste groups in college admissions (e.g., Bertrand, Hanna, and Mullainathan 2010; Bagde, Epple, and Taylor 2016).

[2] This figure is based on data from 2006 Cooperative Institutional Research Program Freshman Survey. According to 2006 Current Population Survey from Census Bureau, the middle 60 percent of household income ranges from about $20,000 to $97,000. Elite institutions are defined as those in Tier 1 and 2 of Barron's 2009 selectivity index (e.g., Harvard University and University of California, Berkeley).

[3] Table 1 shows states that have banned affirmative action in college admissions.

order to understand mechanisms, I also explore how the enrollment composition of selective public universities change by parental income and race.

I estimate the average treatment effect of statewide affirmative action bans by exploiting the variation in bans across states and time (Antman and Duncan 2015; Backes 2012; Blume and Long 2014; and Hinrichs 2012, 2014, 2016). The analysis is based on unique, longitudinal, institution-level statistics on upward mobility rates, economic enrollment composition, and overall future earnings obtained from Chetty et al. (2017). I also make use of the Cooperative Institutional Research Program (CIRP) Freshman Survey.[4] This dataset allows me to construct the share of first-generation students and enrollment composition by socioeconomic status and race, which are not available in the public release of Chetty et al. (2017).

Statewide affirmative action bans increase the enrollment share of low-income and first-generation students at selective public universities.[5] The positive impact on low-income college access is driven by low-income Asian students. There is little change in the share of low-income white students. In fact, the enrollment of low-income URM students declines following the bans, which implies that the *new* poverty preferences may not be as beneficial as racial preferences.

Banning the use of race in admissions also raises the upward mobility rates of selective public universities. Upward mobility rate measures the extent to which an institution contributes to intergenerational income mobility.[6] It is defined as the enrollment share of students who come from families in the bottom income quintile and end up in the top quintile. Importantly, admitting more low-income students does not lead to a significant decrease in

[4] CIRP Freshman Survey is administered to about 300 thousand incoming college students at about 400 baccalaureate colleges and universities every year.

[5] Selective institutions are defined as those in Tier 1-5 of Barron's 2009 selectivity index

[6] I cannot rule out the possibility that the low-income students admitted due to race-neutral policies would have ranked high in the income distribution regardless of institutions they attend. It is also possible that the low-income students would have attended the selective private institutions which offer full scholarships for economically disadvantaged students.

overall student earnings or the income rank of low-income students at institutions, a finding that may mitigate concerns over the negative impact of such policies.

Consistent with an increased emphasis on socioeconomic factors, the estimated impacts of affirmative action bans are largest for students from the lowest income quintile, and the estimates tend to decrease and become negative for students from the higher income quintile. In particular, a decrease in the enrollment of high-income URM students is quite large in relative terms. However, at the same time, I find a significant increase in the share of students from the wealthiest families, defined as those from the top 5% in the national income distribution. One plausible explanation is that the black to white ratio in the U.S. is lower at the right tail of income distribution, suggesting that only a small fraction of those students are hurt by the removal of racial preferences. In addition, students from the wealthiest families are the most-qualified on average.[7]

This paper makes several important contributions to the literature on affirmative action. To my knowledge, it is the first to examine how the removal of racial preferences in admissions affects low-income college access using nationally representative data. Existing studies have focused on the effect of affirmative action bans on different race and ethnicity groups (Backes 2012; Hinrichs 2012, 2014; Long 2004). A few papers examine the effect on outcomes by economic status, but they are either theoretical (Epple, Romano, and Sieg 2008; Fryer, Loury, and Yuret 2008) or focus on individual reforms (Antonovics and Backes 2014; Ellison and Pathak 2016; Long and Tienda 2008).

This paper also contributes to the literature by providing some of the first systematic evidence on how affirmative action bans affect labor market outcomes. According to the *mismatch theory,* admission preferences for specific groups may make intended beneficiaries

[7] The average SAT scores monotonically increase with family income (College Board 2009).

worse off because they can be misplaced in terms of academic preparation (e.g., Bertrand, Hanna, and Mullainathan 2010; Bagde, Epple, and Taylor 2016). However, there is little understanding of how these policies affect long-term outcomes such as earnings. Arcidiacono (2005) is the only study that examines the impact on future earnings by estimating a structural model of the college decision-making process.

This paper adds to the existing set of studies on the policy response to address the limited college access among low-income students. The existing literature has focused on policies such as financial aid, recruiting, and information provision (e.g., Hoxby and Turner 2013, Angrist, Hudson, and Pallais 2014, Andrews, Imberman, and Lovenheim 2016). The effectiveness of poverty preference in admissions decisions has not received much attention, and most existing papers focus on outcomes by race (e.g., Long 2004). In this paper, I explore the change in enrollment composition by detailed socioeconomic and race groups.

The remainder of the paper is structured as follows. Section 2 describes affirmative action bans and institutions' responses. Section 3 describes the data, and Section 4 presents the empirical strategy. The main results are presented in Section 5. Section 6 presents a variety of robustness checks. Section 7 concludes the paper.

2. Background

2.1. Affirmative Action in the United States

Race-based affirmative action has been one of the most contentious features of postsecondary education in the U.S. It grants admissions preferences to URM groups such as African Americans, Native Americans, and Hispanics. Previous studies document significant SAT score gaps between majority and minority students at selective post-secondary institutions, which suggests the existence of racial preferences (e.g.. Arcidiacono, Khan, and Vigdor 2011).

Since affirmative action was applied to college admissions in the late 1960s, there have been numerous legal challenges regarding its constitutionality. Although the U.S. Supreme Court has narrowed universities' options, race-based affirmative action remains constitutional as long as race is considered as one of many factors. In *Regents of the University of California v. Bakke* (1978), the Supreme Court ruled that racial quotas are not permissible and that diversity is the only justifiable goal of affirmative action. In *Gratz v. Bollinger* (2003), the Supreme Court struck down the mechanical points system which gave specific extra points to minority applicants. The court decision in *Fisher v. University of Texas* (2013) emphasized "strict scrutiny" for racial preference which tests whether or not there is a race-neutral alternative to achieve diversity.

2.2. Statewide Affirmative Action Bans

States have banned affirmative action through voter referenda (California, Washington, Michigan, Nebraska, Arizona, and Oklahoma), lower courts decisions (Texas and Georgia), state legislation (New Hampshire), and an executive order (Florida). Although most of these states ban affirmative action at all public institutions, Texas and Georgia limit the practice at a few flagship public universities. Texas is the first state that banned affirmative action in 1996 but reopened the possibility of considering race in admissions in 2003. As a result, the University of Texas at Austin began using affirmative action again in 2005.[8] In Georgia, only one institution, the University of Georgia, discontinued using racial preferences. There are also states under an uncertain legal situation about affirmative action: Alabama, Georgia, Louisiana, and Mississippi. They were subject to important affirmative action litigation, but they do not completely ban the use of affirmative action (Hinrichs 2012, 2014, 2016).[9]

[8] Texas A&M University maintained race–neutral policies.
[9] I drop these states in analysis following Hinrichs (2012, 2014, 2016).

2.3. Admissions Policies under Affirmative Action Bans

Most universities and colleges in the U.S. pursue diversity as a core value (Chan and Eyster 2003, Epple et al. 2014). Therefore, institutions under affirmative action bans have used a variety of methods to ensure a diverse student body without the explicit consideration of race (Kahlenberg 2014).

First, the institutions modified their admission policies. In particular, they increased emphasis on socioeconomic factors that are correlated with race such as family income and parent education (Long 2007). These "color-blind" alternatives are often called *poverty preference* admissions policies because they target students from low-income families. Examples include top-x percent programs in Texas, California, and Florida. Under the programs, a fixed portion of graduates from each high school is guaranteed admission to state universities. A similar approach puts more weight on high school GPA than SAT scores. Considering school segregation in the U.S., low-income students are likely to benefit from these policy changes.

Second, institutions have strengthened their financial aid and recruitment programs. For example, Nebraska implemented *Collegebound Nebraska,* its expanded financial aid program in response to the affirmative action ban in 2008. It offers free tuition for state residents who are eligible for Pell Grant and maintain full-time status with a minimum GPA of 2.5. The University of Texas at Austin introduced several recruitment programs targeting underrepresented regions and high schools.[10]

Third, universities have put effort to grow a pool of qualified, disadvantaged students through partnerships with K–12 schools. For instance, *The Center for Educational Outreach* at

[10] Examples are *Longhorn Game Weekends* and *Longhorn for a Day.*

the University of Michigan was established to coordinate programs linking the university with K–12 schools. It has funded preparatory courses, summer programs, and mentoring for disadvantaged students in the state.

3. Data

3-1. The Equality of Opportunity Project

Longitudinal institution-level statistics on upward mobility rates, economic enrollment composition, and average future earnings are obtained from Chetty et al. (2017).[11] Summary statistics are reported in Table 2 and 3. The measures are based on administrative data from federal income tax returns and the Department of Education, covering over 30 million college students between 1999 and 2013. To be specific, rosters of college attendance at all Title IV institutions were obtained using Form 1098-T records and the National Student Loan Data System. Additionally, earnings of students and their parents were obtained using federal income tax returns and third-party information returns.[12]

Combining these data, Chetty et al. (2017) estimate each college's upward mobility rate, which measures the extent to which an institution contributes to intergenerational income mobility. An institution's upward mobility rate is defined as the product of *low-income access* (the share of students coming from families in the bottom income quintile) and *success rate* (the share of such students who end up in the top quintile). The low-income access and success rate can be considered as the quantity and quality of college's contribution, respectively. For example, at Stony Brook University, 17.2% of students come from families in the bottom income quintile, and 55.64% of them reach the top quintile.[13] Thus, Stony Brook's mobility

[11] Source: Equality of Opportunity Project (http://www.equality-of-opportunity.org)
[12] Students' incomes are measured in 2014, and their income percentiles are assigned by comparing them to children in the same birth cohort. Parents' incomes are averaged over the five years when the child is between 15 and 19 years old. Parental income percentiles are assigned by comparing them to parents whose children are in the same birth cohort.
[13] The figures are based on data for the 1980 birth cohort.

rate is 9.57%, which indicates about 10% of students come from the bottom quintile and end up in the top quintile. However, this index ignores those who move up to some point under the top quintile. Therefore, I construct an alternative upward mobility rate, which is the product of low-income access and the average income percentile of students coming from the bottom quintile. I use this index as my preferred measure of upward mobility rate.

Chetty et al. (2017) also report parental income distributions by the institution, separately by birth cohort. They estimate the percentage share of students coming from each quintile of the national parent income distribution. They also measure the share of students coming from the top 10%, 5%, and 1% families. Table 3 shows access to college in the U.S. greatly depends on socioeconomic status. Students whose parents are in the bottom quintile of the national income distribution comprise 8.61% of enrollment in the selective public universities, while those from the top quintile account for 33.67%.

3-2. Cooperative Institutional Research Program Freshman Survey

CIRP Freshman Survey is administered to about 300 thousand incoming college students at about 400 baccalaureate colleges and universities every year. It collects rich information on students' family background such as parental income and education as well as ethnicity. Pooling data from 1991 to 2006, I construct institution-level data on enrollment composition by parental income and race as well as the share of first-generation students. Parental income groups are defined to be consistent with measures from Chetty et al. (2017).[14] Summary statistics are presented in Table 3. The first two rows of Table 3 show parental income distributions of selective public universities from two different sources are quite comparable.

Figure 3 shows parent income distribution for each race at selective public universities.

[14] Categories vary by year based on the income distribution of the year.

Less than 5% of white students come from families in the bottom income quintile, while about 40% of white students come from the top income quintile families. For black and Hispanic students, parental income is more equally distributed. Figure 4 shows the share of first-generation students at different types of institutions.[15] On average, public universities have a higher share of first-generation students than private universities. In addition, less selective institutions have a higher share of first-generation students.

4. Empirical Analysis

Estimating the impact of affirmative action bans on enrollment composition is challenging because it depends on institutions' responses to the bans as well as the distribution of applicant characteristics. In particular, there is a lack of information on how exactly institutions have redistributed the weight given to each admissions factor. Moreover, institutions have used other approaches such as financial aid in different ways to pursue diversity.[16] Despite a variety of responses to bans, one common feature of those measures is that they tend to favor students from low-income families (Kahlenberg 2014). Especially, low-income white and Asian students are likely to benefit from the policy changes because they receive poverty preferences that they did not have before. URM students from low-income families are also eligible for poverty preferences, but they lose racial preferences. Therefore, the net effect depends on the relative size of each type of preference. High-income white and Asian students are not directly affected by the policy changes. The enrollment of high-income URM students is likely to decrease as they are no longer beneficiaries of racial preferences.

I estimate the average treatment effect of statewide affirmative action bans by exploiting the variation in bans across states and time (Antman and Duncan 2015; Backes 2012;

[15] First-generation students are defined as those whose parents didn't attend any college.
[16] See Section 2.3 for details.

Blume and Long 2014; and Hinrichs 2012, 2014, 2016). My empirical strategies rely on the idea that selective public universities in states without bans in a given year construct a close counterfactual of those in ban states in that year. However, states that prohibited the use of race in college admissions may differ from states without the bans in many other ways: for instance, they may have other progressive policies as well. To isolate the effect of affirmative action bans, first, I utilize Difference-in-Differences (DID) design which accounts for institution fixed effects, common birth cohort effects, and state-specific linear birth cohort trends. Second, I estimate event-study models which provide indirect tests of an assumption behind DID model. Lastly, I perform a set of additional robustness checks to support my causal interpretation.[17]

4-1. Difference-in-Differences

For a birth cohort b at institution i located in state s, I estimate the following specification:

$$\mathrm{Y}_{isb} = Ban_{sb}\alpha + \mu_i + \delta_b + \eta_s \mathrm{t} + \varepsilon_{isb} \tag{1}$$

where Y_{isb} is the outcome of interest, and Ban_{sb} is equal to 1 if affirmative action ban was in place when a birth cohort b in state s turned 18 years old and 0 otherwise. μ_i and δ_b indicate institution and birth cohort fixed effects which account for fixed differences between institutions and birth cohorts, respectively. $\eta_s \mathrm{t}$ is a full set of state-specific linear birth cohort trends taking into account differential trends across states. I test the sensitivity to including institution specific trends and time-varying state characteristics.[18] Standard errors are clustered at the state-level.[19] Note that the sample is first restricted to selective public institutions which are the intended targets of the policy, although I also examine the impacts on other types of

[17] See Section 6 for details.
[18] State controls include economic characteristics when students turn age 18 such as unemployment rate, household median income, and poverty rate. I also control for demographic variables such as total population and shares of male, white, black, Hispanic, Asian, and Native American.
[19] I also compute standard errors that are wild-cluster bootstrapped by state.

institutions. It is also important to note that I estimate the specification separately for each parental income and race group, depending on the outcomes.

The parameter of interest, α, measures the impact of affirmative action bans. The estimates should be interpreted as the average treatment effect considering the heterogeneous responses of institutions described in Section 2. The key identifying assumption is that outcomes would have moved in parallel in treated and untreated states in the absence of the program, after controlling for state-specific linear birth cohort trends. Thus, the main concern is my results are driven by trends in outcomes that are associated with affirmative action bans in a way that state linear trends do not capture.

4-2. Event Study

To check the validity of the pre-trends in outcomes and examine dynamic treatment effects, I estimate event study models of the following form:

$$\mathrm{Y}_{isb} = \sum_{j=-8}^{10} \gamma_j T_{j,sb} + \mu_i + \delta_b + \eta_s \mathrm{t} + \varepsilon_{isb} \quad (2)$$

where $T_{j,sb}$ represents a series of event time indicators and all other terms as defined above. The timing indicators equal 1 if the year cohort b from state s turned 18 minus the year of statewide affirmative action ban equals j and 0 otherwise. Values of j between -8 and -1 denote unexposed cohorts who turned age 19 or order in the year of the state wide affirmative action ban; a value of 0 and greater represent exposed cohorts who turned age 18 or younger in the year of the ban.[20] The reference category is a value of -1. The coefficients of interest are the γ_j, which map out the dynamic treatment effects of the affirmative action bans. In particular, the estimated coefficients for unexposed cohorts ($\gamma_{-8},\ldots,\gamma_{-1}$) provide evidence on systematic changes in outcomes prior to the affirmative action bans.

[20] Note that the indicator for event time 10 includes all years of exposure with event time above 10. Similarly, the indicator for event time -8 includes all years of exposure with event time less than minus -8.

5. Results

5-1. Low-income access, success rate, and upward mobility rate

Statewide affirmative action bans increase the enrollment share of low-income students at selective public universities, which is consistent with findings in individual states (Antonovics and Backes 2014; Long and Tienda 2008).[21] The first column of Table 4 suggests that an affirmative action ban is associated with a 0.54 and 0.33 percentage point higher share of low-income students at selective and elite public universities, respectively.[22] These changes translate into 6.27 and 5.77 percent increases, relative to average low-income access at each type of institutions.

Column 2 of Table 4 shows that admitting more low-income students does not lead to a significant decrease in the success rate of the institutions. The estimate for selective universities is negative, but the effect size is small in relative terms and insignificant. The estimate for elite institutions is positive and not statistically distinguishable from 0. These results mitigate the concern that institutions may admit less-qualified low-income students as a result of increased emphasis on socioeconomic factors (Antonovics and Backes 2014).[23]

Affirmative action bans raise the upward mobility rate of selective public universities. In column 3 of Table 4, banning the use of race in admissions is associated with a 0.31 percentage point increase in the upward mobility rates at both selective and elite public universities. Because the bases are small, these effects are large in relative terms, 6.46 and 8.49 percent increases. Interpreting these findings require caution because I cannot rule out the possibility that the low-income students admitted due to race-neutral policies would have

[21] Antonovics and Backes (2014) and Long and Tienda (2008) find that universities put more weight on socioeconomic factors after affirmative action bans in California and Texas, respectively.
[22] Selective and elite public universities indicate Tier 1-5 and 1-2 public institutions of Barron's 2009 index, respectively.
[23] I'm not able to separate the impact for students who are admitted as a result of policy changes.

ranked high in the income distribution regardless of institutions they attend. It is also possible that the low-income students would have attended the selective private institutions which offer full scholarships for economically disadvantaged students.

To test for endogeneity of the timing of bans, I present event study estimates from equation (2). Figure 2-A and 2-B graph event study estimates for low-income access and upward mobility rates at selective public universities, respectively. Each point indicates the coefficient estimate on event time indicators, and the bars extending from each point show 95 percent confidence intervals. In both graphs, there is little indication of systematic pre-event trends, supporting my assumption that the timing of affirmative action ban is exogenous. Although the upward mobility rate rises a little bit among unexposed cohorts, it could be sampling error. For exposed cohorts, I find positive impacts of affirmative action bans which increase with years of exposure. One explanation for the increasing treatment effect is that it took a few years for some institutions to introduce poverty preference policies following affirmative action ban.[24] In addition, there might be motivation effect of poverty preference policies for disadvantaged K-12 students (e.g., Hickman 2013; Cotton, Hickman, and Price 2015; Khanna 2016). If poverty preference programs encourage low-income students to study harder prior to college entry, it is likely that the impacts are larger for younger cohorts.

5-1-1. First-generation students

In Table 5, I investigate how affirmative action bans affect the enrollment of first-generation students at selective public universities. I use two different definitions of first-generation college students: 1) students whose parents didn't attend any college and 2) those whose parents didn't obtain a college degree. Consistent with the positive impact of affirmative action

[24] For instance, in Texas and California, affirmative action was banned in 1997 and 1998 admission cycle, and they introduced Percentage Plan in 1998 and 2001.

bans on the enrollment of low-income students, I find a highly significant increase in the enrollment share of first-generation students at selective public universities. Table 5, column 1, row 1, shows that an affirmative action ban is associated with a 4.84 percentage point or a 20.83 percent increase in the share of students whose parents didn't attend any college. In Table 5, column 2, row 1, I find a 7.22 percentage point or a 17.96 percent increase in the share of students whose parents didn't obtain a college degree. For elite public institutions, the estimates are positive but insignificant.

5-2. Enrollment composition by parental income and race

Table 6 presents the estimated effect of affirmative action bans on the enrollment composition by parental income, using data from Chetty et al. (2017). The first row shows estimates for selective public universities. Consistent with an increased emphasis on socioeconomic factors, I find that the estimated impacts are largest for students from the lowest income quintile, and the estimates tend to decrease and become negative for students from the higher income quintile.

However, at the same time, I find a significant increase in the share of students from the wealthiest families, defined as those from the top 5% in the national income distribution. One plausible explanation is that the black to white ratio in the U.S. is lower at the right tail of income distribution, suggesting that only a small fraction of those students are hurt by the removal of racial preferences. In addition, students from the wealthiest families are the most-qualified on average. For instance, the average SAT scores monotonically increase with family income (College Board 2009).

In the second row of Table 6, I find similar patterns for elite public universities. Notable differences compared to those in the first row are that the coefficients become negative from the 2nd quintile and that an increase in the share of students from the top 5% students is much larger.

The last column of Table 6 presents the estimated impact of affirmative action bans on total enrollment. For both selective and elite public institutions, the estimates are positive, but not statically significant.

Table 7 examines the changes in the economic and racial enrollment composition of selective public universities, using data from CIRP Freshman Survey.[25] Column 1 reveals that the positive effect on low-income college access is driven by Asian students. The enrollment share of Asians from the bottom quintile families increases by 1.66 percentage points, which is quite large in relative terms (Panel A, column 1, row 3). For low-income white students, I find little indication of change in the enrollment share (Panel A, column 1, row 1). Importantly, despite various policies designed for disadvantaged minority students after affirmative action bans, the share of low-income URM students decreases at selective public universities (Panel B, column 1).

In Panel B of Table 7, results show that affirmative action bans reduce the enrollment share of high-income URM students at selective public universities. Affirmative action ban is associated with a significant decrease of 0.65 and 0.76 percentage points in the share of URM students from the 4th and 5th quintile families, respectively (Panel B, column 4-5, row 1). It is also noteworthy that the enrollment share of black students decreases regardless of parental income group.

5-3. Expected Future Student Earnings

[25] I find similar patterns for elite public universities.

In Table 8, I examine how affirmative action bans affect average and median future student earnings of selective public universities. Despite a significant shift in the enrollment composition, I find little evidence that expected future student earnings changed at selective public institutions (row 1). For elite public universities, I find that affirmative action bans are associated with significant increases in average and median future student earnings (row 2). This may stem from a large increase in the share of students from the wealthiest families who have higher expected earnings on average.

6. Robustness

6-1. Sensitivity test

Table 9 shows the results of sensitivity tests using alternative measures of outcomes and specifications. In the third and fifth row, I present estimates where the dependent variable is the share of low-income students who reach the top quintile and the share of students who come from the bottom quintile families and end up in the top quintile, respectively.[26] The first three columns use state-specific linear birth cohort trends, and the latter three columns use institution-specific trends. In columns 2 and 5, I add time-varying state characteristics that could potentially impact outcomes and be correlated with affirmative action bans. State controls include economic characteristics when students turn 18 years old such as unemployment rate, household median income, and poverty rate. In addition, because my findings may capture demographic changes in states, I control for total population and percentages of male, white, black, Hispanic, Asian, and Native American. In columns 3 and 6, I limit the control group to states that are adjacent to ban states and use state-specific trends.

[26] Low-income students indicate those coming from the bottom quintile families in the national income distribution.

The results are robust across specifications for all outcomes. In row 2, the estimates for the main measure of success rate slightly fluctuate. However, the fluctuations are small and not statistically significant. Moreover, the coefficients are in different directions in different specifications, indicating little impact of affirmative action bans on the success rate.

6-2. Falsification Test

As a placebo falsification test, I estimate the impact of affirmative action bans that occurred after students had already entered universities. To be specific, I estimate the coefficient of an indicator for whether a cohort was either 20 or 21 years old in the year when a ban was applied statewide.[27] The results are presented in Table 10. Panels A and B provide estimates for selective and elite public institutions, respectively. The first row of each panel presents estimates of equation (1) for comparison purposes. For all outcomes, the placebo estimates are small and insignificant.

6-3. Endogenous Interstate Migration

One concern is that an increase in the enrollment of low-income students may be explained by endogenous interstate migration.[28] For instance, it is possible that low-income students move to adjacent ban states to be enrolled in selective public universities. I test this concern by estimating the effect of affirmative action bans in the *adjacent* states on the economic enrollment composition of selective public institutions. The results are presented in Table 11. The first row presents estimates of equation (1) for comparison purposes. The second row presents the estimated effect of affirmative action bans in the adjacent states. The coefficients

[27] Backes (2012) shows that affirmative action bans coming either two or three years in the future do not predict changes in minority enrollment at public institutions.
[28] Using institution-level data on the share of out-of-state students from the Integrated Postsecondary Education Data System (IPEDS), Backes (2012) find little evidence of endogenous residential mobility.

are small and insignificant, indicating that endogenous interstate migration is not an important source of bias.

6-4. Non-Selective and Private Institutions

The implication of admitting more low-income students at selective public institutions would be quite different depending on where they would have been placed without policy changes. Although this study is not able to identify counterfactual outcomes of the low-income students, the estimates for non-selective and private institutions presented in Table 12 provide some suggestive evidence on this issue. For instance, a decrease in the share of students from the bottom quintile families at non-selective 4-year public institutions (Panel A, column 1, row 1) is roughly comparable to an increase in the share of low-income students at selective public institutions (Panel A, column 1, row 2). Thus, one may infer that the changes in admission policies help low-income students attend more selective institutions and climb the income ladder. However, the estimate for low-income students at selective private institutions also shows a similar decrease (Panel B, column 1, row 2), suggesting the possibility that low-income students would have attended the selective private institutions without affirmative action bans.

7. Conclusion

Affirmative action has been a contentious feature of postsecondary education in the U.S. since its introduction in the late 1960s. Although the Supreme Court has upheld the use of race as one of the various admissions factors, many states have banned affirmative action at their public universities. Public institutions in these states have put more weight on socioeconomic factors such as family income to ensure diverse student bodies without the explicit consideration of race (e.g., Chan and Eyster 2003; Antonovics and Backes 2014).

Using a unique institution-level dataset, I find that affirmative action bans increase the enrollment share of low-income and first-generation students at selective public universities. Banning the use of race in admissions also raises the upward mobility rate, which measures the extent to which an institution contributes to intergenerational income mobility. These findings imply that *equal opportunity without regard to race* can be better achieved in the absence of affirmative action. In addition, I find that admitting more low-income students does not lead to a significant decrease in overall student earnings or the income rank of low-income students at institutions, a finding that may mitigate concerns over the negative impact of such policies.

However, it is important to consider how affirmative action bans affect different groups of students. Although there is an overall improvement of low-income access, the enrollment of low-income URM students declines following affirmative action bans. I also find a significant increase in the share of students from the wealthiest families.

Affirmative action policies alter how scarce resources are allocated. In the context of college admissions, the trade-offs can be especially large, as the benefit to one student comes at the cost of another student. To improve the targeting and better understand welfare implications, future research should focus on how different types of institutional responses to affirmative action bans change the characteristics of a student body including race, socioeconomic status, and academic qualifications. It is also important to look at other types of long-term outcomes such as employment and marriage. This knowledge is particularly important from a policy-making perspective, especially for those who are considering alternative forms of affirmative action policies.

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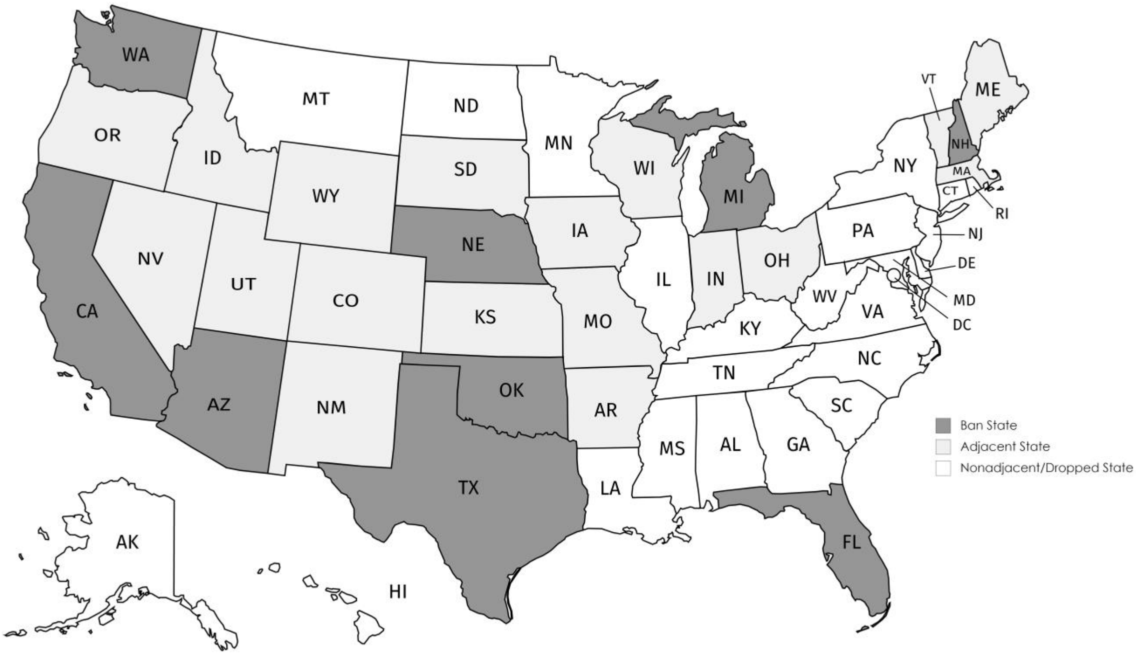
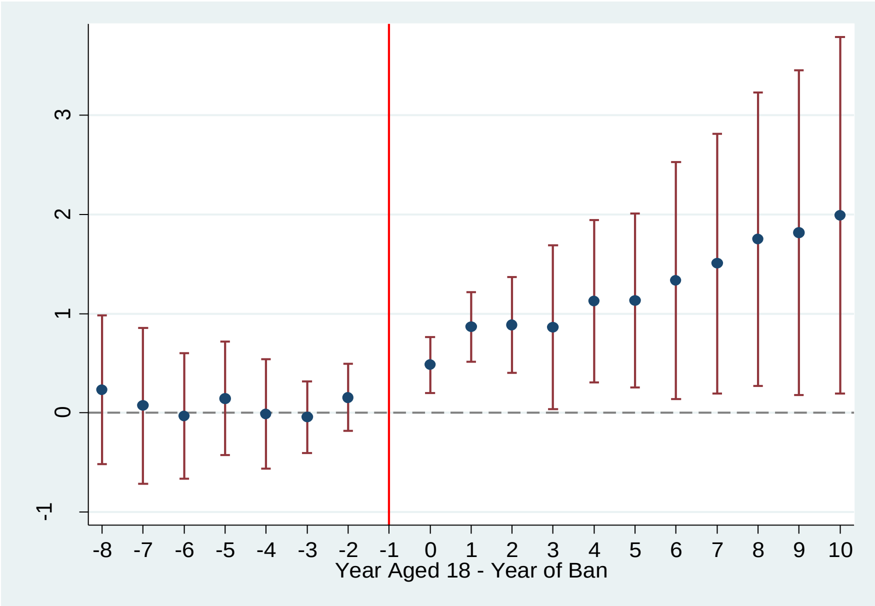
Figure 1. Statewide Affirmative Action Bans



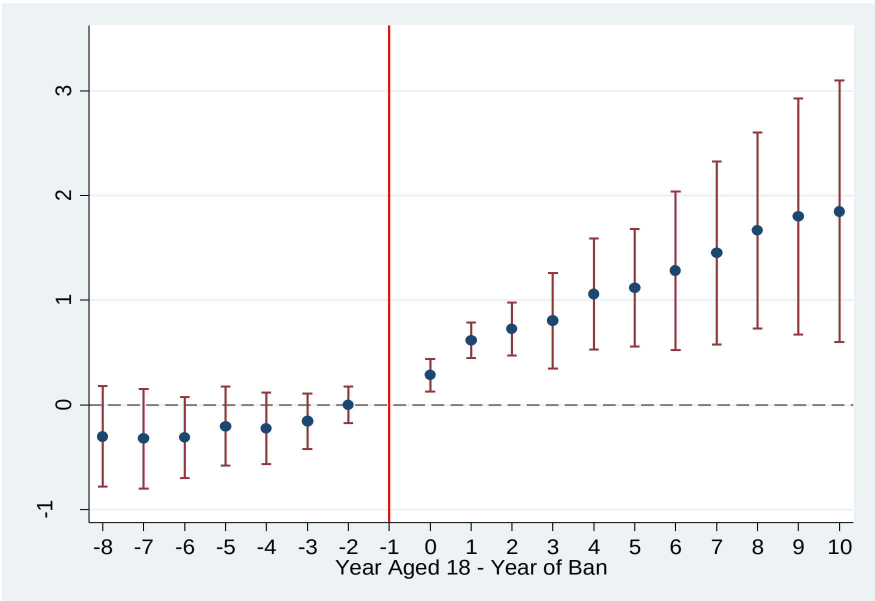
Notes: Map indicates states that banned race-based Affirmative Action, as listed in Table 1.

Figure 2. Event Study Estimates of Effects of Affirmative Action Bans on Low-income Access and Upward Mobility Rate of Selective Public Universities

A. Low-income Access

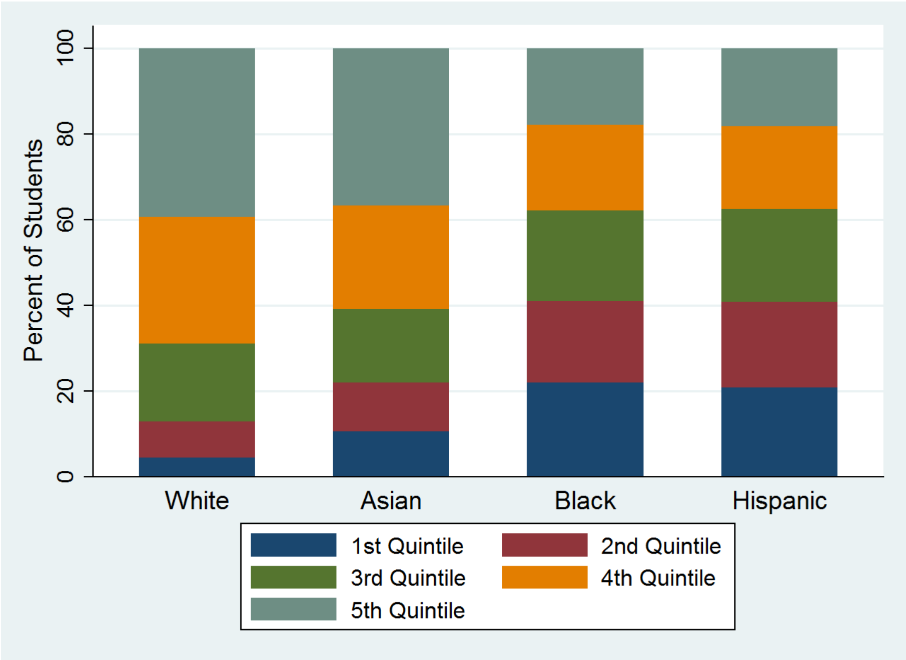


B. Upward Mobility Rate



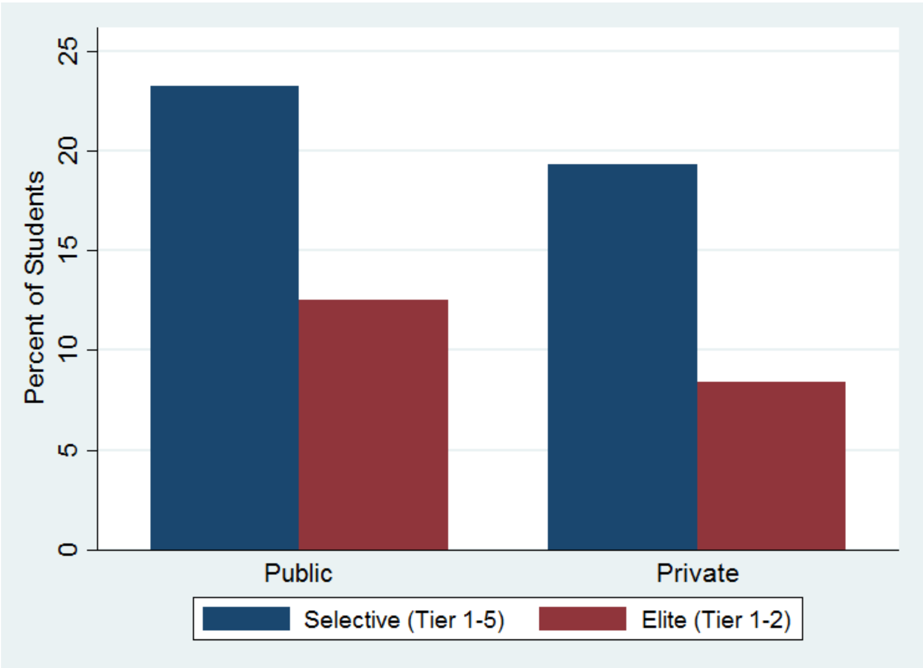
Notes: College-level statistics from Chetty et al. (2017), selective public universities. Each point represents the coefficient estimate on event time indicators from equation (2), and the bars extending from each point show 95 percent confidence intervals. Dependent variables are Low-income Access (Panel A) and Upward Mobility Rate (Panel B). Low-income Access is the share of students from the bottom quintile families, and Upward Mobility Rate is the product of the share of students from the bottom quintile families and the average income percentile of such students. All regressions control for institution FEs, birth cohort FEs, and state-specific birth cohort trends. The regressions are weighted by enrollment, and standard errors are clustered by state.

Figure 3. Parent Income Distribution by Race at Selective Public Universities



Notes: Institutional data based on CIRP Freshman Survey, selective public universities (public institutions in Tier 1-5 of Barron's 2009 index).

Figure 4. Share of First-generation Students



Notes: Institutional data based on CIRP Freshman Survey, Selective/Elite universities indicates Tier 1-5/1-2 institutions of Barron's 2009 index.

Table 1: Timing of Affirmative Action Bans

State	Year
Texas	1997
California	1998
Washington	1999
Florida	2001
Michigan	2007
Nebraska	2009
Arizona	2011
New Hampshire	2012
Oklahoma	2013

Notes: The timing of bans is based on the year a ban first applied to public institutions statewide (Hinrichs 2016).

Table 2. Summary Statistics on Upward Mobility Rate and Average Future Earnings

	All states	Ban states	Nonban states
Low-income access	8.61	9.56	8.27
	(5.73)	(5.79)	(5.67)
Success rate I	57.10	58.90	56.40
	(6.69)	(6.42)	(6.67)
Success rate II	25.40	29.10	24.10
	(11.50)	(11.30)	(11.20)
Upward mobility rate I	4.80	5.55	4.54
	(3.09)	(3.26)	(2.98)
Upward mobility rate II	2.03	2.62	1.82
	(1.56)	(1.58)	(1.50)
Average future earnings	38,182	40,058	37,514
	(13,880)	(15,218)	(13,310)
Median future earnings	34,260	35,543	33,802
	(12,093)	(13,031)	(11,710)
Enrollment	2,450	2,555	2,413
	(2,987)	(1,855)	(3,298)
Number of observations	3,744	984	2,760

Notes: College-level statistics from Chetty et al. (2017), selective public universities (public institutions in Tier 1-5 of Barron's 2009 index). This table reports unweighted means and standard deviations (in parentheses). Ban states are those that had affirmative action bans in place by the 2009. The *Low-income Access* is the share of students from the bottom quintile families in the national income distribution (low-income students). *Success rate I* is the average income percentile of low-income students in the national distribution. *Success rate II* is the share of low-income students who reach the top quintile. *Upward Mobility I* is the product of the *Low-income Access* and *Success rate I*. *Upward Mobility II* is the product of the *Low-income Access* and *Success rate II*. Statistics are expressed in percentage terms for *Low-income Access*, *Success rate*, and *Upward Mobility*.

Table 3. Summary Statistics on Enrollment Composition

	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Panel A. Data from Chetty et al. (2017)					
All races					
Mean	8.61	12.89	18.61	26.21	33.67
S.D.	(5.73)	(5.48)	(4.60)	(5.36)	(13.75)
Obs.			3,744		
Panel B. CIRP Freshman Survey					
All races					
Mean	6.89	9.84	18.40	28.22	36.70
S.D.	(4.80)	(4.95)	(6.28)	(5.88)	(14.02)
Obs.			1,121		
White					
Mean	3.69	6.68	14.33	23.48	31.16
S.D.	(2.66)	(4.38)	(6.98)	(7.50)	(12.53)
Obs.			1,121		
Asian					
Mean	0.87	0.81	1.04	1.34	2.02
S.D.	(1.47)	(1.25)	(1.44)	(1.79)	(2.92)
Obs.			1,121		
Black					
Mean	1.42	1.23	1.31	1.23	1.12
S.D.	(1.84)	(1.37)	(1.23)	(1.07)	(0.91)
Obs.			1,121		
Hispanic					
Mean	1.41	1.23	1.25	1.03	0.98
S.D.	(3.07)	(2.35)	(2.24)	(1.54)	(1.22)
Obs.			1,121		

Notes: This table reports summary statistics of enrollment composition of selective public universities (public institutions in Tier 1-5 of Barron's 2009 index). Statistics are expressed in percentage terms. Panel A displays statistics for data from Chetty et al. (2017). Panel B reports statistics for data from CIRP Freshman Survey.

Table 4: Effects of Affirmative Action Bans on Low-income Access, Success Rate, and Upward Mobility Rate of Selective Public Universities

	Low-income Access	Success Rate	Upward Mobility
	(1)	(2)	(3)
Selective Public	0.54***	-0.16	0.31***
	(0.18)	(0.48)	(0.10)
Mean	8.61	57.09	4.80
No. of observations		3,744	
Elite Public	0.33***	1.44	0.31***
	(0.11)	(1.40)	(0.05)
Mean	5.72	63.78	3.65
No. of observations		324	

Notes: College-level statistics from Chetty et al. (2017), selective public universities. Each cell corresponds to a separate regression estimate of equation (1). Estimates are expressed in percentage terms. The dependent variables are *Low-income Access* (the share of students from the bottom quintile families in the national income distribution), *Success Rate* (the average income percentile of low-income students in the national distribution), and *Upward Mobility* (the product of the *Low-income Access* and *Success rate*). *Selective/Elite Public* indicates Tier 1-5/1-2 public institutions of Barron's 2009 index. Mean indicates the mean of the dependent variable for the corresponding group of institutions. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by enrollment, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effects of Affirmative Action Bans on the Share of First-generation Students at Selective Public Universities

	% of First-generation Students (Attendance)	% of First-generation Students (Degree)
	(1)	(2)
Selective Public	4.84***	7.22***
	(1.21)	(1.27)
Mean	23.24	40.19
No. of observations	1,121	1,121
Elite Public	2.41	1.80
	(1.61)	(1.81)
Mean	12.54	24.51
No. of observations	153	153

Notes: Institutional data based on CIRP Freshman Survey, selective public universities. Each cell corresponds to a separate regression estimate of equation (1). Estimates are expressed in percentage terms. The dependent variables are the enrollment shares of first-generation students. *% of First-generation Students (Attendance)* indicates the share of students whose parents didn't attend any college. *% of First-generation Students (Degree)* indicates the share of students whose parents didn't obtain a college degree. *Selective/Elite Public* indicates Tier 1-5/1-2 public institutions of Barron's 2009 index. Mean indicates the mean of the dependent variable. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by the sum of student weights in the institution, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Effects of Affirmative Action Bans on Economic Composition of Selective Public Universities

	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	Top 20 to 5%	Top 5%	Top 1%	Enrollment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Selective Public	0.54***	0.24	0.09	-0.52***	-0.68**	0.34**	0.23***	106.47
	(0.18)	(0.14)	(0.22)	(0.06)	(0.29)	(0.15)	(0.07)	(172.20)
Mean	8.61	12.89	18.61	26.21	26.01	7.66	1.15	2450
No. of observations				3,744				
Elite Public	0.33***	-0.35***	-0.66***	-1.24*	-0.68	2.60***	1.04***	178.77
	(0.11)	(0.05)	(0.12)	(0.59)	(0.51)	(0.30)	(0.07)	(203.59)
Mean	5.72	8.69	12.95	21.36	34.93	16.34	2.79	5418
No. of observations				324				

Notes: College-level statistics from Chetty et al. (2017), selective public universities (public institutions in Tier 1-5 of Barron's 2009 index). Each cell corresponds to a separate regression estimate of equation (1). Estimates are expressed in percentage terms. In column 1-8, the dependent variables are the enrollment shares of students in the corresponding groups. In column 9, the dependent variable is total enrollment. *Selective/Elite Public* indicates Tier 1-5/1-2 public institutions of Barron's 2009 index. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by enrollment, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Effects of Affirmative Action Bans on Economic and Racial Composition of Selective Public Universities

	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)
Panel A. White and Asian					
White and Asian	1.66*	1.22***	0.22	1.12**	-1.98**
	(0.86)	(0.43)	(0.50)	(0.48)	(0.96)
Mean	4.16	7.19	15.08	24.53	32.80
No. of observations			1,121		
Whites	-0.01	0.62**	-0.27	1.33**	-2.47***
	(0.25)	(0.24)	(0.56)	(0.51)	(0.78)
Mean	3.69	6.68	14.33	23.48	31.16
No. of observations			1,121		
Asians	1.67**	0.60**	0.49**	-0.22**	0.50
	(0.70)	(0.29)	(0.23)	(0.10)	(0.33)
Mean	0.87	0.81	1.04	1.34	2.02
No. of observations			1,121		
Panel B. Black, Hispanic, and Native American					
Black, Hispanic, and Native	-0.46	-0.64	-0.17	-0.65*	-0.76*
	(0.28)	(0.44)	(0.14)	(0.38)	(0.43)
Mean	2.34	2.10	2.28	2.08	1.95
No. of observations			1,121		
Blacks	-0.17	-0.18	-0.36***	-0.21**	-0.52***
	(0.17)	(0.14)	(0.10)	(0.10)	(0.11)
Mean	1.42	1.23	1.31	1.23	1.12
No. of observations			1,121		
Hispanics	-0.25*	-0.42	0.17	-0.41	-0.21
	(0.13)	(0.31)	(0.13)	(0.29)	(0.37)
Mean	1.41	1.23	1.25	1.03	0.98
No. of observations			1,121		

Notes: Institutional data based on CIRP Freshman Survey, selective public universities (public institutions in Tier 1-5 of Barron's 2009 index). Each cell corresponds to a separate regression estimate of equation (1). Estimates are expressed in percentage terms. The dependent variables are the enrollment shares of students in the corresponding groups. Mean indicates the mean of the dependent variable. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by the sum of student weights in the institution, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Effects of Affirmative Action Bans on Expected Future Student Earnings of Selective Public Universities

	ln(Avg. Earnings)	ln(Median Earnings)
	(1)	(2)
Selective Public	-0.0004	-0.0051
	(0.0099)	(0.0166)
No. of observations	3,744	
Elite Public	0.0503***	0.0742***
	(0.0119)	(0.0225)
No. of observations	324	

Notes: College-level statistics from Chetty et al. (2017), selective public universities. Each cell corresponds to a separate regression estimate of equation (1). The dependent variables are the natural log of average and median future student earnings. *Selective/Elite Public* indicates Tier 1-5/1-2 public institutions of Barron's 2009 index. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by enrollment, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. Effects of Affirmative Action Bans on Upward Mobility Rate of Selective Public Universities using Alternative Measures and Specifications

	(1) State trends	(2) State trends and controls	(3) State trends and adjacent states	(4) University trends	(5) University trends and controls	(6) University trends and adjacent states
Low-income Access	0.54***	0.53***	0.52***	0.52**	0.51***	0.50**
	(0.18)	(0.14)	(0.17)	(0.20)	(0.15)	(0.19)
Success Rate I	-0.16	0.06	-0.16	-0.07	0.14	-0.07
	(0.48)	(0.53)	(0.59)	(0.56)	(0.60)	(0.67)
Success Rate II	-0.69	-0.60	-0.70	-0.54	-0.48	-0.54
	(0.75)	(0.75)	(0.80)	(0.85)	(0.84)	(0.89)
Upward Mobility I	0.31***	0.33***	0.30***	0.31***	0.32***	0.30***
	(0.10)	(0.09)	(0.08)	(0.10)	(0.09)	(0.08)
Upward Mobility II	0.10**	0.11*	0.09***	0.10***	0.11*	0.10***
	(0.04)	(0.06)	(0.03)	(0.04)	(0.06)	(0.03)
No. of observations	3,744	3,744	2,100	3,744	3,744	2,100

Notes: College-level statistics from Chetty et al. (2017), selective public universities (public institutions in Tier 1-5 of Barron's 2009 index). Each cell corresponds to a separate regression estimate of equation (1). Estimates are expressed in percentage terms. All regressions control for institution fixed effects and birth cohort fixed effects. Column 1-3 add state-specific linear birth cohort trends, and column 4-6 add institution-specific trends. Column 2 and 5 add time-varying state characteristics: unemployment rate, median household income, poverty rate, total population, and other demographic variables explained in Section 4. Column 3 and 6 drop nonadjacent control states in the analysis. The dependent variables are *Low-income Access* (the share of students from the bottom quintile families in the national income distribution), *Success rate I* (the average income percentile of low-income students in the national distribution), *Success rate II* (the share of low-income students who reach the top quintile), *Upward Mobility I* (the product of the *Low-income Access* and *Success rate I*), and *Upward Mobility II* (the product of the *Low-income Access* and *Success rate II*). The regressions are weighted by enrollment, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Effects of Affirmative Action Bans in Age 20 or 21 on Low-income Access and Upward Mobility Rate of Selective Public Universities

	Low-income Access	Upward Mobility I	Upward Mobility II
	(1)	(2)	(3)
Panel A. Selective public institutions			
Ban in age 18 or younger	0.54***	0.31***	0.10**
	(0.18)	(0.10)	(0.04)
Ban in age 20 or 21	-0.17	-0.08	0.03
	(0.11)	(0.08)	(0.05)
Mean	8.61	2.03	4.80
No. of observations		3,744	
Panel B. Elite public institutions			
Ban in age 18	0.33***	0.31***	0.30**
	(0.11)	(0.05)	(0.11)
Ban in age 20 or 21	-0.04	-0.05	-0.09
	(0.06)	(0.05)	(0.05)
Mean	5.72	3.65	2.36
No. of observations		324	

Notes: College-level statistics from Chetty et al. (2017), selective public universities. Each cell corresponds to a separate regression estimate. Estimates are expressed in percentage terms. The first row of each Panel presents the estimate of equation (1) for comparison purposes. The second rows show coefficient estimates of an indicator for whether a cohort is either 20 or 21 years old in the year when a ban was first applied statewide. The dependent variables are *Low-income Access* (the share of students from the bottom quintile families in the national income distribution), *Upward Mobility I* (the product of the share of students from the bottom quintile families and the average income percentile of such students in the national distribution), and *Upward Mobility II* (the product of the share of students from the bottom quintile families and the share of such students who reach the top quintile). *Selective* and *elite* public institutions indicate Tier 1-5 and 1-2 public institutions of Barron's 2009 index, respectively. Mean indicates the mean of the dependent variable for the corresponding group of institutions. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by enrollment, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Effects of Affirmative Action Bans in the Adjacent States on Economic Composition of Selective Public Universities

	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile	Top 10%	Top 5%	Top 1%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ban in the state	0.54***	0.24	0.09	-0.52***	-0.34	0.31*	0.34**	0.23***
	(0.18)	(0.14)	(0.22)	(0.06)	(0.36)	(0.18)	(0.15)	(0.07)
Ban in the adjacent state	0.08	0.02	-0.19	-0.07	0.16	-0.11	-0.04	-0.03
	(0.14)	(0.12)	(0.19)	(0.29)	(0.54)	(0.37)	(0.22)	(0.07)
No. of observations					3,744			

Notes: College-level statistics from Chetty et al. (2017), selective public universities (public institutions in Tier 1-5 of Barron's 2009 index). Each cell corresponds to a separate regression estimate. Estimates are expressed in percentage terms. The first row presents estimates in the first row of Table 5 for comparison purposes. The second row presents estimates of the effect of affirmative action bans in the adjacent states. The dependent variables are the enrollment shares of students in the corresponding groups. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by enrollment, and standard errors are clustered by state. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12. Effects of Affirmative Action Bans on Economic Composition of Non-Selective and Private Universities

	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile	Top 10%	Top 5%	Top 1%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Public 4-year								
Non-selective Public 4-year	-0.59	-0.46	-0.90**	0.50	1.44**	0.74**	0.33**	0.03
	(0.53)	(0.30)	(0.40)	(0.40)	(0.56)	(0.25)	(0.12)	(0.03)
No. of observations	588							
Selective Public	0.54***	0.24	0.09	-0.52***	-0.34	0.31*	0.34**	0.23***
	(0.18)	(0.14)	(0.22)	(0.06)	(0.36)	(0.18)	(0.15)	(0.07)
No. of observations	3,744							
Panel B. Private 4-year								
Non-selective Private 4-year	0.57	-1.15**	-0.38	0.43*	0.53**	0.33***	0.07	0.06**
	(0.41)	(0.44)	(0.82)	(0.23)	(0.21)	(0.12)	(0.08)	(0.03)
No. of observations	816							
Selective Private	-0.49	-0.49	-0.57***	0.39***	1.17	0.79	0.10	0.08
	(0.43)	(0.32)	(0.21)	(0.11)	(0.88)	(0.78)	(0.30)	(0.21)
No. of observations	5,844							
Panel C. 2-year								
2-year	1.40***	0.26	-0.62***	-0.42	-0.63*	-0.05	-0.05	0.01
	(0.39)	(0.16)	(0.21)	(0.41)	(0.34)	(0.14)	(0.10)	(0.01)
No. of observations	6,036							

Notes: College-level statistics from Chetty et al. (2017). Each cell corresponds to a separate regression estimate of equation (1). Estimates are expressed in percentage terms. The dependent variables are the enrollment shares of students in the corresponding groups. *Selective* indicates Tier 1-5 institutions of Barron's 2009 index. All regressions control for institution fixed effects, birth cohort fixed effects, and state-specific linear birth cohort trends. The regressions are weighted by enrollment, and standard errors are clustered by state. *** p<0.01, ** p<0.05, * p<0.1.