Labor Market Effects of Preferential College Admission

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Preferential college admission, commonly referred to as affirmative action, is currently a hot topic in economics as well as the popular media. As universities and policy makers reevaluate current admission policies, it is important they understand the full impact of these policies. In this paper I examine the effects of a school's level of affirmative action on the wages of the school's graduates. School selectivity is valuable to employers in part because it carries information about a graduate's unobservable ability. I develop a model that builds on this idea. In the presence of affirmative action employers will have lower expectations as to the true ability of a preferentially admitted group and will pay them less than employees from the non-preferentially admitted group. Furthermore, affirmative action will increase the variance in ability of the preferentially admitted group, causing them to face lower returns to school selectivity. I test the model using data from the Baccalaureate and Beyond Longitudinal Study of 1993. I find that black graduates do face lower wages as the level of affirmative action at their school increases. The decrease in wages due to an increase in affirmative action offsets approximately 75% of the return to an equivalent increase in school selectivity. Affirmative action has no significant impact on the wages of white graduates. These results indicate that initial wages of black college graduates depend on how selective their school is in its admission of black students, with the school's admission policy for white students having little impact.

1. INTRODUCTION

Preferential college admission, commonly referred to as affirmative action, has a long history and an uncertain future. Most Americans believe that the goals of affirmative action policies are noble, but much disagreement remains concerning the efficacy and equity of the policies. Of crucial importance to the effectiveness of affirmative action policies is their impact on labor-market outcomes. University admission policies are not made in a vacuum. Changes in these policies not only affect the school population, but also the beliefs held by potential employers about the school's population. This paper examines the effects of a school's level of affirmative action on the wages of the schools' graduates.

Much research has been done concerning the effects of preferential college admission on the composition of a student population. Card and Krueger (2004) and Long (2004) explore how the end of affirmative action policies in California and Texas has altered the makeup of students applying to college. Dickson (2004) provides evidence that affirmative action policies not only affect where students apply, but also which individuals apply to college. A large volume of literature also focuses on the effects of affirmative action polices on student educational outcomes. Datcher Loury and Garman (1993,1995), Kane (1998) and Bowen and Bok (1998) examine the college performance of minority students as a function of school selectivity. The results of the three studies are conflicting and inconclusive, but do show that college performance (e.g. GPA) depends on school selectivity and race. These questions are important to institutions when determining their optimal admission policy but do not address the performance of graduates once they leave college.

The purpose of this paper is to measure the effects of a school's preferential admission on the labor-market outcomes of its graduates. Specifically, I look at wages as a function of individual as well as school characteristics including a measure of affirmative action. Past research on affirmative action either focuses on the effects of affirmative action in education on educational outcomes, or the effects of affirmative action in the labor market on labor-market outcomes. Little has been done linking school polices on affirmative action to labor-market outcomes. Some researchers such as Datcher Loury and Garman (1993, 1995) examine wages as a function of school selectivity and race from which they are able to make limited inference about the possible effects affirmative action. They examine the relationship between individual ability and school selectivity noting that under affirmative action black students of a lower ability may be admitted to more selective schools. This paper differs in that I account for affirmative action directly while holding ability, GPA, and school quality constant. If school selectivity is valuable to employers because it carries information about unobservable ability, then affirmative action may impact wages beyond the direct effect of having lower ability black students in more selective schools.

I find that the level of a school's affirmative action does affect wages. Specifically, I find that the marginal effect of graduating from a school with the average level of affirmative action compared to a school of the same quality with no affirmative action is an approximately a 13% reduction in wages for black students one year out of college. This wage gap disappears by the time the individuals have been in the labor market for four years. The wage reduction due to affirmative action offsets approximately 75% of the return to an equivalent increase in school quality. This relationship is consistent with the hypothesis that affirmative action decreases the signaling value of school quality for blacks. There is no significant relationship between affirmative action and white wages.

It is important to note what is not within the scope of this paper. I am not looking at the full effects of affirmative action. Specifically I am not looking at whether individuals are better off before or after affirmative action. Some students may be able to attend college or may move to a higher quality university because of an affirmative action policy. These students may be better off under affirmative action than they would have been without it. What I can say is that they receive a lower wage than had they gone to a school of the same quality with no affirmative action; however such a school may not be in the choice set of many individuals. This research highlights the fact that affirmative action lowers the value of school quality as a signal of student ability to employers.

The paper proceeds as follows: Section two presents a theoretical basis for the effects of affirmative action on graduate wages and discusses their implications. Section three explores the data form the 1993 class of the Baccalaureate and Beyond Longitudinal Study, with section four discussing the measurement of affirmative action. Section five presents empirical evidence based on data. The final section discusses implications of the research and concludes.

2. THEORY

Employers never have perfect information about the productivity of a potential employee at their firm. This idea is the basis for the theory that follows. Without perfect information employers will use easily observable characteristics when making hiring decisions and wage offers. This will be especially important for newly graduated employees as they have less information available on which to base expected productivity. Two easily observable characteristics are school quality and race. Due to pre market factors, it is likely that the underlying distributions of true productivity of college graduates differ systematically between races even without affirmative action. The presence of affirmative action may serve to exacerbate the differences. Not only will it likely lower the expected productivity (conditional on school quality) of blacks, but it will likely increase the variance of the distribution of productivity. Thus, affirmative action will have two effects; blacks from schools with high levels of affirmative action will be treated as though they were from a lower quality school, and the relative importance of school quality as a signal will decrease.

Formally, assume that their is a continuum of individuals, each with ability level a_i that does not vary by firm or school and is unobservable to everyone. True productivity of individual i at firm j is represented by $P_{ij} = a_i + \varepsilon_{ij}$ where ε_{ij} represents the quality of the firm-individual match[1] and is unknown to both individuals and firms. Although firms do not know a_i, they know the distribution of a_i in the population to be $N[\mu_a, \sigma_a]$. Employers receive two signals as to the true value of a_i. First, they receive a direct signal $g_i = a_i + \nu_i$ where $\nu_i \sim N[\mu_\nu, \sigma_\nu]$ represents an individual specific error term in the measurement of ability. This direct signal can be thought of as grades, a test given upon application, or an interview impression. Employers also observe the individual's school s_i. The labor market is competitive with risk neutral workers and firms. Thus, employers make a wage offer equal to the individual's expected productivity.

[1] In the analysis that follows, the inclusion of ε_{ij} is not critical to the results. It is included here because it adds realism to the model and because it allows for straightforward extension of the model to other applications.

Ability a_i is also unobservable to schools. They do observe a test score $T_i = a_i + u_i$ where $u_i \sim N[\mu_u, \sigma_u]$ represents measurement error in the exam. This test can be thought of as the SAT or ACT, and is unobservable to employers. Without fully developing the value function for schools, I assume they follow the acceptance rule: accept individual i if $T_i > \underline{T}$ were $\underline{T}$ is set by the university and represents the lowest acceptable test score. It can be thought of as an admission bar below which students are not accepted. I assume that a_i, ν_i, u_i, and ε_{ij} are independent.

This can be thought of as a school system where all individuals apply[2] to a single university and those with the best test scores are accepted. This may be a strong assumption as in reality there are many universities and applicants apply at multiple schools. By assuming that all students attend the highest quality school they are admitted to, the model extends readily to a market with many schools. Although a change in admission policies may change the applicant pool for a university, as shown by Card and Krueger (2004) and Long (2004), it is likely that the actual pool of potential students does not change. As the admission bar is raised, fewer low score students may be observed applying, but this is because their probability of acceptance is low, not because they are out of the market for that school. A more troubling problem is the top students. If the admission bar is lowered the university becomes less selective, which may cause them to switch to the university that was previously their second choice. The many factors other than selectivity entering into the school choice decision for students at the top of the school's ability distribution will likely make this group of students small.

Given the above parameters, employers will make a wage offer of $w_i =$

[2] This implicitly assumes that the value of college is greater than the cost for all individuals.

$E\left[P_{ij}|s_i, g_i\right]$. Employers receive no signals as to the value of ε_{ij} and I assume $E\left[\varepsilon_{ij}\right] = 0$. Thus the wage offer is equivalent to

$$w_i = E\left[a_i | a_i + u_i > \underline{T}\ ,\ a_i + \nu_i = g_i\right] \tag{1}$$

For simplicity I will continue without subscripts. From equation (1) $a,\ a+u$, and $a+\nu$ have a trivariate normal distribution. Define a' as a normally distributed random variable with mean $\mu_a + \lambda\left(g - \mu_a - \mu_\nu\right)$ and variance $\left(1-\lambda\right)\sigma_a^2$ where $\lambda = \frac{\sigma_a^2}{\sigma_a^2+\sigma_\nu^2}$. It can be shown that a' represents the distribution of a conditional on $g = a + \nu$. Thus equation (1) is equivalent to

$$w = E\left[a' | a' + u > \underline{T}\right] \tag{2}$$

Without loss of generality assume that $\mu_\nu = 0$. Now a' and $a' + u$ have a bivariate normal distribution with a covariance of $\sigma_a^2\left(1-\lambda\right)$. The wage offer becomes[3]

$$w = \lambda g + \left(1-\lambda\right)\mu_a + \frac{\sigma_a^2\left(1-\lambda\right)}{\sqrt{\sigma_a^2\left(1-\lambda\right)+\sigma_u^2}}\left[\frac{\phi\left(\frac{\underline{T}-\lambda g-(1-\lambda)\mu_a-\mu_u}{\sqrt{\sigma_a^2(1-\lambda)+\sigma_u^2}}\right)}{1-\Phi\left(\frac{\underline{T}-\lambda g-(1-\lambda)\mu_a-\mu_u}{\sqrt{\sigma_a^2(1-\lambda)+\sigma_u^2}}\right)}\right] \tag{3}$$

To simplify notation, define $x = \frac{\underline{T}-\lambda g-(1-\lambda)\mu_a-\mu_u}{\sqrt{\sigma_a^2(1-\lambda)+\sigma_u^2}}$ and $\Gamma\left(x\right) = \frac{\phi(x)}{1-\Phi(x)}$. The first two terms in equation (3) look like the standard wage offer from the statistical discrimination literature. They show that wages are a weighted sum of one's own productivity signal and the population average. The third term is more complex and represents the benefit of attending a more selective school conditional on grades and the population mean. It accounts for the skew and the shift in the distribution of ability created by the

[3] See Greene (2003) p. 781.

acceptance rule.

Now it is possible to examine the effects of affirmative action on wages. First note that $\lim_{x\to-\infty}\Gamma(x)=0$ and $\frac{\partial\Gamma(x)}{\partial x}>0$ for all x. For students graduating from a school that admits anyone, the third term in equation (3) disappears and their college diploma adds nothing to the wage. The higher a school sets its admission bar, the higher the wages of the school's graduates. If a school has two different admission bars, one for black students $\left(T^b\right)$ and one for white students (T^w) employers will be able to use race as another signal about true worker productivity. I will use differing admission bars as a theoretical definition of affirmative action. If $T^b<T^w$ then black students will receive lower wages than white students from the same school. What is even more disturbing is that this relationship holds even after grades have been controlled for. Thus a black graduate will earn less than a white student from the same school with the same GPA. This relationship arises from the fact that g is not a perfect predictor of a, causing employers to use additional information to estimate productivity. If employers were allowed to see individual entrance exam scores, affirmative action would not have an impact on wages. Instead, they can only observe the characteristics of the population of graduates. Therefore a lower admission bar hurts the students who would have graduated without the lower bar because it devalues their degree. In essence, employers "undo" the effects of affirmative action.

It is important to consider the reasons for affirmative action. I assume throughout this model that a and ν are distributed identically for blacks and whites. This means that conditional on ability, black and white students have the same expected signal g of ability observed by employers, and that the distribution of true ability does not differ by race. If schools must implement affirmative action plans to maintain a representative population of minority students, it must be that the admission test scores differ by race. This difference enters the test scores through the distribution of measurement error for admission tests (u). I assume that $u^w \sim N\left[\mu_u^w, \sigma_u^w\right]$ and $u^b \sim N\left[\mu_u^b, \sigma_u^b\right]$ represent the distribution of test measurement error in the white and black populations respectively. Whether or not a school's affirmative action policy will be successful in correcting for the differences in u^w and u^b will depend on how exactly they differ.

If it is simply the case that $\mu_u^b < \mu_u^w$ while $\sigma_u^b = \sigma_u^w$ then a university can maintain affirmative action without any negative impact[4] on its graduates wage's. By setting T^w and T^b such that $T^w - \mu_u^w = T^b - \mu_u^b$ the university can perfectly correct for the bias in the entrance exam. One can see from equation (3) that the admission bar and the mean error on the admission exam enter the wage equation in exactly the same manner, making the admission bar an effective tool for maintaining equal distributions of ability (a) between races.

Alternatively, if entrance exams are less precise for black students than they are for white students, the university will not be able to equate the distributions of ability (a) between races. This is the standard assumption in the statistical discrimination literature that $\sigma_u^b > \sigma_u^w$ and $\mu_u^b = \mu_u^w$. Because $\frac{\partial w}{\partial \sigma_u} < 0$ black college graduates will receive a lower wage than white college graduates even when there is no affirmative action $\left(T^w = T^b = \underline{T}\right)$. Lowering the admission bar for blacks will only exacerbate this problem[5].

[4] Note that under this regime black graduates will actually have a higher wage than white graduates in the absence of affirmative action.

[5] This is only a "problem" when looking at the wage differential between black and white college graduates. Lowering T^b will lower black college graduate wages, but will also increase the number of black college graduates and the average quality of school that they attend. Efficiency questions about the policy are beyond the scope of this paper.

A lower admission bar and less precise entrance exam have the same effect on the distribution of true ability a at the university. They both decrease the average ability and increase the variance[6] of ability.

When looking at wages, having $\sigma_u^b > \sigma_u^w$ decreases wages in two ways. First, $\Gamma(x)$ is decreasing with respect to σ_u^b. This represents the "bump" in wages received by graduates for attending a more selective school. At higher levels of σ_u^b applicants who are truly qualified in terms of ability are more likely to be rejected because of a negative realization of T_i, while less qualified applicants are more likely to be accepted because of a high realization of T_i. This serves to lower the expected value of true ability among those accepted. Second, σ_u^b makes school selectivity a worse indicator of true ability. This ensures that employers will put less weight[7] on $\Gamma(x)$, further decreasing wages. This can be seen through the negative relationship between σ_u^b and $\frac{\sigma_a^2(1-\lambda)}{\sqrt{\sigma_a^2(1-\lambda)+\sigma_u^2}}$. If both $\mu_u^b < \mu_u^w$ and $\sigma_u^b > \sigma_u^w$, the university is able to correct for the difference in mean errors, but only at the cost of lowering the expected ability of black graduates, thus lowering their wages.

The model provides several relevant empirical implications. First, black graduates will receive lower wages than white graduates from the same school with the same ability level and GPA if admission exams are less precise for blacks. This wage differential will be larger the more pronounced the school's affirmative action policy. If employers learn about true ability over time, then the wage penalty for going to a school with affirmative action should decrease over time. The model also implies that black graduates

[6] It can be shown that
$VAR[a'|a'+u > \underline{T}] = \sigma_a^2(1-\lambda)\left[1 - \frac{\sigma_a^2(1-\lambda)}{\sigma_a^2(1-\lambda)+\sigma_u^2}\Gamma(x)(\Gamma(x)-x)\right]$
This variance term is decreasing in x, while x is increasing in $\underline{T}$ and decreasing in σ_u^2.

[7] In essecne, $\Gamma(x)$ represents the skewness of ability caused by selectivity. Increasing σ_u decreases the skew and puts more weight on the alternative of 0.

should face a lower return to school quality as affirmative action increases.

3. DATA

The data used come from the Baccalaureate and Beyond Longitudinal Study of 1993 (B&B). The B&B is a large nationally representative sample of college students graduating from college with a bachelor's degree in the 1992/1993 school year. The original sample was drawn from the National Postsecondary Student Aid Study (NPSAS) of 1993, collected by the U.S. Department of Education's National Center for Education Statistics (NCES). All monetary variables are adjusted using the consumer price index[8] retrieved from the Bureau of Labor Statistics.

The B&B is unique in that it follows a large number of college graduates over an extended period. It contains detailed information on each individual's college experience, institution, and post-college work experience. The initial sample contains 11,192 graduates from 649 universities. The baseline data comes from the NPSAS of 1993. Follow-ups took place between June and December of 1994, 1997, and 2003, approximately 1 year, 4 years, and 10 years out of college.

What makes the B&B truly valuable is the level of detail with which the individual's college experience is recorded. Respondents were asked a broad range of questions about their university in 1993 and 1994. Even more important, each individual's transcripts were recorded. These give the graduate's GPA, major, and any admission test scores such as the SAT or ACT.

The B&B also contains a great deal of institution level data. It has a demographic breakdown, graduation rate, NSF classification, whether

[8] The CPI used 1982-1984 as the base period.

the university is public or private, and many other key institution level variables. These data combined with the transcript data allow for precise measurement of a student's educational achievement and outcome. Typically the researcher is only able to control for years of education, but with the B&B this is automatic as the entire sample has the same years of education[9], at least initially. I am able control for much more of what an employer observes. Any subsequent degrees are also recorded.

Concerning labor force experience, the B&B contains information on the employment (full time, part time, unemployed, out of labor force) status of an individual for every month from graduation through the 1997 interview date. It also records the start date of any job held at the interview date. Together these allow me to create accurate tenure and post-college experience variables. Graduate enrollment is also recorded for every month, so I am able to control for subsequent education and determine whether an individual is primarily an employee or a student.

It is important that I be able to measure ability. There is no measure of ability recorded for all individuals, but about 60% of the students have a recorded SAT score and 35% have an ACT score recorded. These measures correspond well to T_i from the theoretical model of the previous section. To have a single measure of ability, I compute each student's percentile ranking on each exam they have recorded on their transcripts[10]. I then create a variable using this value for students that only took one of the exams. For students who took both exams (approximately 13%) I use the higher of the two percentiles, as this is likely what admission decisions are

[9]There are actually a few individuals for whom the degree of record is their second bachelor's degree. I control for this in the empirical work that follows.

[10]I created these percentiles based on my own sample, but later compared these to the percentile rankings for both the SAT and ACT reported by The College Board for 1989. The transformations were almost identical. In what follows I use the created transformation.

based on. For students with no test score reported on their transcripts, I use self reported test scores if they exist. Using this method I am able to assign a percentile score to 8,954 individuals, or about 80% of the sample.

4. MEASURING AFFIRMATIVE ACTION

The biggest hurdle to examining affirmative action is the difficulty faced in measuring affirmative action. Affirmative action is not a binary policy. Most schools have some form of a preferential acceptance policy, whether formal or not. The difficulty becomes quantifying the degree of preferential admission. For example, in 1996 the 5^{th} Circuit Court ruled that the use of race in admission was not permissible in the University of Texas system. With this ruling the University of Texas ended the explicit use of race in admission decisions, but one year later the Texas legislature implemented a plan guaranteeing admission to any public university in Texas to anyone graduating in the top 10% of their high school class. The goal of this plan was the same as that of the affirmative action plan in place before it. For analytic purposes the new plan should also be treated as affirmative action. The question then becomes: How preferential is a preferential admission plan?

As the above example shows, part of the difficulty comes from the ambiguous definition of affirmative action. Ideally I would like to consider any difference in the probability of admission of observationaly equivalent individuals between races to be affirmative action. Summing the difference in probability of admission over all observations would then create an affirmative action score for each school. Figure 1 depicts this for a hypothetical school using only the SAT for admission decisions. Using this definition, affirmative action would be defined by the shaded area. Without a defi-

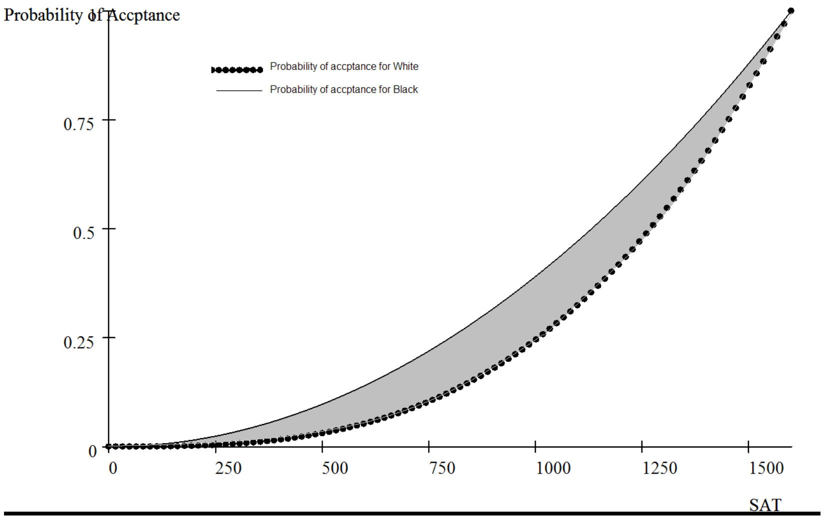

FIG. 1 Ideal measure of affirmative action. The shaded area represents the level of affirmative action at an institution.

nition such as this, it is difficult to move beyond case studies as different schools' admissions policies are not comparable.

Unfortunately, the B&B does not have information on applicants who were not accepted. Thus a working definition of affirmative action must be developed. I use the difference in the average admission exam percentile between blacks and whites for all of the students at a school except for the individual of observation. Schools at which the average black score is above the average white score have their affirmative action measure set to zero as it is unlikely that these schools engage in reverse affirmative action. These schools represent approximately 10% of the schools in the survey. Empirically, the results in the following section are not sensitive to this censoring. This measure is more crude than the ideal measure, but it does provide information about the level of preferential admission. Figure 2 gives the distribution of affirmative action for individuals without

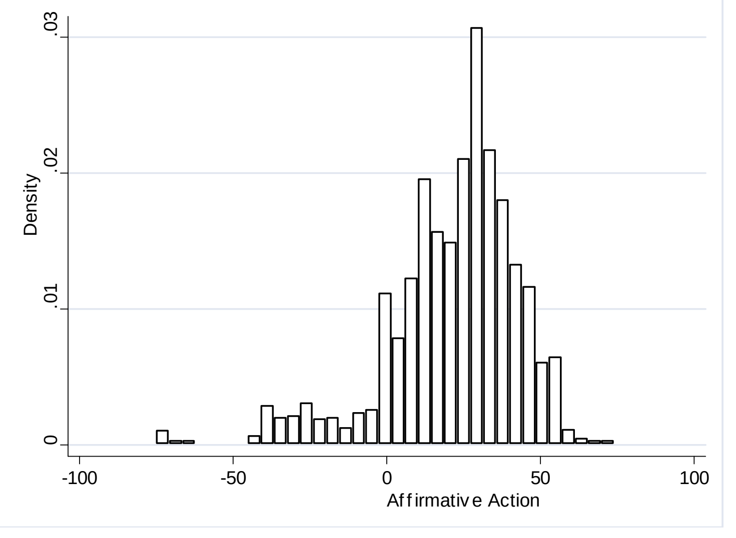

FIG. 2 The distribution of affirmative action. For the empirical work that follows, all negative values of affirmative action (approximately 10%) are set to zero.

censoring negative values to zero.

The B&B has several variables that control for, at least in part, school quality. One such variable is a control for the Carnegie classification of the institution as Research I, Research II, Masters/Bachelor's granting, or Liberal Arts. There is also a control for whether the university is public or private. To augment these, and to approximate the theory more closely, I also use a constructed measure of quality. The measure of quality I use is the average percentile on admissions exams for all students. Figure 3 gives the distribution of school quality. As with the affirmative action variable, this is constructed excluding the individual of observation. This is included to represent what employers expect the average ability level to be for the graduates of a school. It also ensures that the created affirmative action variable does not appear significant simply because it is correlated with

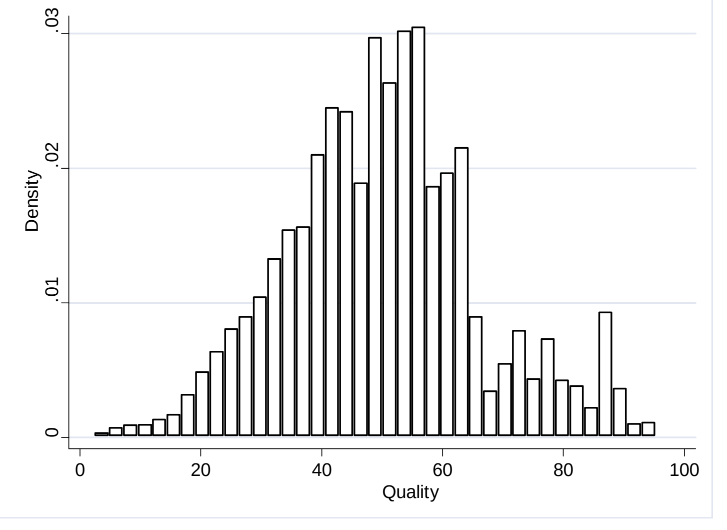

FIG. 3 The distribution of school qulity over individuals.

quality.

Figure 4 plots affirmative action against quality using these measures. From this figure it does not appear that quality and affirmative action are correlated. A regression of *aa* on *quality* using schools as the unit of observation gives a coefficient of 0.09 with a standard error of 0.07.

Tables 1 and 2 give the means and standard deviations of some variable of interest by observation and by school respectively. Note that in Table 1 the average school quality is similar for black and white students but the average entrance exam score is significantly lower for black students, as is GPA. The level of affirmative action roughly the same for black and white students.

I am only able to construct a measure of affirmative action for 216 of the 649 schools in the B&B. To measure *aa* I must observe at least 3 observations from a school, one of which must be black and one of which

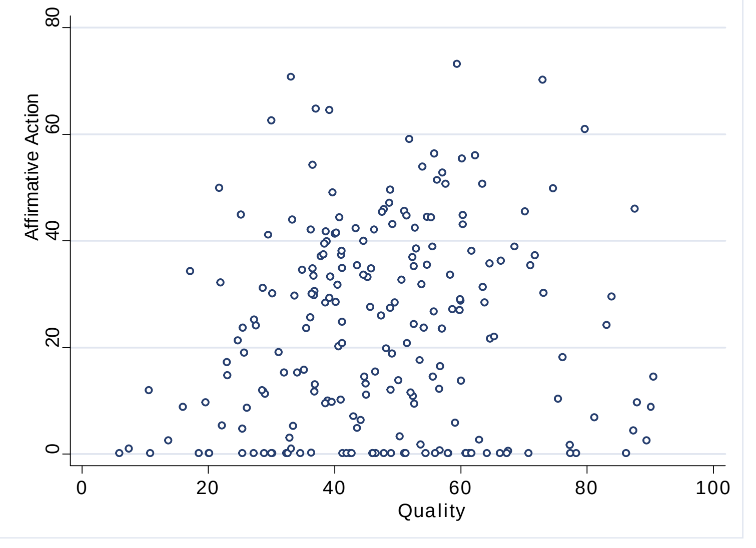

FIG. 4 Quality ploted against affirmative action

must be white. Table 2 compares schools with at least one individual in the final sample to all of the schools in the B&B. It shows that the schools in the final sample tend to be slightly larger than the average school. For this reason I am slightly more likely to include public schools. Except for these variables, the schools included in my final sample resemble the schools of the full sample.

Note that the theory from section 2 refers to college admission, while in the data I only observe students graduating. This should not pose a problem as I am in essence looking at effective affirmative action. I am concerned with the individuals who have a diploma and what that diploma says about their ability. If a school admitted black students with a lower test score, but then failed out anyone below a certain ability level regardless of race, this school would not considered to have an affirmative action program. The graduates of the school would all have the same expected

TABLE 1
Mean value of given variables by observation. Standard deviations are given in parenthesis.

		Full	Sample White	Black
	1993 Hourly Wage	10.30 (6.39)	10.21 (5.74)	11.36 (11.57)
	1994 Hourly Wage	10.44 (5.86)	10.40 (5.48)	10.99 (9.21)
	1997 Hourly Wage	15.20 (10.15)	15.23 (9.98)	14.87 (12.10)
	2003 Hourly Wage	26.63 (20.83)	26.87 (21.31)	23.67 (13.07)
	GPA	2.98 (0.49)	3.0 (0.48)	2.67 (0.43)
	Entrance Exam Percentile	49.4 (27.8)	50.1 (27.3)	31.9 (27.2)
	Black	8.1% –	0 –	100% –
	Male	44.4% –	45% –	35% –
	Age Entered College	18.1 (1.5)	18.1 (1.5)	17.9 (1.5)
School Variables	% Black	7.8 (8.0)	7.4 (6.1)	13.1 (18.5)
	Affirmative Action	23.9 (15.2)	24.1 (15.3)	21.5 (14.8)
	Quality	50.1 (14.2)	50.2 (13.9)	49.4 (17.9)
	N	1813	1667	146

TABLE 2
Mean value of given variables by school. Schools in the included sample have at least one observation included in the empirical work that follows. The number of valid observations represents the number of schools with at least one individual observation of the given variable.

	Sample		# Valid
	Included	Full	In Full Sample
Individual Observations	25 (18.4)	17.2 (15.6)	649
White Observations	20.4 (16.2)	14.4 (13.9)	649
Black Observations	2.3 (2)	1.2 (2.2)	649
Avg. Percentile	47.5 (17.2)	46.7 (17.9)	621
Avg. White Percentile	51.2 (18.1)	49.5 (17.9)	585
Avg. Black Percentile	31.8 (25.7)	31.5 (25)	242
Avg. GPA	3.1 (0.2)	3.1 (0.3)	648
Avg White GPA	3.1 (0.2)	3.1 (0.3)	618
Avg. Black GPA	2.7 (.4)	2.8 (.4)	305
% Black	12.3 (17.7)	10.1 (17.7)	642
% White	74.6 (20)	75.6 (17.7)	642
Public	%60 –	%50 –	648
Enrolment	11,413 (10,280)	8,331 (9,920)	641
Affirmative Action	23.1 (18.7)	23.1 (18.7)	216
N	216	649	

ability. An affirmative action program that does not change the composition of a school's graduates should not be considered affirmative action in relation to the model presented in section two. Studying the effectiveness of admissions policies at changing the makeup of graduates is interesting and useful to policy makers, but it has no bearing on the question addressed by this paper.

5. EVIDENCE

To determine the effects of preferential admission on wages, I first regress the natural log of hourly wage on demographic and school level variables.

$$\ln(hourly\ wage_{it}) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2it} + e_{it} \tag{4}$$

Equation (4) gives the empirical specification used, where X_1 represents the school level variables, X_2 represents individual level variables, and e is the error term. The equation is estimated separately for 1994, 1997, and 2003[11], as denoted by the subscript t. The variables included in X_1 are *aa*, *quality*, the percentage of the student population that is black (*%_black*), an indicator for whether the school is public, and a set of indicators of the Carnegie classification of the school[12]. The percentage of the student population that is black, *aa*, and *quality* are also interacted with an indicator *black* assigned to black students.

The vector of individual variables X_2 contains *black*, an indicator for

[11] Data were collected between June and December of each survey year. The 1993 and 2003 surveys asked about the individual's current job wile the 1994 and 1997 surveys asked about the primary job held in April of that year. Thus the years given in Table 3 refer to approximately 4 months, 1 year, 4 years, and 10 years after graduation.

[12] The Carnegie classification used breaks schools into four categories, Research I, Research II, BA/MA Granting, and Liberal Arts.

gender (*male*) , GPA, entrance exam percentile (*percentile*), tenure and its square, post college work experience and its square, age and its square, and an indicator for whether the student was a resident of the school's state. Also included were sets of indicator variables to control for college major, any previous degrees, any subsequent degrees, and region[13]. Interactions of *black* with *percentile*, GPA, *tenure* and its square,and *experience* and its square were also included.

The B&B collected data in 1993 as well as 1994, 1997, and 2003, but I do not use the 1993 data. Instead, I use the 1994 data as the first labor-market observation. There are two primary reasons for this. First, because of the collection procedure, the length of time between graduation and the 1993 observation is more variable than that of 1994. Each surveys was collected between June and December of the given year. While the 1994 survey refers to the job held in April[14], the 1993 data refer to the job held at the time of the interview. Thus, in the 1993 survey some individuals had been out of college for up to one year and four months, while others had only been out of school for one month. Because the 1994 survey refers to the April job, all individuals had been out of college for between one year and one year and 8 months. The second advantage provided by the 1994 observation is that by the time people have been out of college for one year, they have typically moved into the job that will become their career. In the empirical work that follows, I restrict the sample to individual not

[13]Four indicators were used to control for both previous and subsequent degrees, one each for another bachelor's degree, a masters degree, a Ph.D., and professional degrees. Six indicators were used to control for college major and five were used for region. One of each was of course omitted from all regressions.

[14]The 1997 survey also refers to the job held in April. The 2003 survey refers to the job held at the time of the interview just as the 1993 survey. I continue to use the 2003 data because it should not suffer from the problems associated with the 1993 data. As the graduates have been out of school for approximately ten years, it is unlikely that the difference in the length of time since graduation will have an effect on the results.

working in a job they held during college. I do this because I am interested in the labor market for college graduates, and such individuals are likely not in that market[15]. Even after limiting the data in this manner, it is likely that in the 1993 data some individuals are working full time in new jobs but still looking for a job in the field they prefer[16]. By April of 1994 all of the graduates have had at least one year to move into a job that will likely become their career. For these reasons I treat the 1994 observation as the initial labor market observation.

Table 3 gives the results of estimating equation (4) using ordinary least squares. Asterisks indicate significance with "*", "**", and "***" indicating that we can reject the hypothesis that the coefficient is zero at a 10%, 5%, and 1% significance level respectively. The sample for each year is restricted to those individuals working at least thirty-five hours each week. As mentioned in the preceding paragraph, I also restrict the sample to individuals not working at a job they held during college. I am able to do this because the B&B records the start date of all jobs on which it reports. This primarily affects the data from the 1993 survey, but a small subset of this group were still in their pre-degree jobs in April of 1994. Virtually all individuals changed jobs before April 1997.

Individual wages in 1994 provide the most insight into the questions addressed by this paper. By the time the individual has been out of college for 4 years, the market has provided a great deal of information about

[15] There are two likely reasons we observe individuals not leaving a full time job they held during college. First, some students may continue working full time at jobs they used to pay for college while they search for jobs that require their degree. Second, there may be some students who have a developed career and go to college because it enhances their career. There will likely be little signaling value to a college degree when the graduates already have an established relationship with their employer.

[16] An example of this would be a graduate with a degree in engineering who does not have a job offer upon graduation and so takes a job waiting tables while continuing to search for a job in engineering.

TABLE 3
Ordinary Least Squares regression results of the natural log of hourly wages for the given year on the X1 and X2. Standard errors are reported in parenthesis. Included variables that are not reported are: tenure and its square as well as their interaction with the black indicator, experience and its square as well as their interaction with the black indicator, age and its square, a set on indicator variables for previous degrees (5), a set of indicator variables of subsequent degrees (5), an in-state indicator, a set of indicator variables for region (5), a public school indicator, a set of indicators for the school's Carnegie Classification (4), and a set of indicators for college major (6).

		1994	1997	2003
University Variables	*aa*	0.0008	0.0007	0.0012*
		(0.0006)	(0.0005)	(0.0006)
	quality	0.0024***	0.002**	0.0012
		(0.0009)	(0.0009)	(0.001)
	% black	0.0046***	0.0035**	−0.0005
		(0.0015)	(0.0014)	(0.0017)
Individual Variables	black	0.1784	0.3019	0.398
		(0.2377)	(0.2839)	(0.5732)
	male	0.0412**	0.0801***	0.1825***
		(0.018)	(0.0173)	(0.0196)
	GPA	0.0249	0.0647***	0.0316
		(0.0202)	(0.0187)	(0.022)
	percentile	0.0035	0.0002	0.0005
		(0.004)	(0.0004)	(0.0004)
Black Interactions	*aa*	−0.0064***	−0.0019	−0.0001
		(0.0024)	(0.0019)	(0.0023)
	quality	0.0051***	−0.0026	−0.0015
		(0.0025)	(0.0023)	(0.0026)
	% black	−0.0035	−0.0041**	0.0007
		(0.0023)	(0.0021)	(0.0026)
	GPA	0.0061	−0.0175	0.0541
		(0.0734)	(0.0642)	(0.0743)
	percentile	−0.0045***	0.0007	0.001
		(0.0016)	(0.0013)	(0.0017)
	N	1817	2108	2284
	R^2	0.19	0.19	0.23

true ability and the value of the signal sent by school level variables has diminished. This is supported by Table 3, which suggests that college level variables become less important over time, while individual level characteristics become more important. The coefficients on the college level variables and their interaction with the race indicator decrease in both magnitude and significance over time, while the opposite trend is seen in individual level characteristics such as GPA[17] and *male*. In what follows I focus on the 1994 results.

The variables of primary interest in Table 3 are *aa* and the interaction of *black* with *aa*. These measure the full effect of being in a school with a higher level of preferential admission on wages. For straightforward interpretation, Table 4 reports the marginal effects of school quality and affirmative action on the wages of white and black students separately. The effect of affirmative action on white wages is only marginally significant in 2003, and even in this year the magnitude is small. For black graduates, the effect is relatively large and significant in 1994 but disappears by 1997. To get a feeling for the size of the impact on wage, note that the average value of *aa* is 24. Thus, the marginal effect of affirmative action on black graduates of -0.0056 in 1994 indicates that one year out of college there is an approximate 13% wage differential between black individuals from schools with no affirmative action and black individuals from schools with the average level of affirmative action[18].

The coefficient on *quality* in 1994 is 0.0024, with black graduates realiz-

[17] The fact that college GPA becomes more important over time might indicate that grades not only signal ability but also of effort. It does not seem likely that the return to grades increases over time. It seems more likely that GPA is picking up people who work hard in college, and then continue to work hard in the labor force.

[18] The marginal effect of -0.0056 is robust to changes the variables included in X_1 and X_2. It remains significant and fluctuates between -0.005 and -0.007 depending on the other variable in the regression. It is even robust to the exclusion of the sets of indicators for industry, occupation, and major.

TABLE 4
Estimated marginal effects of affirmative action and school quality on the natural log of hourly wages for white and black graduates.

		1994	1997	2003
White Students	*aa*	0.0008	0.0007	0.0012*
		(0.0006)	(0.0005)	(0.0006)
	quality	0.0024***	0.002**	0.0012
		(0.0009)	(0.0009)	(0.001)
Black Students	*aa*	−0.0056**	−0.0012	0.0011
		(0.0023)	(0.0018)	(0.0022)
	quality	0.0074***	−0.0006	−0.0003
		(0.0024)	(0.0023)	(0.0025)

ing an extra return of 0.0051. The total return to school quality realized by blacks is 0.0074. Quality is measured as average entrance exam percentile at the university, giving it the same units of measurement as *aa*. For black students, the loss in wages due to a 1 point increase in affirmative action is approximately 75% of the gain in wages due to a one point increase in quality. This finding lends strong support to the model. It indicates that black wages depend primarily on the average ability level of the black population at a given school, with the school's overall average ability playing only a minor role[19]. For example, say there are two schools. School A has no preferential admission and the average entrance exam percentile of 50 for both black and white students. School B admits white students such that their average entrance exam percentile is 69, but preferentially admits blacks such that the average for black students is 44 ($aa = 25$). According to these findings, the black students at both schools should receive the same

[19] This relationship only strictly holds if the black population is small enough that it does not change the overall average entrance exam score for the school. This may not be true in the sample due to the construction of *aa*. If the black population is large enough that it has a significant impact on *quality*, then the loss due to affirmative action will actually be larger than 75% of the gain to quality. To see his note that if the average black entrance exam percentile drops, not only will *aa* increase, but *quality* will decrease.

wage offer conditional on their other characteristics. The black students at school B receive a small benefit from going to a school that is more selective for white students, but they are not treated by employers as having come from the same population as the white students.

It should be noted that the although affirmative action offsets most of the returns to school quality for black students one year out of college, the relationship does not hold at later dates. As expected, the wage penalty for black students going to schools with higher levels of affirmative action disappears as the market acquires more information as to their true ability. In 1997, when the graduates have been out of school for four years, the marginal effect of affirmative action on the wages of black graduates is -0.0012 with a standard error of 0.0018. By 2003 the coefficient is actually positive but with a large standard error. A similar relationship holds for the extra return to quality received by black graduates above white graduates. The return to quality observed by white students is significant in 1994 and decreases slightly but remains significant in 1997. In 2003 the point estimate of return to school quality for white students has dropped to about one half or its initial value and is no longer significant. In 1994 the estimated return to school quality for black students is significantly higher than it is for white students, but by 1997 this return is virtually zero. Thus, by 1997 black students no longer realize a wage differential for affirmative action, but they no longer realize positive returns to school quality either.

Also of interest from Table 3 is the coefficient on the percentage of a school population that is black. It is apparent from the actions of universities that diversity of student population is a goal. This view presumably stems from the fact that students are viewed as an input as well as an output in education, and that minorities provide positive externalities in education (Holzer and Neumark, 2000). The coefficient of 0.0046 on *% black* indicates a positive correlation between wages of white graduates and the relative size of black student population as compared to the white student populations. The marginal effect of the size of the black student population on the wages of black graduates is virtually zero. Whether this relationship is due to a causal link or merely a correlation is beyond the scope of this paper, but the finding is consistent with the hypothesis that there are sailplaners associated with increasing diversity. Affirmative action may benefit a school's graduates (and society) as a whole, even if it provides no direct benefit to black graduates.

5.1. Small Schools and Measurement Error in Affirmative Action

I do not explicitly restrict the sample used in Table 3 based on number of observations from a school, but the construction of *aa* requires that all schools must have at least three observations, with a minimum of one black and one white observation. Affirmative action is measured by the difference in average entrance exam percentile and omits the individual of observation, so there must be at least one other black and one other white student observed from the school. Although this measure gives information as to the true level of affirmative action, it is inherently noisy. This is especially true for smaller schools with fewer observations. Table 5 reports the results or a regression of the natural log on 1994 wages on X_1 and X_2 with each column progressively eliminating schools with smaller observed samples. The first column is identical to the 1994 results from Table 3 as this is the implicit restriction created by the construction of *aa*. The second, third, and fourth columns respectively limit the sample to individuals from schools with at least six, ten, or fourteen observations. Each column gives a progressively more accurate measure of affirmative action, but this comes at the cost of eliminating individuals from smaller schools.

Most of the estimated coefficients reported in Table 5 remain fairly consistent as the sample becomes more restrictive. This is especially true for the coefficient on *aa*, the variable measuring affirmative action. The estimated marginal effects of *aa* on black graduates is exactly the same when school sample size is restricted to 6 as when it is not explicitly restricts. It moves around a small amount in the more restrictive samples but remains significant and within the standard errors of the less restrictive estimates. The estimated effects of school quality are slightly less consistent. The marginal effect are almost identical for both black and white students in the two least restrictive samples, but change in the more restrictive samples.

5.2. Empirical Specification

The results reported in Table 3 are given while controlling for an individual's occupation and industry. Because occupation and industry are outcomes that depend on education and might be related to race as well as affirmative action, it is important to examine the results without these controls. Other included variable might have similar problems. In my data, experience is created from spells of unemployment. If affirmative action makes it harder for black graduates to find jobs then the inclusion of experience will create results that understate the effects of affirmative action. Finally, according to the "fit" hypothesis, black students who attend more selective schools because of affirmative action may choose less lucrative majors. Table 6 reports the results of a regression of the natural log of 1994 hourly wages on X_1 and X_2 progressively omitting the variables of concern.

TABLE 5
Ordinary Least Squares regression results of the natural log of hourly wages for 1994 on the X1 and X2. Standard errors are reported in parenthesis. The columns are restricted to schools with the given number of black and white observations. Included variables that are not reported are: tenure and its square as well as their interaction with the black indicator, experience and its square as well as their interaction with the black indicator, age and its square, a set on indicator variables for previous degrees (5), a set of indicator variables of subsequent degrees (5), an in-state indicator, a set of indicator variables for region (5), a public school indicator, a set of indicators for the school's Carnegie Classification (4), and a set of indicators for college major (6).

		Dependant Variable: Natural log of 1994 hourly wage			
School Observation Restriction		# black $\geq$ 1 # white $\geq$ 1	# black $\geq$ 3 # white $\geq$ 3	# black $\geq$ 5 # white $\geq$ 5	# black $\geq$ 7 # white $\geq$ 7
University Variables	*aa*	0.0008	0.0007	0.0009	0.0016*
		(0.0006)	(0.0007)	(0.0008)	(0.0009)
	quality	0.0024***	0.0025***	0.0008	0.0028*
		(0.0009)	(0.001)	(0.0013)	(0.0017)
	% black	0.0046***	0.0045***	0.005**	0.0088**
		(0.0015)	(0.0018)	(0.0027)	(0.0039)
Individual Variables	black	0.1784	0.0066	0.131	0.0905
		(0.2377)	(0.2691)	(0.3522)	(0.4883)
	male	0.0412**	0.0433**	0.0233	0.0202
		(0.018)	(0.0198)	(0.0231)	(0.0265)
	GPA	0.0249	0.0242	0.0186	−0.0083
		(0.0202)	(0.0221)	(0.0255)	(0.0296)
	percentile	0.0004	0.0006	0.0006	0.0012**
		(0.004)	(0.0004)	(0.0005)	(0.0005)
Black Interactions	*aa*	−0.0064***	−0.0063**	−0.0053*	−0.0082**
		(0.0024)	(0.0026)	(0.0031)	(0.0042)
	quality	0.0051***	0.0056**	0.0049	0.0101**
		(0.0025)	(0.0027)	(0.0035)	(0.0049)
	% black	−0.0035	−0.0037	−0.005	−0.0008
		(0.0023)	(0.0025)	(0.0032)	(0.0145)
	GPA	0.0061	0.0589	0.0225	−0.0216
		(0.0734)	(0.0854)	(0.1034)	(0.1254)
	percentile	−0.0045***	−0.0047***	−0.0042**	−0.0062***
		(0.0016)	(0.0018)	(0.002)	(0.0023)
	N	1817	1554	1143	756
	R^2	0.19	0.17	0.19	0.26

TABLE 6

Ordinary Least Squares regression results of the natural log of hourly wages in 1994 on the given variables as well as those listed below. Inclusion of industry, occupation, experience and major is denoted by an X. There are 15 industry categories, 12 occupation categories, 6 major categories, and experience is included along with its square as well as their interaction with the black indicator. Included variables that are not reported are: tenure and its square as well as their interaction with the black indicator, age and its square, a set on indicator variables for previous degrees (5), a set of indicator variables of subsequent degrees (5), an in-state indicator, a set of indicator variables for region (5), a public school indicator, and a set of indicators for the school's Carnegie Classification (4).

		I	II	III	IV
University Variables	*aa*	0.0001	0.0008	0.0008	0.0006
		(0.0005)	(0.0006)	(0.0006)	(0.0006)
	quality	0.0017**	0.0024***	0.0024***	0.0026***
		(0.0009)	(0.0009)	(0.0009)	(0.001)
	% black	0.0043***	0.0047***	0.0046***	0.006***
		(0.0014)	(0.0015)	(0.0015)	(0.0016)
Individual Variables	black	0.2737	0.207	0.0417	0.1435
		(0.2282)	(0.2318)	(0.2258)	(0.2371)
	male	0.031*	0.041**	0.0431**	0.0688***
		(0.0177)	(0.018)	(0.018)	(0.0184)
	GPA	0.0227	0.0247	0.0232	0.0122
		(0.0196)	(0.0202)	(0.0201)	(0.0208)
	percentile	0.0002	0.0035	0.0003	0.0008**
		(0.0004)	(0.004)	(0.0004)	(0.0004)
Black Interactions	*aa*	−0.0061***	−0.0064***	−0.0064***	−0.0072***
		(0.0023)	(0.0024)	(0.023)	(0.0025)
	quality	0.0045**	0.005***	0.0052***	0.0054**
		(0.0024)	(0.0025)	(0.0025)	(0.0026)
	% black	−0.003	−0.0035	−0.0034	−0.0039*
		(0.0022)	(0.0022)	(0.0023)	(0.0024)
	GPA	−0.0342	0.0056	0.0308	0.0098
		(0.0704)	(0.0733)	(0.0718)	(0.0755)
	percentile	−0.0041***	−0.0045***	−0.0043***	−0.0048***
		(0.0016)	(0.0016)	(0.0016)	(0.0017)
Controlling for:	ind. occup.	X			
	Experience	X	X		
	Major	X	X	X	
	N	1813	1817	1817	1817
	R^2	0.27	0.18	0.16	0.07

The first column of Table 6 estimates equation (4) while also including controls for industry and occupation[20].The second column of Table 6 reports results identical to the 1994 result of Table 3, while column III omits industry, occupation and experience. In general, the measured coefficient on the interaction of the black indicator and affirmative action is fairly robust to the specification of the model. The significant coefficients in columns I and III are virtually identical to those in column II. These results indicate that affirmative action does not push students, black or white, into less lucrative industries or occupations.

The inclusion of industry and occupation does slightly decrease the return to school quality for both black and white graduates, indicating that students from more selective schools enter into more lucrative industries and occupations. Under this specification, there is a one to one trade off between affirmative action and school quality for black students, indicating that their wages depend entirely on the average ability level of other black students regardless of the ability level of white students at their school. The difference between the estimated return to quality in column I and column II indicates that one benefit black graduates gain from going to higher quality schools is the ability to enter into higher paying industries and occupations. The results also suggest that this benefit may account for the 25% of returns to school quality that are not offset by affirmative action. In other words, if a black student is able to "buy" one point of school quality at the price of one point of affirmative action, the affirmative action may completely offset the direct wage gains to school quality, but the student at the higher quality school retains the ability to take a job in a more lucrative industry or occupation. This result makes sense if the quality of employers

[20]Fifteen categories were used to control for industry and twelve categories were used to control for occupation.

a graduate is exposed to is correlated with school quality, but employers fully discount for affirmative action.

As shown in column IV of Table 6, the absence of controls for college major does increase size of the marginal effect of affirmative action on black wages form -0.0056 to -0.0062. This lends some support to the hypothesis that black students admitted under affirmative action may struggle in school. These results indicate that under affirmative action, black students may choose less lucrative majors. I proceed maintaining the specification from column II, but it is important to note that affirmative action may have detrimental effects on the choice of major for black students.

5.3. Endogenous Affirmative Action

It might be believed that aa is correlated with wage for non-causal reasons. For instance, it could be that students who receive a poor realization on their entrance exam are more likely to take advantage of affirmative action programs in an attempt to better "match" themselves. If this occurs, then OLS estimates will underestimate the effects of affirmative action. A similar result holds if schools have better measures of ability than entrance exams. Alternatively, students receiving a high realization of entrance exam scores might be more likely to take advantage of affirmative action, in which case OLS will overestimate the effects of affirmative action. For these reasons, one might expect the OLS estimates to biased, but it is not clear in which direction. To account for possible bias, I next estimate equation 4 after instrumenting affirmative action[21]. The results are reported in Table 7.

To obtain the results of Table 7 I instrument aa and the interaction

[21] This procedure will also solve some of the problems associated with the measurement error associated with affirmative action.

TABLE 7
Instrumental Variables regression results of the natural log of hourly wages on the X1 and X2. Standard errors are reported in parenthesis.

	1994	1997	2003
aa	−0.0028	−0.0182	−0.0127
	(0.0043)	(0.0061)	(0.0081)
black**aa*	−0.0057	−0.0016	−0.1159
	(0.0133)	(0.0237)	(0.1283)
N	1817	2108	2284

of *black* and *aa* using the percentage of the school's state that voted Democratic in the 1992 presidential election[22] ($\%dem$) and the interaction of *black* and $\%dem$. There is no reason to believe that a state's political makeup should influence wages after controlling for region. On the other hand, it is highly likely that the political persuasion of the state should influence admission polices within the state. In fact, a regression of *aa* on $\%dem$, $black * \%dem$, X_1, and X_2 places a highly significant coefficient on $\%dem$. The coefficient fluctuates between -0.4 and -0.47 depending on the year, with a standard error never above 0.084. Similar results hold for the interaction of *black* and $\%dem$.

As is common with IV estimates, the standard errors in Table 7 are much larger than those of the OLS estimates. Although the large standard errors make inference difficult, the point estimates for the coefficients on *aa* have all become negative. The point estimates of the interaction coefficient for 1994 and 1997 have changed little. Because the coefficient on *aa* in these years has grown, the marginal effects has become more negative for black graduates. These results suggest that if *aa* is endogenous, the OLS

[22] The use of alternative instruments such as the percentage of the state voting Democratic in the 1988 presidential election, the number of Democratic senators representing a state in 1992, and whether the individual attended a private high school provide similar results.

estimates likely underestimate the true effect of affirmative action on wages for both black and white graduates.

Although there may be some concern that aa is endogenous, the lack of a clear reason for believing a specific direction of bias may ease this concern. Indeed, testing for endogenaity[23] of aa using the Durbin-Wu-Hausman test produces a test statistic of 0.91. Comparing this to the critical value taken from a $\chi^2(2)$ distribution, I cannot reject the null hypothesis that aa is exogenous.

6. CONCLUSION

Much economic research has been done on the effects of preferential college admission on educational outcomes. This is important, but economists are often concerned with educational outcomes because of their strong correlation with labor market outcomes. To my knowledge this is the first attempt to directly link college affirmative action policies to the wages of college graduates. College not only serves as an institution for producing human capital, but also as a signal to employers about true ability. Rational employers will take into account the distribution of ability in a given population based on easily observable characteristics such as race. The introduction of affirmative action plans will change this distribution of ability for selected groups.

This paper develops a model that examines the effects of preferential college admission on the wages of college graduates, and then applies the model to data collected by the B&B survey of 1993. I show that affirmative action can potentially hurt minority graduates in two ways. First, it

[23] The second instrument used for this test was the percentage of the school's state voting independent in the 1992 presidential election. Recall that Ross Perot ran in 1992 and captured a significance portion of the popular vote.

decreases employers expectations about the ability of graduates of a particular university, causing them to make lower wage offers. Second, affirmative action decreases the signaling value of school quality.

Using data from the B&B, I find evidence to support the theory. My results indicate that the initial expected wage of black graduates from a school with the average level of affirmative action will be approximately 13% lower than those of a black graduate from a school of similar quality with no affirmative action. This wage differential disappears as time passes. There is no significant change in wages for white graduates.

Although I find evidence that affirmative action lowers wages of black college graduates, it is not clear that the policy will actually make them worse off. Affirmative action lowers beneficiaries' wages conditional on school quality, but under affirmative action they are able to go to higher quality schools. I find that the loss in wages faced by black students due to increasing affirmative action offsets approximately 75% of the return to increasing quality. These results suggest that the wages of black graduates depend on the average ability level of other black graduates from the same school, with the distribution of ability in the white population of graduates having little effect.

In this paper I treat affirmative action policies as though they differ only in size, but in reality they may differ in other substantive ways. Preferential admission is instituted through many different types of policies, each of which will have different effects on the student population. Race neutral policies such as the "percent plans" instituted by Texas, California and Florida may actually cause more problems than the explicit affirmative action plans they are meant to replace. Under these plans the variance in true ability might actually increase for both black and white students.

They might also lead to lower expected ability for both groups of students. Some researchers such as Fryer, Loury, and Yuret (2003) have begun to look at the implications of these plans but further research is needed into the effects of policy structure on labor market outcomes.

The implications of the model I develop extend beyond its direct application to preferential college admission. For example, the practice of "race norming" used the United States Employment Service (USES) in the 1970s likely created similar results. The USES used an aptitude test to refer the best applicants to jobs. Because blacks scored lower on the aptitude test, the USES normed the results by race (Jencks, 1998). Given their knowledge of this practice, it is likely that employers held lower expectations of black referrals. In a situation such as this, the practice could result in lower wages for blacks, or alternatively, fewer black hires if the firms cannot pay differentially because of regulation or because they are only willing to offer the minimum wage.

The model also extends beyond the labor market. Similar results will arise anytime one institution or individual screens quality for a second. Take for instance a used car lot that sells two types of used cars, "certified" used cars that have been checked by a mechanic and used cars being sold with no such quality screening process[24]. The cars may initially come from the same population, and are sold on the same lot, yet the certified used cars will command a higher price because the initial screening process informs the consumer that the cars are less likely to break down or require repair.

[24]For this example I am assuming that cars that fail the screening are not sold as unscreened cars.

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