Race-based Affirmative Action and Student Effort [*]

Mitra Akhtari — *Harvard University* [§]

Natalie Bau — *University of Toronto* [†]

February 7, 2016

Preliminary and incomplete

Abstract

Race-based affirmative action policies are widespread in higher education. Despite the prevalence of these policies, there is little evidence on whether affirmative action policies in higher education affect students *before* they reach college. We exploit the 2003 Supreme Court ruling in *Grutter v. Bollinger*, which overturned Texas' affirmative action ban, to study the effect of race-based affirmative action on high school students' outcomes. Using administrative data from a large, urban school district, we find that the reinstatement of affirmative action narrowed the achievement gap between minority (black and Hispanic) and white high school students in standardized test scores, course grades, and the likelihood of taking advanced courses. Survey data suggest that students' behavior and aspirations responded to the policy reversal. In future drafts, we will estimate the heterogeneous effects of affirmative action by location in the ability distribution and explore the effects of affirmative action in administrative data for the entire state of Texas.

[*]We thank Alberto Alesina, Raj Chetty, Roland Fryer, Larry Katz, Asim Khwaja, and Nathan Nunn for guidance and support. We would also like to thank David Cutler, Will Dobbie, Raissa Fabregas, Diana Moreira, Pascal Noel, Alexandra Roulet, Heather Sarsons, and Laura Trucco.

[§]1805 Cambridge Street. Cambridge, MA 02138, USA. Phone (617) 495-2144. Email: mitraakhtari@fas.harvard.edu.

[†]150 Saint George St. Toronto, ON M5S 2E9, Canada. Phone (416) 978-0147. Email: natalie.bau@utoronto.ca.

1 Introduction

Affirmative action policies that weigh race or ethnicity as one factor in the college admission process are widespread in higher education in numerous countries including the United States, Canada, Brazil, and India. In the U.S., affirmative action policies in public universities have repeatedly been challenged by court cases at the sub-national and national level,[1] and eight states have banned race-based affirmative action at all public universities. Despite the importance of race-based affirmative action policies, and the controversy surrounding them, there has been relatively little research on whether or how affirmative action policies affect students *prior* to reaching college.

Theoretically, the effects of affirmative action policies that favor minority students in the college admissions process on human capital investment prior to college entry are ambiguous. On the one hand, affirmative action policies may lead secondary school minority students to invest less in their human capital by lowering the threshold for college admissions (Coate and Loury, 1993). On the other hand, affirmative action policies may incentivize minority students to work harder by increasing the probability that their hard work will translate into college admission (Fryer and Loury, 2005). Since the theoretical effects of affirmative action are ambiguous, we turn to empirical methods to determine which of these theories best describes the behavior of minority students.

To investigate the effects of affirmative action[2] on the human capital investment of high school students, we exploit a natural experiment that induced a policy reversal in Texas. In 2003, the Supreme Court decision in *Grutter v. Bollinger* ruled that a race-conscious admissions process that does not amount to a quota system is constitutional. This effectively reversed an earlier, lower court ruling that had prohibited the use of race in the admissions process in Texas public universities. Therefore, we can examine how affirmative action policies affect student outcomes prior to college entry by comparing white and minority (black and Hispanic) students' outcomes before and after the 2003 court ruling.[3]

Using administrative data from a large, urban school district in Texas, we estimate how the within school-year racial achievement gap changes for 11^{th} graders following the introduction of

[1] Such cases include: *Regents of the University of California v. Bakke* in 1979, *Hopwood v. Texas* in 1996, *Grutter v. Bollinger* and *Gratz v. Bollinger* in 2003, *Fisher v. University of Texas* in 2013, *Schuette v. Coalition to Defend Affirmative Action* in 2014, and, most recently, *Fisher v. University of Texas* in 2015.

[2] For simplicity, unless otherwise noted, we use "affirmative action" to refer to race-based affirmative action in the college admissions process.

[3] The Texas "Top 10% Rule," which guarantees admission to any Texas public university to high school students graduating in the top 10% of their class, was held constant throughout our study period.

affirmative action. We find that after the 2003 introduction of affirmative action, the achievement gap between minority and white high school students narrows for standardized test scores and course grades. Furthermore, the relative improvement in grades occurs despite minority students enrolling in more advanced courses after the policy change. The reduction in the racial achievement gap following the 2003 policy reversal is large and economically meaningful. The racial achievement gap narrows by .17 standard deviations for standardized test scores (20% of the within-school-year gap between minorities and whites) and by .07 standard deviations for course grades (19% of the within-school-year gap). Importantly, we compare minority and white students within the same school-year. Therefore, our estimates of the reductions in the achievement gap after 2003 cannot be attributed to a general improvement of poorly performing schools that are predominantly composed of minority students. Moreover, using placebo tests that move the policy change earlier in time, we find no evidence that our results are driven by differential time trends across races. We also do not observe any changes in the achievement gap between Asian-American and white students following the 2003 court ruling: this finding is consistent with the fact that Asian-American students are not favored by race-based affirmative action policies.

To better understand the mechanisms underpinning these results, we analyze survey data from high school seniors across Texas collected before and after the policy change. Our analysis suggests that students' behavior and aspirations respond to the policy change: minority students are more likely to spend time on their homework and they are more likely to apply to their first-choice college after 2003 compared to white students. We do not find that parental behavior or frequency of discussions about college applications with guidance counselors changes after the policy change. Overall, our estimates provide evidence that race-based affirmative action in higher education in Texas reduced the average racial achievement gap in student outcomes in high school.

Broadly our results relate to a large literature that studies the effects of affirmative action policies. This literature has focused primarily on affirmative action policies in higher education and their impact on college application behavior, college admissions, and college graduation. This extensive literature includes Bowen and Bok (1998), Card and Krueger (2005), Arcidiacono (2005), Sander (2004), and Rothstein and Yoon (2008). Our main contribution is to a much smaller literature about the implication of affirmative action for student behavior *prior* to college admissions.

In this literature, Antonovics and Backes (2014) study California's ban on affirmative action and conclude that SAT scores and high school GPA changed little after the ban on race-based affirmative action. However, they study a selected sample of students who took the SAT. Additionally, students' responses to the introduction of affirmative action and the banning of affirmative action may be asymmetric and, therefore, our study of the effect of the introduction of affirmative action is complementary to the Antonovics and Backes (2014) study of the ban of affirmative action. Ferman and Assunção (2005) study the effects of race-based university admissions quotas in Brazil on high school students' test scores. They find that aggressive university quotas for black students in public high schools undercut the incentives of this group and had a negative effect on these students' test scores. However, the quotas they study are very aggressive. In fact, other groups of students, such as black students in private schools or mixed race students in public or private schools, which had relatively less aggressive quotas implemented in their favor, did not respond to the policy change. Therefore, the adverse effects on test scores they find may be particular to extreme cases of affirmative action.

Perhaps the papers most closely related to ours are Cotton et al. (2015) and Hickman (2013). Cotton et al. (2015) combines a theoretical framework with a field experiment. Their model assumes the existence of two demographic groups of students who have different learning costs and allows for a period of investment in human capital running up to a matching game between colleges and students. They model affirmative action as the admissions board basing placement decisions partially on demographic status. Overall, their model predicts that affirmative action increases the disadvantaged group's investment in human capital on average. They conduct a field experiment which confirms the predictions of their model: they pay middle school students based on their relative performance on a national math exam, using grade-cohort as the demographic delimiter, and find that affirmative action increases the human capital investment of the disadvantaged group, as well as their proficiency. In contrast, Hickman (2013) structurally estimates the college admissions market and generates counterfactuals under race-neutral admissions. These counterfactuals suggest that eliminating race-based affirmative action would greatly reduce pre-college human capital investments by minorities. Our analysis is consistent with the findings of Cotton et al. (2015) and Hickman (2013) and confirms that affirmative action can increase minority students' human capital investment prior to the college matching process. We complement the findings of these papers by studying a real policy change using data that reveals the investments of high school students using their behavior on multiple dimensions, such as test scores, grades, and difficulty of courses.

Finally, our study relates to another strand of research on the effects of "color-blind" affirmative action on student effort. Cortes and Zhang (2011) study the incentive effects of the Top 10% Rule, which guarantees admission to a public university for Texas students in the top 10% of their high school graduating class. Cortes and Zhang (2011) find that the plan incentivized students to increase their effort in high school. While these results are consistent with ours, the Top 10% Rule and race-based affirmative action are quite different. First, unlike race-based affirmative action, the Top 10% Rule is manipulable since students can switch schools to help ensure better outcomes (Cullen et al., 2013). Second, unlike race-based affirmative action, the Top 10% Rule has an explicit tournament structure with clear cutoffs. Therefore, it is unclear how similar the incentive effects of these policies will be.

In future drafts, we will expand upon the findings here. Theoretically, the response to affirmative action depends on a student's ability, the distribution of her competitors, and how she compares to her competitors overall. In other words, high ability students and low ability students may respond differently to affirmative action. The model of Cotton et al. (2015) predicts that affirmative action will decrease human capital accumulation for the highest ability minority students while increasing human capital accumulation by intermediate and low ability students. Therefore, while we find that affirmative action reduces the racial achievement gap on average, it is important to investigate the distributional effects of the 2003 policy change. To this end, we have recently acquired lagged outcomes for our repeated cross-sections of 11^{th} graders. Using this information, we plan to estimate heterogeneous effects of affirmative action based on a student's position in the distribution *before* the affirmative action policy was reinstated. This exercise will allow us to quantify the effect of affirmative action beyond the average treatment effect and estimate the response for different groups of students more precisely.

Finally, we are in the process of linking individual-level records from the Texas Education Agency for all students in Texas to college administrative data from the Texas Higher Education Coordinating Board and to employment data from the Texas Workforce Commission. This will allow us to: (i) estimate the effect of using race-based affirmative action in college admissions on *all students* in Texas; (ii) estimate the effect of affirmative action on college applications, college enrollment, and college graduation for those students who continue on to higher education within the state;[4]

[4]Approximately 90% of Texas high school students who continue onto college do so within the state.

(iii) leverage the comprehensive nature of the dataset to investigate the heterogeneity in response to the policy across the state; and (iv) study the effect of affirmative action on long-run employment outcomes, which will be a new contribution to the affirmative action literature. Although the comprehensive nature of the TEA data allows us to track *all* Texas students throughout their educational careers and employment records, our current study using data from one school district in Texas offers some advantages and is, therefore, also of importance. In particular, the TEA data measures student performance primarily using state-wide standardized tests; however, the Texas-wide TAAS changed to a different test, TAKS, in 2003, making comparisons before and after 2003 difficult. In our school district data, we observe a different standardized test that allows us to sidestep the use of the Texas-wide standardized tests. In addition, we observe students' course grades, which are unavailable in the TEA data. Once we begin using the TEA data, we will focus on student performance measures such as attendance, course completion, disciplinary violations, and dropouts. While we work to complete this more extensive study, we believe our current results are also of importance and provide evidence on the incentive effects of affirmative action.

The remainder of the paper will introduce the context in more detail in Section 2, discuss the data in Section 3, and present the analysis and results in Section 4. Section 5 concludes and discusses directions for future work.

2 Context

In 1996, the U.S. Court of Appeals for the Fifth Circuit, which has jurisdiction over Texas, Louisiana and Mississippi, ruled in *Texas v. Hopwood* that universities may not use race as a factor in deciding which applicants to admit. In the wake of this ruling, the Texas legislature passed the "Top 10% Rule" in 1997, which guaranteed admissions to *any* public university in Texas to those students graduating in the top 10% of their class. This law was passed as a means to promote diversity in universities by ensuring college access to high-achieving students from across Texas' somewhat segregated high schools. Then, in June 2003, the Supreme Court ruled in *Grutter v. Bollinger* that a race-conscious admissions process that does not amount to a quota system is constitutional. This Supreme Court decision repealed the ban on using race as a factor in the admissions process in Texas. Thus, Texas public universities were unable to use race explicitly in the admissions process prior to 2003 and were able to do so again after 2003.

We use this policy reversal to assess the effect of the introduction of race-based affirmative action on high school students' performance.[5] During our period of interest, there were no changes in the Top 10% Rule. However, the Top 10% Rule may affect the external validity of our results, since race-based affirmative action policy may interact with the clear admissions cutoffs under the Top 10% Rule. For instance, students in the top decile of their class may not respond to affirmative action since they are already guaranteed admission to Texas public universities. Nonetheless, while the Top 10% Rule may affect the external validity of our results, we believe that this policy experiment is still of interest. First, Texas is a large state containing nearly 10% of the United States' population. From a welfare point of view, understanding the effects of Texas' affirmative action policies is important. Second, while the Top 10% Rule may affect our estimates at the top of the distribution, it is unlikely to affect the incentives of the median student. To the extent that our estimates are driven by the responses of students in the middle of the distribution (and preliminary quantile regressions suggest that this is indeed the case), our estimates are likely to be informative for other contexts.

On the day that the *Grutter v. Bollinger* decision was issued, UT Austin's president stated that the Texas flagship campus intended to return to considering race in the admissions process. Only the University of Texas Board of Regents could authorize the actual implementation of such a change and, in August 2003, the Board of Regents voted to allow all its campuses to return to considering race. The Texas Tech University Board of Regents also outlined a plan in October 2003 to include race as an element in admitting prospective students. Thus, from the onset of the 2003 Supreme Court ruling, it was clear that the state flagship university, UT Austin, and other public universities in Texas would begin to consider race in the admission process.

Due to the existence of the Top 10% Rule, Texas public universities first admit students who qualify for automatic admission. Students who are not eligible for automatic admission (i.e. are not in the top decile of their graduating class) are admitted based on a "holistic" review process which, after 2003, included consideration of race and ethnicity. While some portion of public university classes are admitted under the Top 10% Rule, the holistic admissions process still plays an important role in determining students' admission status. UT Austin, which has the highest percentage of freshmen admitted under the Top 10% Rule, admitted two-thirds of its entering freshmen class under

[5] The first policy change in 1996 combines a ban on race-based affirmative action and the introduction of the Top 10% Rule, which is akin to a "race-blind" affirmative action policy in a setting with somewhat racially segregated high schools. Therefore, the 1996 policy change does not provide a clean experiment for estimating the effects of an affirmative action ban on student incentives.

automatic admission around 2003. The remainder of admitted freshmen were admitted through the holistic review process (Office of the President, 2008).

Figure 1 shows the trend in the racial composition of UT Austin's fall enrollment around the 2003 policy change using data from the Integrated Postsecondary Education Data System (IPEDS). As this figure illustrates, the percentage of blacks and Hispanics in the UT Austin student body increased after 2003. This came at the cost of a decrease in the portion of white and Asian students.[6] Enrollment data from other UT campuses shows a similar pattern, although there is more noise when all the campuses are pooled together, possibly due to the demographic changes in Texas throughout this period.

Overall, the 2003 Supreme Court ruling reintroduced the use of race-based affirmative action in college admissions in Texas. Shortly after, universities expressed interest in considering race as one factor in the admissions process, and university enrollment figures show an increase in racial and ethnic diversity in the student body. Even if students were not directly aware of the court ruling, our conversations with administrators in Texas suggest that guidance counselors and school administrators were aware of the policy and did try to communicate this policy to their students.

3 Data

We use two sources of data. Our main data source is administrative data from a large, urban school district in Texas. We have repeated cross-sections of individual-level data for all 11^{th} graders in the school district between 1997 and 2010. The data contains information on students' demographics (race/ethnicity, gender, and zip code), standardized test scores, courses and course grades, attendance rates, and whether the student dropped out of school in the 11^{th} grade. For our standardized test results, we focus on the norm-referenced Stanford Achievement Test (hereafter, Stanford), a low-stakes achievement test that the school district has administered since 2000.[7]

Summary statistics in Table 1 provide an overview of the students in our administrative data. The majority of students in our school district are black or of Hispanic decent: in a typical campus, 85% of students are black or Hispanic and the remaining students are white and Asian. As the columns

[6] The raw number of students enrolled shows a similar pattern.

[7] We focus on the Stanford test rather than the Texas-wide standardized tests because the Texas-wide tests changed from TAAS to TAKS in 2003, and more importantly, the sample of 11^{th} graders who took the exam changed. Prior to 2003, only 11^{th} graders who had previously failed the TAAS were required to take the exam (exit-level). After 2003, all 11^{th} graders were required to take the TAKS.

pertaining to "Entire Sample" in Table 1 show, students in our school district rank approximately in the 50^{th} percentile of the national distribution for the Stanford test and, on average, earn a 76 (out of 100) in their enrolled courses. Thirty seven percent of students are enrolled in at least one Advanced Placement (AP), Pre-AP, or honors course and 3% of students drop out of high school in the 11^{th} grade. The attendance rate indicates that students are present for 90% of the days they are enrolled in school.

These aggregate measures of performance mask the racial achievement gap. As shown in the remaining columns of Table 1, black and Hispanic students have lower achievement than white students along all dimensions. Black and Hispanic students score significantly lower on the Stanford standardized test in terms of national percentile ranking compared to white students, have lower grades in their courses, are less likely to be enrolled in advanced courses, and are more than twice as likely as white students to drop out of high school in the 11^{th} grade. Because black and Hispanic students have similar educational attainment and affirmative action in college admissions applies similarly to both groups, we pool black and Hispanic students together as "minority students" and compare these minority students to whites in our analysis.[8]

We complement our administrative data with survey data from the Texas Higher Education Opportunity Project (THEOP). THEOP surveyed high school seniors from a random sample of 105 public high schools in Texas in 2002 and in 2004 regarding their demographics, college perceptions, parental involvement, and other activities in high school. Unfortunately, the two waves of the survey are not identical: for instance, the first wave asks about student-teacher interactions, while the second wave does not. The set of questions that are consistent across the two waves allow us to compare the following outcomes, relevant to this study, for Texas seniors one year before and one year after the implementation of affirmative action: time spent on homework outside of school (in minutes), whether the student applied to their first choice college, a series of questions about parental behavior which we combine to construct a "parental involvement index" ranging from 5 to 20,[9] and whether the student discussed the college application process with his/her guidance

[8] Results are similar if we estimate coefficients for black and Hispanic students separately.

[9] More precisely, we use a series of questions that ask "How often do your parents ... (i) give you special privileges because of good grades, (ii) try to make you work harder if you get bad grades, (iii) know when you are having difficulty in school, (iv) help with your school work, and (v) talk with you about problems in school." Students' responses range from "very rarely" (1) to "almost all the time" (4). We sum across the answers to these questions to construct the "parental involvement index" in a way that a higher index corresponds to more involvement along these dimensions.

counselor. Table 2 shows an overview of this data. The timing of the survey allows us to compare high school seniors right after the 2003 court ruling to high school seniors right before. We use this survey to provide suggestive evidence on students' and parents' response to affirmative action policy with the caveats that this survey only exists for two time periods and the sample size in 2004 is small.

In addition to the administrative data from the school district and the THEOP survey data, we have recently gained access to individual-level administrative records on all Texas high school students from the Texas Education Agency. This data is linked to (in-state) college administrative data, as well as unemployment records and wage data. This comprehensive dataset will allow us to analyze and trace the effect of affirmative action on *all* Texas students during high school, throughout the college application process, in college, and later on in the workforce. Results using this extensive dataset are currently in preparation.

4 Analysis and Results

4.1 Empirical Strategy

We use a differences-in-differences empirical strategy to identify changes in the achievement gap between minority and white high school students due to affirmative action. We compare the within-school achievement gap between minority and white students after the reintroduction of affirmative action in 2003 to the achievement gap before 2003. In our main specification, we estimate the following regression for student i, in school s, at time t using administrative data from our school district:

$$y_{ist} = \beta_0 + \beta_1 I(Minority_i) + \beta_2 I(Minority_i) \times I(Post2003_t) + \alpha_{st} + \varepsilon_{ist}, \tag{1}$$

where y_{ist} is student outcomes in high school in terms of standardized test scores, course grades, and course selection in the 11^{th} grade, $I(Minority_i)$ is an indicator variable equal to 1 if a student is black or Hispanic and 0 if the student is white, $I(Post2003_t)$ is an indicator variable equal to 1 if a student is observed after 2003 and 0 otherwise, and α_{st} are campus-year fixed effects.[10] Standard errors ε_{ist} are clustered at the campus-year level. We include α_{st} to account for campus-year specific shocks that could result in changes in the racial achievement gap narrowing independently

[10]We do not include a $I(Post2003_t)$ indicator in the regression as it is subsumed by the campus-year fixed effects.

of affirmative action policy.[11] Accounting for variation at the school-level also accounts for course offerings, grading procedures, the quality of guidance counselors, and other factors that determine educational attainment and are determined at the campus level rather than the district level.

4.2 Main Results

Table 3 reports the estimates from equation 1. Column 1 shows a significant gap between minority and white students in the within-school Stanford score in terms of standard deviations: minorities score .81 SDs lower on the Stanford test than white students in the same school. After the reinstatement of affirmative action in 2003, the racial achievement gap in Stanford narrows by .17 SDs ($p < 0.01$), or 21% of the within-school gap. Column 2 shows a similar pattern for course grades: the racial achievement gap in grades improves by .07 SDs ($p < 0.01$) or 19% of the within-school gap. The improvement in grades does not come at the cost of "taking easier courses:" column 3 shows that minority students are 4 percentage points ($p < 0.05$) more likely to enroll in at least one advanced course (honors, Pre-AP, or AP course) after affirmative action policy is reinstated compared to whites.

Overall, Table 3 shows that on multiple dimensions (standardized test scores, grades, and difficulty of courses), minority high school students' performance improves relative to whites' after the implementation of affirmative action policy in a statistically significant and economically meaningful way. Since our identification strategy relies on comparing the achievement of minorities and non-minorities over time, we are concerned that a general improvement of minorities' outcomes over time could bias our results. We offer three pieces of evidence that a general improvement of minorities' outcomes over time is not driving our results. First, we consider whether the dropout rate changes for minorities relative to whites after 2003. Since students who drop out are unlikely to be on the margin of attending 4-year universities, it may be indicative of other underlying time trends if the dropout rate also improves along with grades and test scores. As column 4 of Table 3 shows, we do not find that the dropout rate of minority studentes relative to whites changes after 2003. Although minority students are approximately twice as likely as white students in the same school to drop out in the 11^{th} grade before 2003, there is no significant change in this relative dropout rate after

[11]For instance, if schools that are predominantly comprised of minority students are improving over time (perhaps due to school accountability policies), then we would observe a reduction in the achievement gap between minority and white high school students over time that cannot be attributed to affirmative action policy. With the inclusion of campus-by-year fixed effects, we account for this by comparing minority and white students *within the same school.*

affirmative action is put in place. Therefore we observe an effect of affirmative action on outcomes that matter for college admissions, such as test scores and courses, but not for outcomes where affirmative action is much less relevant, such as the dropout rate.

Additionally, to rule out general changes in the achievement gap over time that may bias our results, we conduct two placebo tests. In the first placebo test, we assign the policy change to earlier years, controlling for the true policy effect. If our results are biased by pre-trends, we should see significant effects on outcomes before the policy was reinstated. In our second test, we compare the outcomes of Asians to whites after 2003. Since Asians do not benefit from affirmative action, if our natural experiment is valid, we do not expect $I(Asian_i) \times I(Post2003_t)$ to have a significant coefficient. We discuss these results below.

Placebo Policies. To detect any pre-trends in minority students' outcomes, we assign years prior to 2003 to be "placebo" cutoffs and estimate the effect of these placebo cutoffs controlling for the effect of the true policy change. More formally, we estimate

$$\begin{aligned} y_{ist} = \beta_0 + \beta_1 I(Minority_i) + \beta_2 I(Minority_i) \times I(Post2003_t) + \\ \beta_3 I(Minority_i) \times I(PostPlaceboYear_t) + \alpha_{st} + \varepsilon_{ist}, \end{aligned} \tag{2}$$

where $I(PostPlaceboYear_t)$ indicates whether a student is observed after the placebo cutoff. We can vary the placebo cutoff to be any year from 2000 to 2002 for the Stanford test[12] and from 1997 to 2002 for grades and courses. If the changes in the racial achievement gap began earlier than 2003, then we should observe a positive and significant β_3 coefficient. The results for Stanford test appear in Table 4, for course grades in Table 5, and for selection of courses in Table 6. Column 1 in Table 4 replicates our main specification for the effect of the 2003 policy change on the Stanford test. In each subsequent column, we add a different $I(PostPlaceboYear_t)$ variable, starting with 2000. None of the placebo interactions prior to 2003 are significant, and they are typically small in magnitude relative to the estimates for the true policy change. Similarly, column 1 in Table 5 replicates our main specification for the effect of affirmative action policy in 2003 on the racial gap in course grades. Again, there is no evidence that the change in the racial achievement gap began prior to the year of the policy change. In terms of course selection, there is also no evidence of pre-trends as shown in Table 6. These results suggest that our estimates of the effect of affirmative

[12]The Stanford began being administered in our school district in 2000.

action are not driven by pre-trends in minority students' outcomes.

Placebo Minorities. We now investigate whether Asian students improved relative to white students after 2003. We re-estimate equation 1, but we replace minorities with Asians. The sample now only contains whites and Asians. Since Asians do not benefit from affirmative action, we do not expect their outcomes to improve (or decline) relative to whites after 2003. As Table 7 shows, although Asian-American students generally outperform white students, this gap does not change after the implementation of affirmative action policy in 2003. This result is consistent with the idea that affirmative action should only have an effect on students for whom affirmative action policy applies. Even if affirmative action policy had an impact on white and Asian high school students, its effect should not be differential as these two groups are treated the same for purposes of affirmative action.[13] This is confirmed in the data.

4.3 Suggestive Evidence on Mechanisms

So far, we have shown that the achievement gap between minority and white students in terms of test scores, course grades, and course selection narrowed after the introduction of affirmative action policy in 2003. How did this reduction come about? Perhaps high school students changed their behavior or effort. Alternatively, teachers may have become more lenient toward minorities after the policy change or teachers may have focused more on improving minority students' outcomes. The relative improvement in the standardized test scores is unlikely to be explained by teachers grading minorities more leniently, but this does not rule out the possibility that they focused more attention on improving minorities' learning. Similarly, the change in affirmative action policy may have led parents or guidance counselors to become more involved with students. To determine what drives minority students' improved outcomes, we analyze students' responses from the THEOP survey.

As mentioned previously, the THEOP survey asked high school seniors across Texas about their demographics, college application behavior, and high school activities in 2002 and then again in 2004. Unfortunately, the two waves of the survey are not identical. The set of questions that are consistent across the two waves allow us to compare the following outcomes for Texas seniors one year before and one year after the implementation of affirmative action: time spent on homework

[13] Kane (1998) has shown that racial preferences in admissions are given only at the most elite 20% of colleges and universities and, even at these colleges, the impact of racial preferences on the typical white (or Asian) applicant's admission probability is small.

outside of school (in minutes), whether the student applied to his/her first choice college, a series of questions about parental behavior which we combine to construct a "parental involvement index," and whether the student discussed the college application process with his/her guidance counselor. For each of these outcomes, we run the following regression:[14]

$$y_{it} = \beta_0 + \beta_1 I(Minority_i) + \beta_2 I(Post2003_t) + \beta_3 I(Minority_i) \times I(Post2003_t) + \varepsilon_{it}, \tag{3}$$

where $I(Post2003_t)$ is an indicator equal to 1 for seniors surveyed in 2004. Table 8 shows these results. As column 1 shows, after the implementation of affirmative action, minority high school seniors spend 8% more time on homework outside of school relative to white students (a relative increase of approximately 5 minutes per day). Minority students are also 5 percentage points more likely to apply to their first choice college after the policy change compared to whites. We do not see any changes in the parental involvement index or the likelihood of discussing college applications with guidance counselors for minorities relative to white students after affirmative action is put in place. Overall Table 8 provides suggestive evidence that student behavior (such as time spent on homework) and college aspirations did respond to the introduction of affirmative action policy.

5 Conclusion and Next Steps

In this paper, we study the effects of a 2003 U.S. Supreme Court ruling that effectively reinstated race-based affirmative action policies in public universities in Texas. Comparing minority (black and Hispanic) and white students in the same schools in a large, urban school district in Texas, we find that this reinstatement substantially reduced the racial gap in standardized test scores, grades, and likelihood of enrolling in at least one advanced course. Our results are consistent with experimental work by Cotton et al. (2015) and the structural estimates of Hickman (2013), both of which find that affirmative action incentivizes greater human capital investment by minority high school students. We complement these findings by studying the effects of a real policy change that targeted students based on race. In addition, our large effect sizes suggest that policy debates that ignore the pre-college incentive effects of affirmative action policies ignore a significant benefit of these policies. Given the role the racial achievement gap may play in determining gaps in long-

[14] In this analysis, we cannot include campus fixed effects because we do not know the campus the student belongs to.

term outcomes (Neal and Johnson, 1996), reductions in the achievement gap may translate into substantial reductions in the wage gap.

Using survey data, we examine how students' behavior, in addition to their outcomes, respond to the affirmative action policy. We find that minority students spend more time on their homework and are more likely to apply to their first choice college after the policy change. This is consistent with the idea that minority students respond to the affirmative action policy by changing their college aspirations and adjust their effort accordingly. We also speculate that these results are consistent with work by Hoxby and Avery (2012) and Hoxby and Turner (2013), which show that qualified, disadvantaged students are less likely to apply to highly selective four-year institutions. If affirmative action leads minority students to perceive admission to a selective school as more attainable, it may change both their application behavior and their pre-college human capital investment.

This paper presents our preliminary results using data from one large, urban Texas school district. In the future, we will expand on these results in two ways. First, using data from the Texas Education Agency, we will re-estimate our main specifications for the entire state of Texas. This dataset will also allow us to test for important heterogeneity in the effects of affirmative action. For example, the effects of the policy may be particularly large for students who live near selective, 4-year public institutions. This data will also allow us to follow students' over a long time horizon. We will be able to observe their outcomes in college and in the labor market. Thus, we will be able to see if affirmative action policy actually did affect minority students' likelihood of college admission and which students were most likely to be affected. Moreover, we can see how these students fared in terms of grades, majors, and wages once they matriculated to college and entered the labor force.

Second, using lagged student outcomes from before affirmative action was reinstated, we will be able to see which part of the student distribution was most affected by the policy change. Since some commentators have argued that affirmative action only benefits already-advantaged minorities, this will provide us with important evidence on the distribution of the benefits of the policy. Additionally, estimating heterogeneous effects by location in the achievement distribution will allow us to test if *some* students at the top of the distribution decrease their effort, as some models predict (Cotton et al., 2015). Finally, these heterogeneous effect estimates will serve as an additional robustness test for our main results since we expect affirmative action policies to affect the effort of students who would benefit the most from such policies.

References

Antonovics, Kate and Ben Backes, "The effect of banning affirmative action on human capital accumulation prior to college entry," *IZA Journal of Labor Economics*, 2014, *3* (1), 5.

Arcidiacono, Peter, "Affirmative action in higher education: How do admission and financial aid rules affect future earnings?," *Econometrica*, 2005, *73* (5), 1477–1524.

Bowen, William G and Derek Bok, *The Shape of the River. Long-Term Consequences of Considering Race in College and University Admissions.*, ERIC, 1998.

Card, David and Alan B Krueger, "Would the elimination of affirmative action affect highly qualified minority applicants? Evidence from California and Texas," *Industrial & Labor Relations Review*, 2005, *58* (3), 416–434.

Coate, Stephen and Glenn C Loury, "Will affirmative-action policies eliminate negative stereotypes?," *The American Economic Review*, 1993, pp. 1220–1240.

Cortes, Kalena E and Lei Zhang, "The incentive effects of the top 10% plan," *Working Paper*, 2011.

Cotton, Christopher, Brent R Hickman, and Joseph P Price, "Affirmative action and human capital investment: Theory and evidence from a randomized field experiment," *Working Paper*, 2015.

Cullen, Julie Berry, Mark C Long, and Randall Reback, "Jockeying for position: Strategic high school choice under Texas' top ten percent plan," *Journal of Public Economics*, 2013, *97*, 32–48.

Ferman, Bruno and Juliano Assunção, "Affirmative action in university admissions and high school students' proficiency," *Working Paper*, 2005.

Fryer, Roland G and Glenn C Loury, "Affirmative Action and Its Mythology," *Journal of Economic Perspectives*, 2005, *19* (3), 147–162.

Hickman, Brent R, "Pre-college human capital investment and affirmative action: a structural policy analysis of US college admissions," *Working Paper*, 2013.

Hoxby, Caroline and Sarah Turner, "Expanding college opportunities for high-achieving, low income students," *Stanford Institute for Economic Policy Research Discussion Paper*, 2013, (12-014).

Hoxby, Caroline M and Christopher Avery, "The missing "one-offs": The hidden supply of high-achieving, low income students," *NBER Working Paper*, 2012.

Kane, Thomas J, "Racial and ethnic preferences in college admissions," *Ohio St. LJ*, 1998, *59*, 971.

Neal, Derek A and William R Johnson, "The Role of Premarket Factors in Black-White Wage Differences," *The Journal of Political Economy*, 1996, *104* (5), 869–895.

Office of the President, "A Report on the Top Ten Percent Law," Technical Report, The University of Texas at Austin 2008.

Rothstein, Jesse and Albert H Yoon, "Affirmative Action in Law School Admissions: What Do Racial Preferences Do?," Technical Report, NBER 2008.

Sander, Richard H, "A systemic analysis of affirmative action in American law schools," *Stanford Law Review*, 2004, pp. 367–483.

Table 1: Overview of Administrative Data

Panel A: Summary Statistics

	Entire Sample		Whites		Blacks		Hispanics		Asians	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Campus Minority Share	0.85	0.20								
Stanford Percentile	48.27	26.38	71.58	25.07	42.00	23.62	43.97	23.52	70.80	26.02
Course Grades	75.87	12.32	80.78	10.72	74.47	12.09	74.88	12.42	82.94	10.19
Prob. Advanced Courses	0.37	0.48	0.63	0.48	0.32	0.47	0.30	0.46	0.75	0.43
Prob. Dropout	0.03	0.17	0.01	0.12	0.03	0.18	0.04	0.18	0.01	0.10
Attendance Rate	0.90	0.13	0.93	0.11	0.90	0.14	0.90	0.14	0.95	0.10

Panel B: Total Numbers

	N
Total Campuses	81
All Students	153,008
Whites	20,703
Blacks	51,247
Hispanics	74,604

This table presents summary statistics by race for the key variables of interest in our administrative data from a large, urban school district in Texas. The dataset spans 1997 to 2010 and consists of repeated cross-sections of 11^{th} graders. Students were coded as taking an advanced course if they enrolled in at least 1 honors, advanced, or advanced placement (AP) course. Dropout is measured as dropout in the 11^{th} grade, so dropout levels in this data will be lower than those implied by final high school graduation rates.

Table 2: Overview of THEOP Survey Data

Panel A: Summary Statistics

	Mean	SD
Time (minutes) Spent on Homework	64.54	56.69
Applied to First Choice College	0.65	0.48
Parental Involvement Index (5-20)	10.98	3.87
Discussed College App. w. Counselor	0.67	0.47

Panel B: Total Numbers

	N
Total Students	13,852
Whites	6,406
Minorities	7,446
Students in 2002	11,025
Students in 2004	2,827

This table presents summary statistics for the Texas Higher Education Opportunity Project (THEOP) survey data for two cohorts of seniors, one in 2002 and one in 2004. For the measure of how many minutes per day students spend on homework, students were asked how many hours per day they spent on their homework and were given the options zero heros, less than 1 hour, 1 to 2 hours, 3 to 4 hours, and 5+ hours. We convert these to minutes so that 0 hours is 0 minutes, less than 1 hour is 30 minutes, 1 to 2 hours is 90 minutes, and so on. The parental involvement index is also constructed using several questions that ask "How often do your parents ... (i) give you special privileges because of good grades, (ii) try to make you work harder if you get bad grades, (iii) know when you are having difficulty in school, (iv) help with your school work, and (v) talk with you about problems in school." Students' responses range from "very rarely" (1) to "almost all the time" (4). We sum across the answers to these questions to construct the "parental involvement index" in a way that a higher index corresponds to more involvement along these dimensions.

Table 3: Minority-white Achievement Gap and Affirmative Action

	(1) Stanford Test	(2) Course Grades	(3) Advanced Course	(4) Dropout
I(Minority)	-0.812***	-0.369***	-0.289***	0.009***
	(0.033)	(0.018)	(0.011)	(0.002)
I(Minority)×*I(Post2003)*	0.173***	0.073***	0.044**	-0.003
	(0.042)	(0.025)	(0.017)	(0.003)
Campus-year FE	Y	Y	Y	Y
N	91,578	118,270	118,386	146,554
Clusters	475	573	573.000	653
R-squared	0.356	0.140	0.167	0.078
Mean Whites Pre-2003	1.023	0.450	0.582	0.011

This table presents difference-in-difference estimates of the effect of being a minority student post 2003 in the Texas administrative data. The dataset consists of repeated cross-sections of 11^{th} graders from 1997 to 2010. Asians are excluded from the regression. All regressions include campus-by-year fixed effects. Standard errors are clustered at the campus-year level.

Table 4: Test for Pre-trends in Stanford Test Scores

	(1) Stanford Test	(2) Stanford Test	(3) Stanford Test	(4) Stanford Test
I(Minority)×*I(Post2003)*	0.173***	0.163***	0.123**	0.135**
	(0.042)	(0.046)	(0.048)	(0.061)
I(Minority)×*I(Post2000)*		0.039		
		(0.076)		
I(Minority)×*I(Post2001)*			0.103	
			(0.063)	
I(Minority)×*I(Post2002)*				0.050
				(0.068)
Campus-year FE	Y	Y	Y	Y
N	91,578	91,578	91,578	91,578
Clusteres	475	475	475	475
R-squared	0.356	0.356	0.356	0.356

This table presents tests for pre-trends in Stanford scores which may bias the estimates of the effect of affirmative action. In addition to the difference-in-difference specification (column 1), we assign placebo policy changes to 2000 (column 2), 2001 (column 3), and 2002 (column 4). The dataset consists of repeated cross-sections of 11^{th} graders from 2000 to 2010. Asians are excluded from the regression. All regressions include campus-by-year fixed effects. Standard errors are clustered at the campus-year level.

Table 5: Test for Pre-trends in Course Grades

	(1) Course Grades	(2) Course Grades	(3) Course Grades	(4) Course Grades	(5) Course Grades	(6) Course Grades	(7) Course Grades
I(Minority)×I(Post2003)	0.073***	0.069***	0.072***	0.074***	0.055*	0.043	0.052
	(0.025)	(0.026)	(0.027)	(0.029)	(0.029)	(0.032)	(0.042)
I(Minority)×I(Post1997)		0.028					
		(0.053)					
I(Minority)×I(Post1998)			0.003				
			(0.042)				
I(Minority)×I(Post1999)				-0.003			
				(0.036)			
I(Minority)×I(Post2000)					0.031		
					(0.034)		
I(Minority)×I(Post2001)						0.042	
						(0.034)	
I(Minority)×I(Post2002)							0.024
							(0.042)
N	118,270	118,270	118,270	118,270	118,270	118,270	118,270
Clusters	573	573	573	573	573	573	573
R-squared	0.140	0.140	0.140	0.140	0.140	0.140	0.140
Campus-year FE	Y	Y	Y	Y	Y	Y	Y

This table presents tests for pre-trends in grades which may bias the estimates of the effect of affirmative action. In addition to the difference-in-difference specification (column 1), we assign placebo policy changes to 1997 (column 2), 1998 (column 3), and 1999 (column 4), 2000 (column 5), 2001 (column 6), and 2002 (column 7). The dataset consists of repeated cross-sections of 11^{th} graders from 1997 to 2010. Asians are excluded from the regression. All regressions include campus-by-year fixed effects. Standard errors are clustered at the campus-year level.

Table 6: Test for Pre-trends in Course Grades

	(1) Advanced Course	(2) Advanced Course	(3) Advanced Course	(4) Advanced Course	(5) Advanced Course	(6) Advanced Course	(7) Advanced Course
I(Minority)×I(Post2003)	0.044**	0.041**	0.040**	0.043**	0.027	0.020	0.035
	(0.017)	(0.018)	(0.019)	(0.020)	(0.020)	(0.022)	(0.028)
I(Minority)×I(Post1997)		0.020					
		(0.036)					
I(Minority)×I(Post1998)			0.016				
			(0.025)				
I(Minority)×I(Post1999)				0.003			
				(0.023)			
I(Minority)×I(Post2000)					0.031		
					(0.022)		
I(Minority)×I(Post2001)						0.034	
						(0.022)	
I(Minority)×I(Post2002)							0.011
							(0.027)
Campus-year FE	Y	Y	Y	Y	Y	Y	Y
N	118,386	118,386	118,386	118,386	118,386	118,386	118,386
Clusters	573	573	573	573	573	573	573
R-squared	0.167	0.167	0.167	0.167	0.167	0.167	0.167

This table presents tests for pre-trends in enrolling in advanced courses which may bias the estimates of the effect of affirmative action. The outcome is an indicator variable for enrolling in at least one honors, advanced, or advanced placement course. In addition to the difference-in-difference specification (column 1), we assign placebo policy changes to 1997 (column 2), 1998 (column 3), and 1999 (column 4), 2000 (column 5), 2001 (column 6), and 2002 (column 7). The dataset consists of repeated cross-sections of 11^{th} graders from 1997 to 2010. Asians are excluded from the regression. All regressions include campus-by-year fixed effects. Standard errors are clustered at the campus-year level.

Table 7: Asian-white Achievement Gap and Affirmative Action

	(1) Stanford Test	(2) Course Grades	(3) Advanced Course	(4) Dropout
I(Asian)	-0.059	0.137***	0.106***	-0.002
	(0.065)	(0.024)	(0.026)	(0.002)
I(Asian)×I(Post2003)	0.071	-0.007	0.021	-0.007**
	(0.075)	(0.030)	(0.034)	(0.003)
Campus-year FE	Y	Y	Y	Y
N	18,029	23,344	23,334	27,049
Clusters	391	461	461	556
R-squared	0.267	0.151	0.125	0.108
Mean Whites Pre-2003	1.023	0.450	0.582	0.011

This table replicates the analyses in table 3, but replaces the indicator variable for minority (black or Hispanic status) with an indicator variable for Asian. The dataset consists of repeated cross-sections of 11^{th} graders from 1997 to 2010. Minorities are excluded from the regression. All regressions include campus-by-year fixed effects. Standard errors are clustered at the campus-year level.

Table 8: Student and Parent Behavior and Affirmative Action

	(1) Time on Homework	(2) Applied to First Choice College	(3) Parental Involvement	(4) Guidance From Counselor
I(Minority)	12.446***	-0.107***	0.122*	0.047***
	(1.016)	(0.011)	(0.073)	(0.009)
I(Post2003)	26.070***	-0.145***	1.759***	0.191***
	(1.912)	(0.017)	(0.128)	(0.014)
I(Minority)×I(Post2003)	5.439**	0.047**	0.172	-0.025
	(2.496)	(0.023)	(0.166)	(0.018)
N	13,452	9,993	13,558	13,699
R-squared	0.061	0.024	0.038	0.026
Mean Whites Pre-2003	51.585	0.732	10.635	0.614

This table presents differences-in-differences analyses using survey data from two cohorts, both in their senior year, of the Texas Higher Education Opportunity Project (THEOP). The earlier cohort was surveyed in 2002 and the later cohort was surveyed in 2004. For the measure of how many minutes per day students spend on homework, students were asked how many hours per day they spent on their homework and were given the options zero heros, less than 1 hour, 1 to 2 hours, 3 to 4 hours, and 5+ hours. We convert these to minutes so that 0 hours is 0 minutes, less than 1 hour is 30 minutes, 1 to 2 hours is 90 minutes, and so on. The parental involvement index is also constructed using several questions that ask "How often do your parents ... (i) give you special privileges because of good grades, (ii) try to make you work harder if you get bad grades, (iii) know when you are having difficulty in school, (iv) help with your school work, and (v) talk with you about problems in school." Students' responses range from "very rarely" (1) to "almost all the time" (4). We sum across the answers to these questions to construct the "parental involvement index" in a way that a higher index corresponds to more involvement along these dimensions. Standard errors are heteroskedasticity robust.

Figure 1: Racial Composition of UT Austin