Inclusion Restrictions: The Impact of Affirmative Action Bans on Economics Degree Attainment

By Derek Situ

Affirmative action, a set of policies that allow institutions to consider race and gender in admissions and employment decisions, was banned federally in June 2023, with several states implementing their own bans as early as 1996. I exploit the staggered implementation of affirmative action bans across states to obtain the first causal estimates of their effect on the number of economics degrees awarded to historically excluded groups. Primary findings reveal limited effects of bans on the outcomes of women and underrepresented minorities across bachelor's, master's and doctoral levels. Evidence of heterogeneity of effects by program selectivity and state political affiliation is mixed.

In the United States, the economics profession is less diverse than the general population. Just over 50% of the population are women in the U.S. (Statista, 2023), while only 23% of academic economists and 30% of government economists are women (Akee, 2020). Furthermore, about 40% of the population are minorities in the U.S. (Wikipedia, 2024), while only 21% of academic economists and 24% of government economists are minorities (Akee, 2020).

An important driver of diversity in the economics profession is the racial/ethnic and gender composition of economics degree holders. Data on degree completions by major area of study, gender, and racial/ethnic background show that some groups are over-represented in economics education, while others are under-represented. Figure 1 shows the historic representation of women by degree level and major. Notably, women are over-represented in education *in general*, as the proportion of bachelor's and master's degrees in all subjects awarded to women is greater than 55% from 1996 to 2023. And, since 2008, the majority of doctoral degrees in all subjects were awarded to women every year. However, in STEM and economics, women are under-represented. At the bachelor's level, the representation of women in economics is even less than in STEM, ranging from 30% to 35% from 1996 to 2023. At the master's level, women are represented at a higher rate in economics than in STEM, however they are still under-represented compared to the population as the proportion of degrees awarded to women in economics from 1996 to 2023 ranged from about 33% to 43%. At the doctoral level, the representation of women in STEM and economics has been about equal, ranging from 20% to 37% from 1996 to 2023. Overall, this demonstrates the low representation of women in economics, especially at the bachelor's level, where the representation of women in STEM, a traditionally male-dominated field, is greater than in economics.

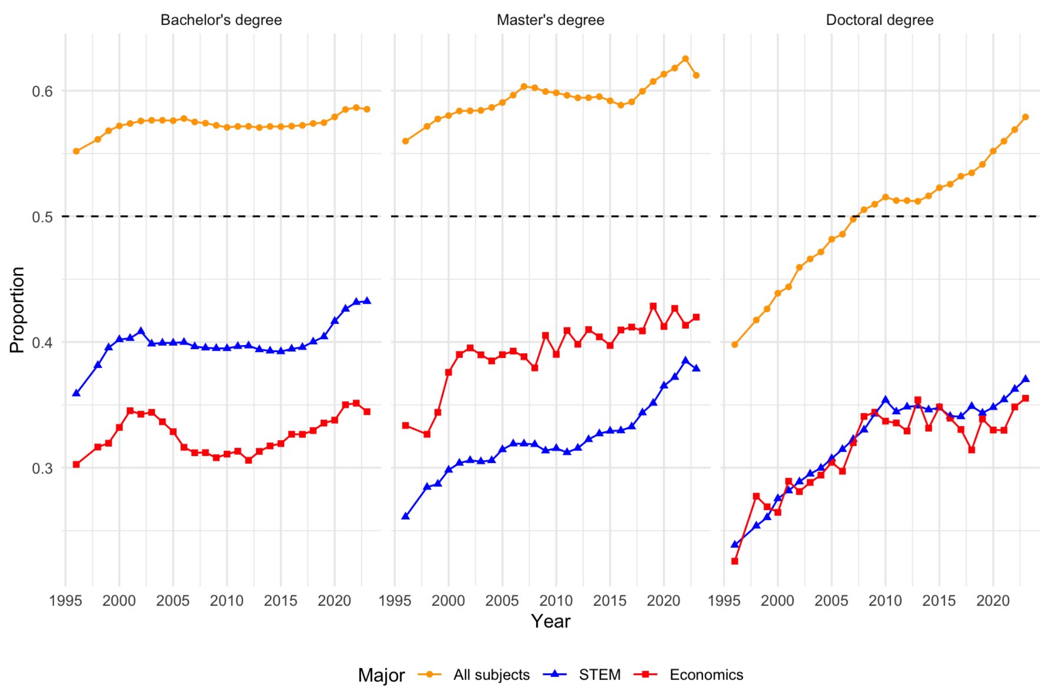

FIGURE 1. HISTORIC REPRESENTATION OF WOMEN BY DEGREE LEVEL AND MAJOR

Note: This figure presents the historic representation of women in academic programs by degree level and major area of study. Orange, blue, and red lines show the representation of women in all subjects, STEM, and economics respectively.

Figure 2 presents a graphical view of the historic representation in bachelor's degrees by race/ethnicity and major. Most notably, Asians/Native Hawaiians/Pacific Islanders and Whites are over-represented in economics at this level, as the proportion of degrees awarded to these groups has been greater than their representation in the general population for all years in this analysis, 1996 to 2023. Asians have been even more over-represented in economics than in STEM since the beginning year of this analysis, while Whites have only been more over-represented in economics than in STEM since 2018. Blacks, Hispanics, and Native Americans are under-represented in all subjects, STEM, and especially in economics, which is the least represented subject for each of these groups. This highlights the extraordinary lack of racial/ethnic diversity in the field of economics, particularly with regard to the representation of Blacks, Hispanics, and Native Americans. Thus, in this analysis I consider these groups under-represented minorities.

Figures A1 and A2 shows the historic representation by race/ethnicity and major in master's degrees and doctoral degrees respectively. The patterns are similar to those seen in Figure 2 for bachelor's degrees.

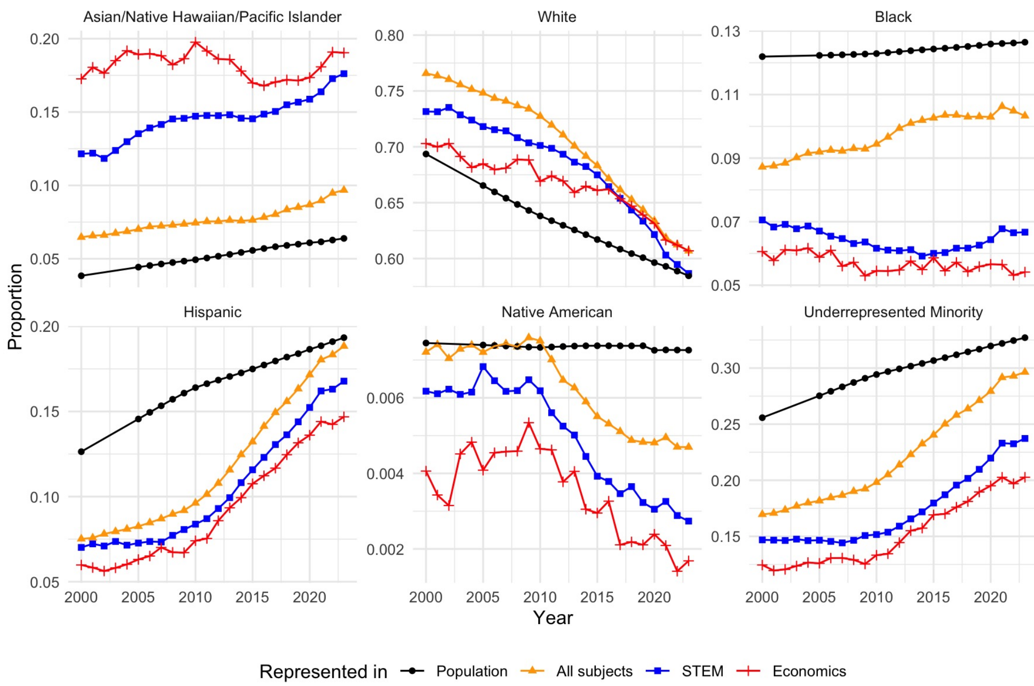

Figure 2. Historic representation in bachelor's degrees by race/ethnicity and major

Note: This figure presents the historic representation in bachelor's degrees by race/ethnicity and major area of study. Black lines show the representation of a race/ethnicity within the general US population. Orange, blue, and red lines show the representation of a race/ethnicity in all subjects, STEM, and economics respectively.

It is unclear whether affirmative action bans in the U.S. affect the number economics degrees earned by historically excluded groups, particularly women and racial minorities. Of special interest is whether affirmative action bans affect the number of economics degrees earned by historically excluded groups at the nation's most selective programs, since these programs disproportionately produce economists who place into public leadership positions and influential government posts, in addition to being awarded prestigious prizes for their work. Hoover and Svorencik (2023) show that over half of the leadership of the American Economic Association since 1985 has consisted of economists who earned their doctorates at five of the most selective U.S. economics programs. Since 2000, 65% of Nobel laureates in economics earned their doctorates from six of the nation's most selective economics departments, and 83% of Clark medalists earned their doctorates at Harvard, MIT, or Stanford (McKenzie, 2023). 24 out of 32 economists who served on the White House's Council of Economic Advisers since 2000 earned their doctorates at Harvard or MIT (McKenzie, 2023). Also, it is plausible that the diversity of admitted applicants at an institution after affirmative action bans depends on the political affiliation of the state.

The aim of this project is thus to estimate the causal impact of affirmative action bans on the number economics degrees earned by historically excluded groups in the U.S., the extent to which any racial or gender groups may be crowded out of selective programs as a result of affirmative action bans, and the extent to which the political affiliation of the state affects the impact.

The primary contribution of this study to the literature is to provide the first causal estimates of the impact of affirmative action bans in the U.S. on historically excluded groups' attainment of economics degrees specifically. I focus on economics degrees as the lack of diversity in economics education as documented by Bayer and Wilcox (2019), coupled with the potential benefits of having a diverse economics workforce, make this an interesting addition to the literature.

Previous studies on affirmative action and educational attainment use dated data and are unable to infer results for states with relatively new affirmative action bans such as Michigan, Nebraska, Arizona, New Hampshire, Oklahoma, and Idaho (Card and Krueger, 2005; Hinrichs, 2012; Backes, 2012). More recent literature focuses on specific universities, as the UC (University of California) system provides an appealing setting to study the mismatch hypothesis and to differentiate between effects on the extensive and intensive margins (Bleemer, 2021; Arcidiacono et al., 2014), while the *Students for Fair Admissions v. Harvard* and *Students for Fair Admissions V. University of North Carolina* cases provide interesting school-specific contexts for debate (Arcidiacono, Kinsler and Ransom, 2023; Card, 2017). Another goal of this study is thus to use newly available data to obtain externally valid estimates of the impact of affirmative action bans on educational attainment in the U.S.

I. Institutional Background

On March 6th 1961, U.S. President John F. Kennedy signed Executive Order 10925 which required government contractors to "take affirmative action to ensure that applicants are employed and that employees are treated during employment without regard to their race, creed, color, or national origin." Affirmative action has since evolved to include policies used by private and public institutions to grant special consideration to historically excluded groups in employment and admissions decisions.

Affirmative action in the U.S. is highly controversial, as supporters and opponents alike cite discrimination as a reason for disagreeing with the other group's stance on the topic. Supporters of affirmative action argue that it corrects discrimination against historically excluded groups, increasing equity and diversity in employment and admissions. Opponents argue that considering race in employment and admissions decisions is discriminatory, or that students admitted under affirmative action policies are not matched to programs at the appropriate difficulty level.

The legality of affirmative action policies has been debated in many high-profile court cases. On June 29th 2023, the Supreme Court banned the use of affirmative action policies federally in *Students for Fair Admissions v. Harvard*, deciding that it violates the Equal Protection Clause of the Fourteenth Amendment. Prior to this decision, several states implemented affirmative action bans of their own. California banned it in 1996, Texas from 1996 to 2003, Washington from 1998 to 2022, Florida in 1999, Michigan in 2006, Nebraska in 2008, Arizona in 2010, New Hampshire in 2012, Oklahoma in 2012, and Idaho in 2020.

II. Data

I use data from the Integrated Postsecondary Education Data System (IPEDS), which is a system of surveys conducted by the U.S. Department of Education's National Center for Education Statistics. IPEDS is a census with mandatory response as the Higher Education Act requires institutions that participate in federal student aid programs provide data on enrolments, completions, graduation rates, faculty and staff, finances, and student financial aid. I use annual, institution-level data on 4153 degree-granting institutions from 1996 and 1998 to 2023 as it is the largest range of data that contains the outcome variables of interest.

The outcome variables of interest are proportions of degrees awarded to groups defined by major, degree level, race/ethnicity, and gender. These are calculated from the data which include the number of degrees conferred to each group. The sample is restricted to responses regarding bachelor's degrees, master's degrees, and research doctorates with economics as a first or second major area of study. Counts are provided separately for men and women, and for students of 4 distinct race/ethnicity categories: American Indian or Alaska Native, Black or African American, Hispanic or Latino, and White, resulting in 6 groups of interest. Counts for Asians, Native Hawaiians, and Pacific Islanders are amalgamated into one group for most census years but not all, making it difficult to identify and compare separate counts for each group across time. For this reason, as well as the fact that Asians are over-represented in economics, I exclude these three groups from my analysis. Three more race/ethnicity categories are available but less informative (unknown race, two or more races, U.S. non-resident), and therefore are also not included in my analysis.

Institution-level controls are not used in my analysis due to a large amount of missing data that makes imputation impractical. In order to control for time- and institution-related characteristics other than affirmative action bans that may be correlated with the outcomes, I use year fixed effects as well as institution or state fixed effects in my analysis.

RePEc (Research Papers in Economics) provides a list of the top 25% U.S. economics departments in terms of research output. As a proxy for high program selectivity we consider whether a department is in the top 75. In this paper, a red state is defined as a state in which Republicans won in at least three of the four elections from 2008 to 2020, and a blue state is defined as a state in which Democrats won in at least three of the four elections from 2008 to 2020. Data on red and blue states is provided by Wikipedia.

III. Empirical Strategy

A. *Regression Discontinuity Design*

I use a sharp regression discontinuity approach to compare outcomes immediately before and immediately after affirmative action bans are expected to have an effect. Specifically, I use local linear regressions to produce the estimated discontinuity

$$\hat{\tau}(h_n) = \hat{\mu}_+(h_n) - \hat{\mu}_-(h_n)$$

where

$$\left(\hat{\mu}_+(h_n), \hat{\mu}_+^*(h_n)\right)' = \arg\max_{\beta_0,\beta_1} \sum_{i=1}^{n} \sum_{t \in T} \mathbb{1}\left(x_{it} \geq 0\right)\left(y_{it} - \beta_0 - \beta_1 x_{it}\right)^2 K\left(\frac{x_{it}}{h_n}\right),$$

$$\left(\hat{\mu}_-(h_n), \hat{\mu}_-^*(h_n)\right)' = \arg\max_{\beta_0,\beta_1} \sum_{i=1}^{n} \sum_{t \in T} \mathbb{1}\left(x_{it} < 0\right)\left(y_{it} - \beta_0 - \beta_1 x_{it}\right)^2 K\left(\frac{x_{it}}{h_n}\right),$$

y_{it} is the proportion of degrees awarded to a group at institution i in year t, $x_{it} = z_{it} - c$ where z_{it} is years relative to the affirmative action ban and is the running variable, c is the cutoff and expected number of years to complete an economics degree (4 for bachelor's degrees, 1 for master's degrees, and 5 for doctorates), $K(u) = \frac{3}{4}(1 - u^2)$ is the Epanechnikov kernel, and h_n is the bandwidth selected using the data-driven approach prescribed by Calonico et al. (2017). Institution and year fixed effects are included in the regressions but omitted from the equations above for simplicity. Standard errors are clustered at the state level. Separate models are run for each degree level and underrepresented group.

B. Difference-in-Differences

The staggered implementation of affirmative action bans across the United States allows me to use staggered difference-in-differences and event study approaches to compare outcomes from treated institutions with not-yet-treated institutions. The difference-in-differences models take the form

$$y_{it} = \alpha_i + \alpha_t + \beta D_{it} + \epsilon_{it}$$

where y_{it} is the proportion of degrees awarded to a group at institution i in year t, α_i is an institution or state fixed effect, α_t is a year fixed effect, and D_{it} is the treatment dummy. The two-way fixed effects estimator β is the effect of interest, which can be thought of as causal under the usual assumptions associated with difference-in-differences approaches. Standard errors are clustered at the state level.

It is plausible that treatment effects evolve over time. I capture this possibility in my modeling with an event study approach. The event study models can be described by the equation

$$y_{it} = \alpha_i + \alpha_t + \sum_{\tau=-q}^{-1} \gamma_\tau D_i + \sum_{\tau=1}^{m} \delta_\tau D_i + \epsilon_{it}$$

where y_{it}, a_i and a_t take the same meaning as before, the first sum captures any pre-treatment effects, and the second sum captures treatment effects. To check that the pre-trends are parallel, I check whether the γ_τ are statistically insignificant. The δ_τ are the effects of interest, and measure the effect of the ban τ year(s) after commencement. Standard errors are clustered at the state level. Separate models are run for each degree level and underrepresented group.

IV. Results

A. Regression Discontinuity Results

Figure 3 presents graphical evidence for the regression discontinuity estimates. Binned sample averages of proportions of degrees awarded to underrepresented minorities or women for a degree level are plotted against number of years after an affirmative action ban. Black vertical bars show cutoffs corresponding to the expected number of years to complete an economics degree for the relevant degree level: 4 years for bachelor's degrees, 1 year for master's degrees, and 5 years for doctorates. Red lines on each side of the cutoffs show regression lines. The difference in the cutoff-intercepts is the regression discontinuity estimate.

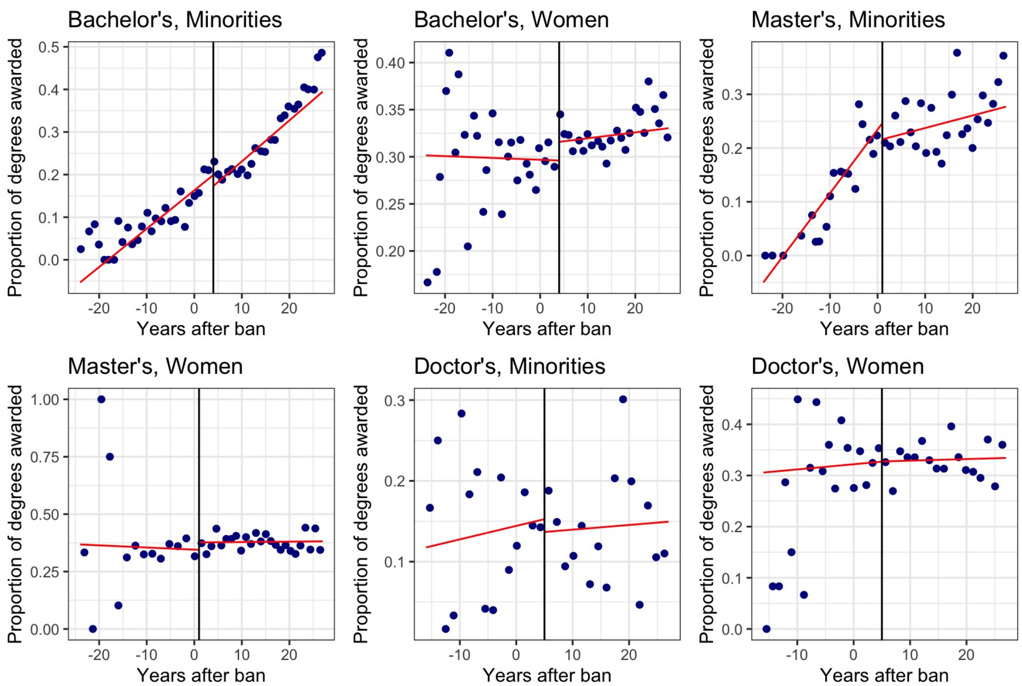

FIGURE 3. PROPORTION OF DEGREES AWARDED RELATIVE TO BAN YEAR BY DEGREE LEVEL AND UNDERREPRESENTED GROUP

Note: These plots present binned sample averages with a linear fit on each side of the cutoff. Titles denote the degree level and underrepresented group associated with the dependent variable. "Minorities" refers to underrepresented minority groups defined in this paper. Vertical bars show cutoffs at 4 years for bachelors, 1 year for masters, and 5 years for doctorates.

Regression discontinuity estimates are presented in Table A1 for the outcomes associated with underrepresented minorities, and Table A2 for the outcomes associated with women. For underrepresented minorities at any degree level, no estimates are significant statistically or in terms of magnitude. For women, conventional estimates are not significant for any degree level. Bias-corrected estimates of 0.036 for the bachelor's level and 0.101 for the master's level are significant at the 10% and 5% level respectively. However, graphical evidence provided in Figure 3 does not suggest the existence of non-linear relationships near the cutoffs, so these estimates may result from overfitting. Thus, for all degree levels, these results show no strong evidence that the proportion of economics degrees awarded to underrepresented groups was affected by affirmative action bans immediately after a time period consistent with the expected time to complete a degree.

B. Difference-in-Differences Results

Tables A3, A4, and A5 present two-way fixed effects estimates for the bachelor's, master's, and doctoral levels, respectively. For any degree level, the outcome for Models 1 and 2 is the proportion of economics degrees awarded to underrepresented minorities, and the outcome for Models 3 and 4 is the proportion of economics degrees awarded to women. All models have year fixed effects. Odd-numbered models have institution fixed effects, while even-numbered models have state fixed effects.

For the bachelor's and master's degree level, no estimates are significant statistically or in terms of magnitude. For women at the doctoral level, the estimated effect is -0.037 with institution and year fixed effects, or -0.043 state and year fixed effects. These are statistically significant at the 10% level. The estimates suggest that the effect of an affirmative action ban on the proportion of economics doctorates awarded to women is a decrease of about 4%.

Figure 4 presents event study estimates and 95% confidence intervals for underrepresented minorities' outcomes. For the bachelor's degree level, 12 out of the 26 estimated coefficients for periods before the cutoff are positive and statistically significant, indicating a lack of parallel pre-treatment trends. The largest estimated pre-treatment coefficient is 0.1 at 21 years pre-ban. The post-treatment estimates trend upwards, up to 0.17 at 27 years post-ban. This estimate passes the threshold for a test of statistical significance at any conventional level, and suggests that the effect 27 years post-ban is an increase of 17% in the proportion of economics bachelor's degrees awarded to underrepresented minorities. For the master's and doctoral degree levels, the event study estimates associated with the underrepresented minorities outcome fluctuate around zero, and are generally not statistically significant.

Figure 5 presents event study estimates and 95% confidence intervals for women's outcomes. At all degree levels, the vast majority of estimated coefficients are approximately zero with small standard errors. The only exceptions are the earliest pre-treatment periods, which have estimates of larger magnitude. This suggests that the pre-treatment trends are parallel except for the earliest pre-treatment periods. These event study results suggest that for all degree levels, no effects from affirmative action bans are detectable for women's outcomes each year up to 27 years post-ban.

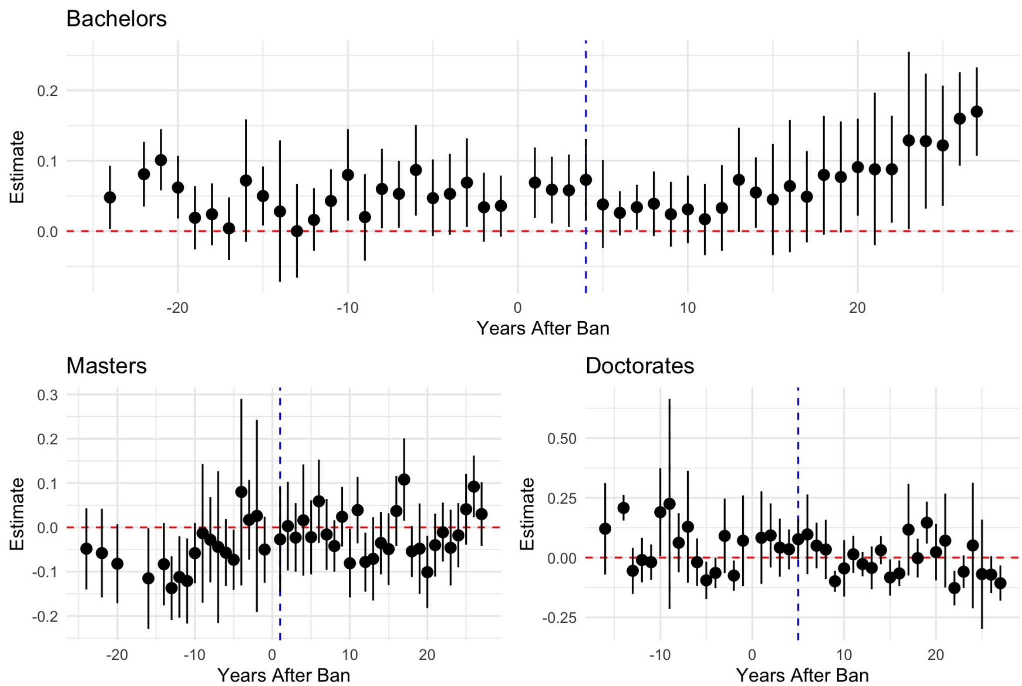

FIGURE 4. EVENT STUDY ESTIMATES: UNDERREPRESENTED MINORITIES

Note: This figure presents event study estimates and 95% confidence intervals of the treatment effect on underrepresented minorities. Titles denote the degree level associated with the dependent variable. Blue dashed lines show cutoffs at 4 years for bachelors, 1 year for masters, and 5 years for doctorates.

C. *Heterogeneity Analysis*

In order to identify heterogeneous effects by department rank and political affiliation states, I run the following difference-in-differences regressions where the treatment dummy is interacted with top 75 institution status or state political affiliation:

$$(1) \quad y_{it} = \alpha_i + \alpha_t + \beta_1 D_{it} + \beta_2 T_i + \beta_3 (D_{it} \times T_i) + \epsilon_{it}$$

$$(2) \quad y_{it} = \alpha_i + \alpha_t + \beta_1 D_{it} + \beta_2 R_i + \beta_3 B_i + \beta_4 (D_{it} \times R_i) + \beta_5 (D_{it} \times B_i) + \epsilon_{it}$$

where y_{it} is the proportion of degrees awarded to a group at institution i in year t, α_i is an institution or state fixed effect, α_t is a year fixed effect, D_{it} is the treatment dummy, T_i is a top 75 institution dummy, R_i is a red state dummy, and B_i is a blue state dummy. For the first model, non-top 75 serves as the baseline institution rank status. For the second model, the baseline political affiliation is purple.

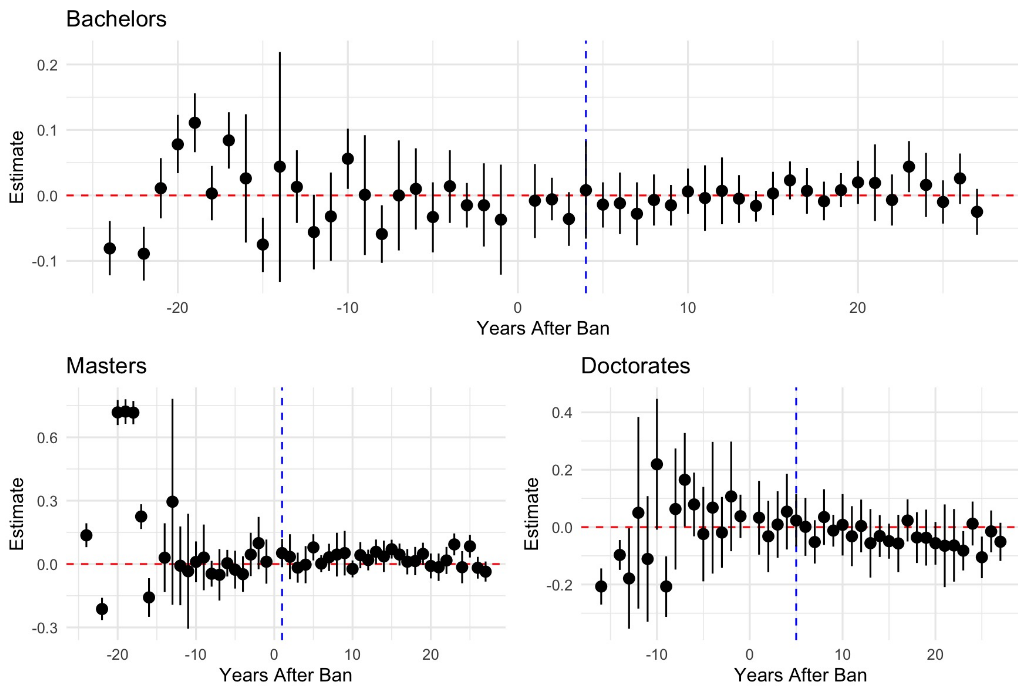

Figure 5. Event Study Estimates: Women

Note: This figure presents event study estimates and 95% confidence intervals of the treatment effect on women. Titles denote the degree level associated with the dependent variable. Blue dashed lines show cutoffs at 4 years for bachelors, 1 year for masters, and 5 years for doctorates.

Table A6 presents results from a heterogeneity analysis for bachelor's degree outcomes using this difference-in-differences approach. The effect at top 75-ranked departments relative to all other departments is calculated as the sum of the coefficients for top institution status and the interaction between treatment status, post-treatment status, and top institution status $\beta_2 + \beta_3$ (equation 1). The estimated effect on underrepresented minorities is a further decrease of 3.7% in proportion of bachelor's degrees awarded to the group relative to all other departments. A Wald test shows that this estimate is not statistically significant at conventional levels (p-value 0.657). The estimated effect at top 75 departments versus non-top departments on women is a relative increase of 4.5 in proportion of bachelor's degrees awarded. A Wald test indicates that this is significant with p-value 0.0019.

The effect in red states relative to blue states is calculated as the difference between the sum of coefficients relevant for red states and the sum of coefficients relevant for blue states $\beta_2 + \beta_4 - (\beta_3 + \beta_5)$ (equation 2). The estimated effect in red states relative to blue states on the proportion of economics bachelor's degrees awarded to underrepresented minorities is a decrease by 9.1%. A Wald test indicates that this estimate is not statistically significant at conventional levels (p-value 0.204). For women's outcomes, this estimated relative effect is a decrease by 2.2%. A Wald test shows that this is also not significant at conventional levels (p-value 0.535).

I also apply separate regression discontinuity models for top 75-ranked economics departments, non-top 75 departments, red states, and blue states in order to identify heterogeneous effects for outcomes associated with the bachelor's degree level. Tables A7 and A8 present the results of this analysis. Most notably, no estimated discontinuity is statistically significant at the 5% level, consistent with the findings of the main regression discontinuity models. A bias-corrected estimate of 0.04 is significant at the 10% level for women's outcomes at non-top 75 departments, but the same estimate is not significant when using heteroskedasticity-robust standard errors.

In order to estimate heterogeneous effects by state and year, I also include in my analysis event study models where the individual terms within the sums of the event study model equation are interacted with state dummies, as prescribed by Sun and Abraham (2021). Figure A3 presents weighted averages of treatment effect estimates and their confidence intervals, obtained from event study regressions in the style of Sun and Abraham (2021). Estimates are relative to the baseline option California, and are aggregated by state and weighted proportional to the associated sample size within each year. Most notably, the largest negative weighted average Sun-Abraham estimate for underrepresented minorities' outcomes is -14.4% for Oklahoma, and the largest positive estimate for underrepresented minorities' outcomes is 6.1% for Arizona. As Oklahoma and Arizona are both red states, this suggests that there is a considerable degree of heterogeneity in treatment effects even among states with the same political affiliation. For women's outcomes, the largest negative weighted average Sun-Abraham estimate is -8.0% for Idaho, and the largest positive weighted average Sun-Abraham estimate is 9.2% for Florida, again demonstrating a degree of heterogeneity in treatment effects among red states, as Idaho and Florida are both red states.

V. Discussion and Conclusions

A. Threats to Identification

This analysis is potentially limited by several factors that can compromise the identification strategy, which I will describe in ascending order of importance. First, identification of effects with regression discontinuity designs require that no manipulation of the running variable near the threshold is performed. Since the running variable in this design is the year of the survey response relative to an affirmative action ban, and the survey is a census with mandatory response, it is not possible for institutions to influence the running variable by selectively participating in the survey depending on its value.

It is plausible that the announcement of affirmative action bans cause some groups of prospective applicants to self-select into less selective programs or not apply for admission at all. It could also embolden other groups to self-select into more selective programs than they would otherwise choose. If present, these selection effects would affect the outcomes observed in this analysis, so that the treatment effects identified in this paper include selection effects. This is not necessarily a problem as selection can be thought of as another mechanism through which the treatment affects the outcome. However, if the separation and identification of selection effects from the main treatment effects are desired, future research should incorporate data on applications and admissions by major, race/ethnicity, and gender in order to estimate the effect of affirmative action bans on the selection behavior of college applicants.

A key assumption of difference-in-differences designs is that of parallel trends which assumes that the outcomes of the treated groups would follow the same trend as those of not-yet-treated groups in the absence of treatment. However, many of the pre-treatment event study estimates for outcomes related to underrepresented minorities in bachelor's degree programs are statistically significant from 0. This can also be observed for women's outcomes at all degree levels for the earliest pre-treatment periods. This provides moderate evidence of non-parallel pre-treatment trends, which calls into question the assumption of parallel trends.

Another assumption of difference-in-differences designs is that there are no contemporaneous shocks other than the treatment of interest that may affect the outcome. However, some states have implemented non-affirmative action policies that may impact the racial/ethnic and gender composition of student bodies. For example, California, Texas, and Florida have implemented "Percent Plans" which exploit racial segregation across high schools to promote diversity within their public universities by automatically granting university admission to a top fraction of high school students by GPA. As these states are some of the earliest states to implement affirmative action bans, this may explain the upward trend in event study estimates seen for underrepresented minorities at the bachelor's level in Figure 4.

A crucial feature of the regression discontinuity design is that it measures the immediate impact of affirmative action bans after a period corresponding to the expected number of years to complete an economics degree. Thus, immediate implementation, compliance, and enforcement of affirmative action bans are required for the effects to be identified. Also, degree completion times must be sufficiently consistent with expected completion times in order to detect effects. However, empirical evidence presented by Stock, Siegfried and Finegan (2011) suggests that the average economics PhD completion time increased from 5 to 6 years during the period relevant to this analysis. These requirements can be relaxed if flexible regression discontinuity cutoffs allowing different cutoff values across states, institutions, or time are used.

B. *Conclusions*

This paper provides the first causal estimates of the effect of affirmative action bans on the number of economics degrees awarded to underrepresented minorities and women in the U.S. Results reveal limited immediate effects of bans on the representation of underrepresented minorities or women at the bachelor's, master's, and doctoral levels. These effects may be masked by heterogeneity in outcomes based on program selectivity and state political affiliation, though the evidence for this is mixed and inconclusive. Long-term increases in diversity at the bachelor's level are detected among states with affirmative action bans, though these estimates are especially vulnerable to confounding from contemporaneous policies like "Percent Plans". Non-parallel pre-treatment trends and potential varied enforcement and timing of affirmative action bans also complicate causal attribution of effects. Future research should aim to decompose treatment effects into self-selection effects and direct effects from admissions committees.

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Appendix

A1. Appendix Figures

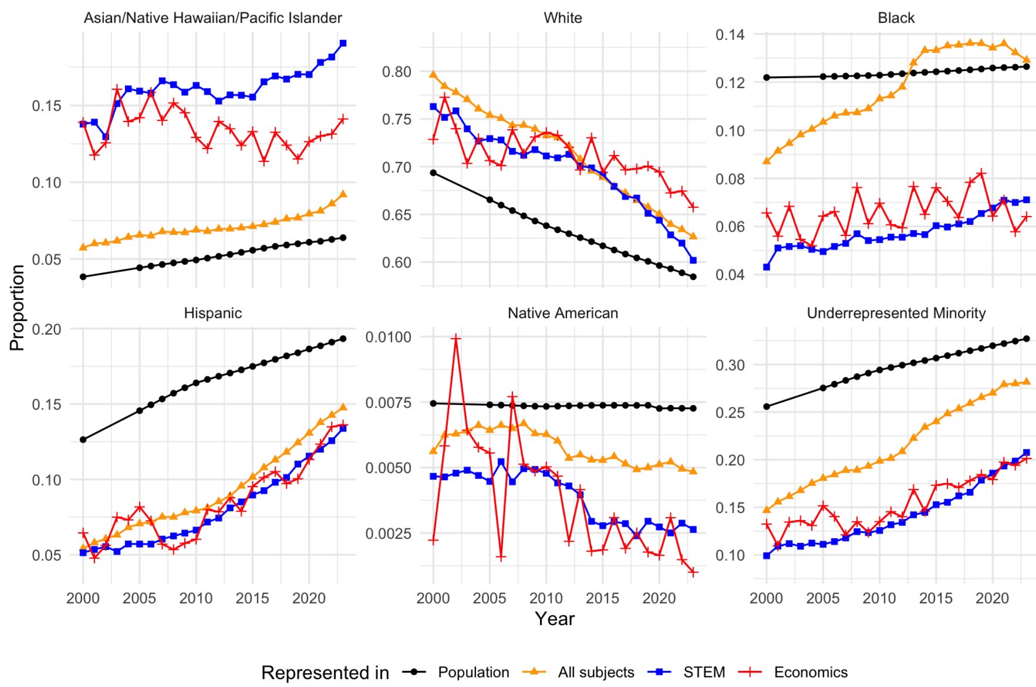

Figure A1. Historic representation in master's degrees by race/ethnicity and major

Note: This figure presents the historic representation in master's degrees by race/ethnicity and major area of study. Black lines show the representation of a race/ethnicity within the general US population. Orange, blue, and red lines show the representation of a race/ethnicity in all subjects, STEM, and economics respectively.

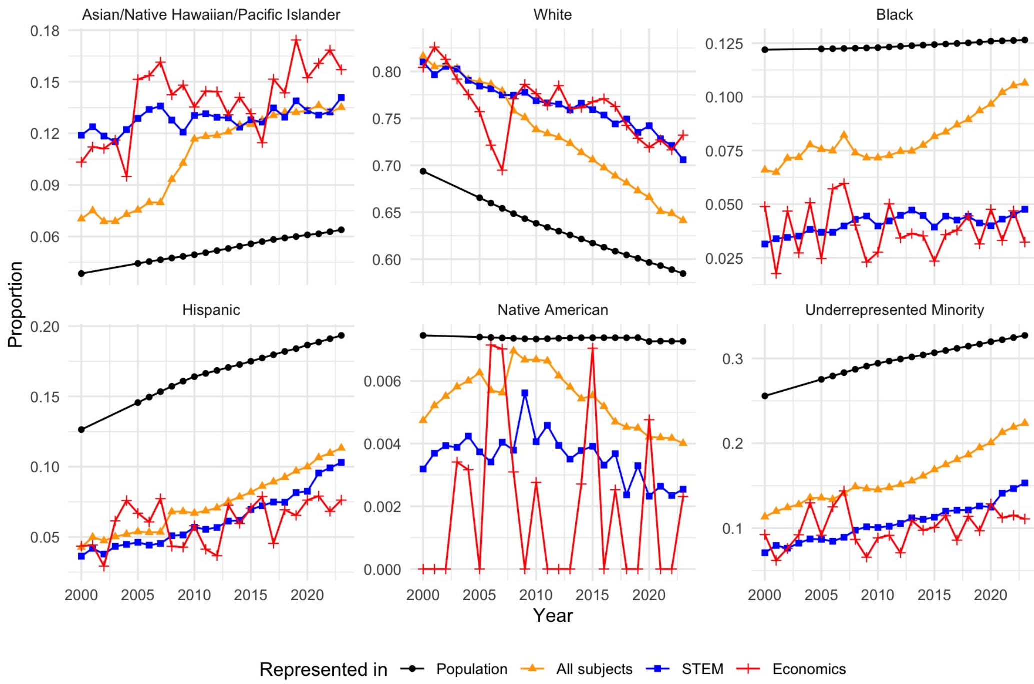

FIGURE A2. HISTORIC REPRESENTATION IN DOCTORAL DEGREES BY RACE/ETHNICITY AND MAJOR

Note: This figure presents the historic representation in doctoral degrees by race/ethnicity and major area of study. Black lines show the representation of a race/ethnicity within the general US population. Orange, blue, and red lines show the representation of a race/ethnicity in all subjects, STEM, and economics respectively.

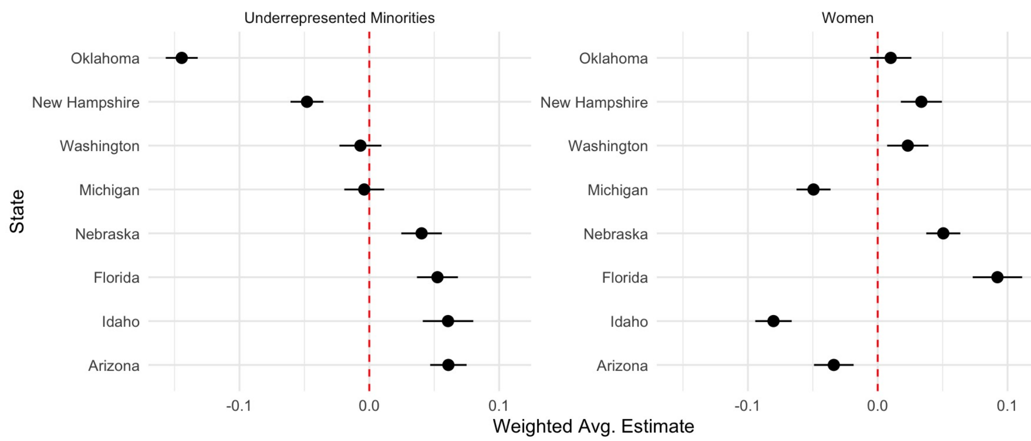

Figure A3. Weighted Average Sun-Abraham Estimates by State (Bachelor's Degrees)

Note: This figure presents weighted averages of treatment effect estimates and their confidence intervals, obtained from event study regressions in the style of Sun and Abraham (2021), applied to data for the bachelor's degree level. Estimates are relative to the baseline option California, and are aggregated by state and weighted proportional to the associated sample size within each year. Titles denote the underrepresented group associated with the outcome.

A2. Appendix Tables

Table A1—Regression Discontinuity Results: Underrepresented Minorities

	Bachelors	Masters	Doctorates
Conventional	-0.018	-0.002	0.055
	(0.041)	(0.063)	(0.092)
Bias-Corrected	-0.031	0.016	0.076
	(0.041)	(0.063)	(0.092)
Robust	-0.031	0.016	0.076
	(0.048)	(0.074)	(0.111)
Obs. Left	955	186	171
Obs. Right	2292	934	401
Effective Obs. Left	576	123	62
Effective Obs. Right	923	308	78
Cutoff	4	1	5

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

This table presents regression discontinuity estimates with the proportion of degrees awarded to underrepresented minorities as the outcome. Bias-corrected estimates use a second-order polynomial to approximate curvatures near the cutoff. Heteroskedasticity-robust standard errors are also reported for bias-corrected estimates.

Table A2—Regression Discontinuity Results: Women

	Bachelors	Masters	Doctorates
Conventional	0.032	0.066	-0.043
	(0.021)	(0.043)	(0.076)
Bias-Corrected	0.036^{+}	0.101*	-0.057
	(0.021)	(0.043)	(0.076)
Robust	0.036	0.101*	-0.057
	(0.025)	(0.049)	(0.097)
Obs. Left	970	209	226
Obs. Right	2341	1007	469
Effective Obs. Left	625	110	116
Effective Obs. Right	1054	250	147
Cutoff	4	1	5

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

This table presents regression discontinuity estimates with the proportion of degrees awarded to women as the outcome. Bias-corrected estimates use a second-order polynomial to approximate curvatures near the cutoff. Heteroskedasticity-robust standard errors are also reported for bias-corrected estimates.

Table A3—Difference-in-Differences Results: Bachelor's Degree

	Minorities		Women	
	Model 1	Model 2	Model 3	Model 4
Treat × Post	−0.019	−0.012	0.006	0.002
	(0.017)	(0.017)	(0.014)	(0.015)
Institution FE	Yes	No	Yes	No
State FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Num. obs.	18202	18202	18637	18637
R^2	0.641	0.222	0.409	0.039
Adj. R^2	0.622	0.219	0.379	0.035

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.

This table presents difference-in-differences estimates of the treatment effect at the bachelor's level.

Table A4—Difference-in-Differences Results: Master's Degree

	Minorities		Women	
	Model 1	Model 2	Model 3	Model 4
Treat × Post	−0.016	0.017	0.001	0.014
	(0.021)	(0.016)	(0.022)	(0.016)
Institution FE	Yes	No	Yes	No
State FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Num. obs.	4809	4809	5239	5239
R^2	0.408	0.176	0.184	0.057
Adj. R^2	0.372	0.163	0.137	0.042

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.
This table presents difference-in-differences estimates of the treatment effect at the master's level.

Table A5—Difference-in-Differences Results: Doctorate Degree

	Minorities		Women	
	Model 1	Model 2	Model 3	Model 4
Treat × Post	−0.023	−0.018	-0.037^{+}	-0.043^{+}
	(0.039)	(0.035)	(0.022)	(0.022)
Institution FE	Yes	No	Yes	No
State FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Num. obs.	2503	2503	3143	3143
R^2	0.240	0.088	0.149	0.070
Adj. R^2	0.186	0.061	0.100	0.049

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.
This table presents difference-in-differences estimates of the treatment effect at the doctoral level.

Table A6—DiD Heterogeneity Analysis: Bachelor's Degree

	Top/Non-Top 75		Red/Blue State	
	Minorities	Women	Minorities	Women
Treat × Post	−0.011	−0.006	0.188**	0.029
	(0.017)	(0.015)	(0.055)	(0.021)
Top Institution	−0.033	−0.022+		
	(0.020)	(0.013)		
Treat × Post × Top Institution	−0.004	0.067***		
	(0.028)	(0.015)		
Red State			0.084*	0.040***
			(0.034)	(0.011)
Blue State			0.073**	0.055***
			(0.026)	(0.011)
Treat × Post × Red State			−0.203**	−0.044
			(0.065)	(0.041)
Treat × Post × Blue State			−0.101	−0.037
			(0.088)	(0.026)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	No	No
Num. obs.	18202	18637	18147	18582
R^2	0.224	0.040	0.046	0.010
Adj. R^2	0.220	0.036	0.044	0.009

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$.
This table presents difference-in-differences estimates of heterogeneous treatment effects at the bachelor's level for top 75 institutions vs. non-top 75 institutions (left 2 columns), and red/blue/purple states (right 2 columns). For top vs. non-top regressions, non-top serves as the baseline level, and for red/blue/purple states, purple is the baseline level.

Table A7—RD Results: Top 75 & Non-Top 75 Institutions, Bachelor's Degree

	Minorities		Women	
	Top 75	Non-top 75	Top 75	Non-top 75
Conventional	-0.016	-0.020	0.005	0.034
	(0.046)	(0.045)	(0.019)	(0.024)
Bias-Corrected	-0.027	-0.033	-0.011	0.040^{+}
	(0.046)	(0.045)	(0.019)	(0.024)
Robust	-0.027	-0.033	-0.011	0.040
	(0.055)	(0.051)	(0.023)	(0.029)
Obs. Left	116	839	116	854
Obs. Right	330	1962	335	2006
Effective Obs. Left	77	504	56	548
Effective Obs. Right	152	787	85	902
Cutoff	4	4	4	4

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

This table presents regression discontinuity estimates for top 75 institutions and non-top 75 institutions separately. Bias-corrected estimates use a second-order polynomial to approximate curvatures near the cutoff. Heteroskedasticity-robust standard errors are also reported for bias-corrected estimates.

Table A8—RD Results: Blue & Red States, Bachelor's Degree

	Minorities		Women	
	Blue States	Red States	Blue States	Red States
Conventional	-0.034	0.028	0.037	0.117
	(0.053)	(0.056)	(0.027)	(0.196)
Bias-Corrected	-0.052	0.022	0.044	0.140
	(0.053)	(0.056)	(0.027)	(0.196)
Robust	-0.052	0.022	0.044	0.140
	(0.062)	(0.066)	(0.037)	(0.245)
Obs. Left	531	254	540	255
Obs. Right	1763	67	1799	67
Effective Obs. Left	387	47	288	24
Effective Obs. Right	763	37	425	23
Cutoff	4	4	4	4

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

This table presents regression discontinuity estimates for blue states and red states separately. Bias-corrected estimates use a second-order polynomial to approximate curvatures near the cutoff. Heteroskedasticity-robust standard errors are also reported for bias-corrected estimates.