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AFFIRMATIVE ACTION IN HIGHER EDUCATION: IMPACTS OF THE NATIONAL EXAM IN BRAZIL

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ABSTRACT

This paper intends to contribute to the debate regarding the impact of quotas (social and racial) in the Brazilian higher education system, estimating their impacts on student grades as measured by a specific test – ENADE – or the National Survey of Student Performance. The implementation of quotas in higher education is an often-discussed policy in several countries which face inequality. The results obtained for Brazil may assist researchers from other regions. We use ENADE 2008 as the main source of data, which comprised 59 courses and surveyed more than 74,000 students. Within the theoretical discussion, we present Su's Job Reservation Model (2005) and Bishop's Effort Decision Model (2006); these models include factors such as degree, coursework selection, future wages, and quality of peers, as factors that affect the degree of effort and the human capital accumulation. We use a difference-in-differences (DD) method combined with the propensity score matching (PSM), where the main goal is to control unobservable characteristics that are related to the performance and some selection biases related to the treated group. The results demonstrate that the implementation of quotas negatively and significantly affected majors such as Pedagogy, History and Physics, and positively and significantly affected only Agronomy major.

Keywords: social and racial quotas, difference-in-differences estimator, propensity score matching

JEL Classification: I24, I25, I28

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1. INTRODUCTION

In recent years, educational issues have been of greater importance in economic analysis. Many papers suggest that education is essential for economic growth as well as an important tool to achieve better equality. These effects have been discussed and confirmed by several researchers, whose papers delineate evidence that education promotes growth, adoption of technologies, increased wages, and additional positive externalities (LANGE and TOPEL; ACEMOGLU and ANGRIST, 2000). As a result, education is primarily considered by governments as a social policy tool. Some of these social policy tools are associated with affirmative action, because their goal is to promote equality by affording better conditions to groups that are initially experiencing worse conditions.

The Brazilian case consists of the designation of some proportion of vacancies in university to blacks, native Indians and low-income people. We can number two main reasons commonly used in Brazil to justify affirmative action policy in higher education: a form of historical reparation for blacks, given that Brazil was the largest slave country in the world; and the small share of blacks, Indians and low-income individuals in higher education.

Even though this paper addresses the specific case of Brazil regarding quotas, it can be useful to support the analysis of studies which approach aims to implement or improve affirmative policies. A large number of countries face problems related to the inequality of opportunity linked to social and racial issues. The implementation of quotas in higher education is a frequently discussed policy in this context. The educational results obtained through the implementation of quotas might be important in analyzing the possibility and means of implementation of affirmative policies in the scope of higher education. Thus, this paper, which addresses the specific case of Brazil, might assist researchers from other countries.

This Brazilian policy began in 2003, when some universities made individual decisions to designate a certain share of their vacancies to these groups. Now this system of quotas is much more integrated, including public universities that are administered by the federal government, the states and municipalities.

There are substantially different views about quotas and their role in promoting equality. Some researchers advocate that the system of quotas offers a means for social improvement among the special groups that are benefitted. Thus it promotes a reduction of inequalities and fosters increases in the supply of opportunities to these people, which may be understood, for instance, as a historic reparation of blacks (BITTAR and ALMEIDA, 2006; MOEHLECKE, 2002; GUARNIERI and MELO SILVA, 2007). Other studies – which we may include in the pro-quota group – state that poor students and blacks who have been affected by this policy experienced success inside their institutions as well as in the job market. On the other hand, there are some who believe that political affirmative action is bad policy. Among the various reasons, two should be highlighted. First, the quota policy faces difficulties in reducing inequalities when the students who really need support do not have even the minimum requirements to be eligible for them. Second, those who are considered eligible for these policies may not be able to overcome the schooling gap between them and others who have passed by merit, which tends to create a qualitative loss of human capital at the universities that implement quotas (SOWELL, 2004; D'SOUZA, 1991).

This paper uses the database of the Exame Nacional de Desempenho de Estudantes (ENADE), or the National Survey of Student Performance, which is a national examination that strives to evaluate the performance of students upon graduation. The Ministry of Education is in charge of this test, which is the only source of information that provides national data about the learning process in each institution, comparing how students arrive at the University and how they leave in terms of knowledge acquired. Here, we used 2008 data, which included 74,000 observations related to 59 courses. This sample provides the grades of incoming and graduating students. It also provides a broad spectrum of socioeconomic data and characteristics of each faculty member that is reported by students, as well as students' impressions about the institution, the professors and the contributions of the courses taken.

To measure the impact of quotas on the average grade for each course, the first methodology to be used will be the difference-in-differences estimator (DD), which aims to overcome the problem of endogeneity when making comparisons between heterogeneous individuals. Thus, it is possible to separate the results into two basic time frames: beginning students and graduating students, and into two groups, control and treatment (benefitted by the quotas system). According to Buckley and Shang (2003), the model

avoids the problem of the influence of time invariant effects not being observable, in addition to being a flexible method which allows for the inclusion of covariates.

In order to cope with the hypothesis of selection by observable treatment characteristics – that there is an observable set of X that settle the probability of receiving the treatment – we will use the DD estimator combined with the propensity score matching (PSM) approach. This specifically aims to pair the students by the probability of receiving treatment, thus eliminating the selection bias problem and allowing for grade comparisons among them.

This paper is divided into seven sections. Following this introduction, the second section shows the reasons for affirmative action in Brazil, the third section presents in a very brief way the literature review on quotas, addressing Brazil's case as well as the situation worldwide. The next section demonstrates two models that aim to justify the chosen variables of the model estimations. The methodologies used are described in the fifth section. In the sixth section, the descriptive database and the results are presented. The last section briefly describes the main conclusions of this study.

2. REASONS FOR IMPLEMENTATION OF THE QUOTA SYSTEM

No doubt the Brazilian case is unique when we observe the reasons for the application of the quota system. According to the Brazilian Institute of Geography and Statistics (IBGE), Brazil is composed of 14 million blacks and browns over 82 million, making up respectively 7.61% and 43.13% of the population, while these groups accounted for 3.2% and 24% of the students in public universities in 2004.

In Brazil, the slave system persisted until 1888, making the country one of the last to abolish slavery in the Americas. Adding the substantial decrease of the Indian individuals since the colonial period, we have formed the historical reparation argument for affirmative policy.

After 1888 no institution, especially in education, adopted a form of segregation, and the relatively long use of the admission form in higher education known as “*vestibular*” - the blind higher education entrance examination – which implies that the low access occurs by the low level of training in earlier stages of education.

Another target group of vacancies reservation policy are poor students coming from the public school system. In this case, proponents of affirmative action argue that college entrance does not guarantee equality of opportunity, since students with best performances are coming from private schools and families with better income and education (BITTAR and ALMEIDA, 2006).

Table 1 provides the proportion of people by race in public higher education in Brazil.

Table 1 - Proportion by race in public higher education in Brazil

	2004		2005		2006		2007		2008	
Color	N	Proportion	N	Proportion	N	Proportion	N	Proportion	N	Proportion
White	23889	68.7%	46360	57.5%	34073	62.8%	23330	61.9%	63337	56.2%
Black	1119	3.2%	5323	6.6%	3198	5.9%	2156	5.7%	9384	8.3%
Brown	8493	24.4%	26437	32.8%	15221	28.1%	10962	29.1%	36555	32.4%
Yellow	950	2.7%	1451	1.8%	1057	1.9%	813	2.2%	2165	1.9%
Indian	338	1.0%	1029	1.3%	688	1.3%	428	1.1%	1354	1.2%
Total	34789		80600		54237		37689		112795	

Source: Original Compilation from ENADE's data

After the first institutions used the system of quotas in 2003 and 2004, the proportion of blacks, mulattos and Indians increased in the university. The table 2 below brings a comparison between the proportion in higher public education in 2008 with the proportion of the Brazilian Population Census of 2010.

Table 2 – Proportion by race in Population Census 2010 and in public higher education in Brazil

Color	Population Census 2010	Proportion of population (%)	Proportion in public higher education in 2008*
White	91,051,646	47.73	56.20%
Black	14,517,961	7.61	8.30%
Brown	82,277,333	43.13	32.40%
Yellow	2,084,288	1.09	1.90%
Indians	817,963	0.42	1.20%
Unidentified	6,608	0.003	
Total	190,755,799		

Source: Original Compilation from IBGE and ENADE's data

In 2008, after almost five years of the quota policy, blacks and Indians showed a significant increase in participation in higher education, with values above the population proportions. IBGE data shows that in 2010 the Brazilian population was composed of 7.61% black, 43.13% of mixed race and 12.42% of Indians. Therefore, except for the brown group, the other breeds have a higher proportion of the public higher education than in the population.

The proportion of the other beneficiaries of the quota policy, students coming from the public school system, are shown in Table 3.

Table 3 - Training of students coming from high school.

	2004	Proportion	2005	Proportion	2006	Proportion	2007	Proportion	2008
Entirely in public schools	11589	33,3%	45231	56,0%	25728	47,4%	14835	39,3%	66186
Entirely in private schools	17861	51,3%	24426	30,2%	21581	39,7%	18344	48,6%	34925
Mostly in public schools	2354	6,8%	5247	6,5%	3106	5,7%	1995	5,3%	5421
Mostly in private schools	2152	6,2%	3652	4,5%	2472	4,6%	1822	4,8%	4254
Half in public schools	873	2,5%	2193	2,7%	1432	2,6%	760	2,0%	2265
Total	34829		80749		54319		37756		113051

Source: Original Compilation from ENADE's data

According to table 3, the proportion of students graduated from high school only in public schools varied significantly over time - given that the test was applied in different courses each year - but still shows a more balanced ratio of students coming only from private schools and public schools.

Next, given the changes in the composition, we discuss about the performance of these new students in higher education.

3. THE QUESTIONABLE ROLE OF RACIAL AND SOCIAL QUOTAS

In Brazil's context and throughout the world, several studies present contradictory evidence regarding the effects of racial and social quotas within the educational context. This section will review some relevant literature, and in this process, we will highlight the gaps that still persist in this field when discussing the methodologies that have been employed.

3.1 THE IMPLEMENTATION OF QUOTAS IN BRAZIL

Regarding the national literature over quotas, we noticed that the great majority of the studies do not use empirical methods to assess the policies implemented. Instead, we found that many papers employ historical, philosophical and pedagogical methods to evaluate the implementation of quotas in Brazil. Among those works that include statistical treatment of the data, it is worth mentioning Durham (2005), which concludes that public initiatives which focus on primary and secondary educational levels are significantly effective than the quotas imposed in higher education.

Lordêlo (2004) studied the profiles of the students in Management at Federal University of Bahia (UFBA) and established relations between their performance and other variables, such as race, income and public or private high school origin. The results brought forward evidence that, for instance, high school origin was not significant. Nevertheless, race – negatively related – and income – positively related – were shown to be significant. The author also demonstrated that the presence of blacks and the poor in Business Administration degree represents a small share of enrolled students, and also their participation is larger in degrees that are characterized by low competition and low social status.

Maia, Pinheiro and Pinheiro (2009) analyzed the students of the University of Campinas (UNICAMP) with respect to the performance heterogeneity from admission to the end of graduation. This research had considered the incoming students from 1997 to 2000 in 45 different courses. They used a variable called “relative improvement,” which is the difference in placement of the students within their class, determined by the comparison between the grade achieved during the admissions process (vestibular) and the final grade reflecting academic performance. The results presented show that students from public schools achieved a relative improvement, which indicates that these students achieved greater progress when compared with students from private schools.

Da Costa and Paez (2010) studied those characteristics of candidates that are related to success in the admissions process. The methodology they used was a Bayesian logistics regression, considering as the dependent variable the success or the failure in the “vestibular.” Their evidence indicates that the attributes of race and public school origin decrease the chances of success in 90 percent without the system of quotas. Therefore, we can infer that the quota system decreases the difference in the probability of success among candidates from different situations.

3.2 THE INTERNATIONAL LITERATURE ON QUOTAS

Regarding the international literature, we highlight Bok and Bowen’s (1998) work, which analyzed the effect of the admissions process under the race criteria between the 1970s and the early 1990s. Their database has more than 80,000 students in 28 colleges and universities. The results of this work demonstrated that the more recognized institutions had more success in graduating students from minority groups. The analysis was extended to the labor market, showing that the same students also secured good jobs.

Carnevale and Strohl (2010) found evidence that ‘highly disadvantaged students’ (low income, blacks, students whose parents have a low educational level, and students from public schools, among other factors) scored, on average, 748 points less on the Scholastic Aptitude Test (SAT)⁴ than ‘highly favored students’ (rich, white, students whose parents have a high level of formal education, and students from private schools, among other factors). They also estimate that from these 748 points, 56 points are attributed to skin color, while 399 points represent the economic difference between the individuals; the remaining points are attributable to other factors.

Holzer and Neumark (2000) is one of studies that used econometrics to study the affirmative action policies, analyzed the relationship between quotas and the labor market, reviewing the externalities, information and imperfections. The main conclusions were: there is still discrimination against minorities in the labor market, even though no significant relationship between the condition of a beneficiary of an affirmative action and negative performance in the labor market could be detected.

⁴The SAT (*Scholastic Aptitude Test* or *Scholastic Assessment Test*) is a standardized educational exam in the United States applied to students in grades 10, 11, and 12 that serves as a criterion for admission into U.S. universities.

Bertrand, Hanna and Mullainthan (2008) studied affirmative action policies in India, examining their effectiveness and costs within the engineering colleges. In the Indian case, the beneficiaries are the groups known as belonging to “low castes.” The authors found much evidence that the affirmative action policies in India have positive returns: among them, the redistribution character, the higher returns to “low caste” members, and low rejection rates from the “upper castes.”

Jencks and Phillips (1998) discussed the results of Intelligence and Knowledge Tests that showed that there is a difference between the results of whites compared to blacks. Although the difference has fallen during the twentieth century, it is still present, even in similar families where the only difference is the race. The evidence shows that this gap is significantly reduced when people of different races are together at the same school. For instance, black children learn better when they are in schools with greater diversity, not in predominantly black institutions. The same is true for the composition of teachers at school. That is, results are better in schools with greater racial diversity than in institutions where blacks are the predominant teachers.

4. ECONOMIC MODELS ON EDUCATION

In this section the discussion is if there is an educational loss derived from affirmative action policies, and, more specifically, from the implementation of quotas. The hypothesis is as follows: considering that the worst students – before the implementation of quotas – were replaced with students affected by quotas, this substitution caused an increase in the difference between the best and the worst students. In other words, the affirmative action policy had a negative impact.

In order to discuss the effects of quotas, we will present the allocation model of Su (2005) and, following this, the effort decision model of Bishop (2006).

4.1 THE MODEL OF VACANCIES RESERVE AT THE UNIVERSITY

Su (2005) developed several models pertaining to different forms for admission in higher education. One of these models is about the manner of reserving places for admission at the university. In general, the quotas are designated to people considered disadvantaged. In this specific case, blacks and low-income students usually fall into this category. Su’s model provides a solid starting point to assess the efficiency of a quota policy, because it considers as endogenous variables the following: the competition for a vacancy in higher education, the human capital of the student before entering the university, the restriction of vacancies at the university, and the consequences of human capital inequality.

Regarding the restriction of places in higher education, knowing that the opportunity to enter higher education is Σ , Su estimates that only a fraction of the population can get a job in higher education. This will be the constraint condition:

$$0 < \Sigma < 1 \quad (1)$$

In Su’s model, there are two groups: blacks and whites. There is no fundamental difference between the groups. However, due to historical factors, the black group did not develop the same opportunities that the white group did. As a result, the black group has less human capital accumulated than the white group, represented as:

$$H_{-1}^B < H_{-1}^W, \quad (2)$$

Where the superscript denotes the groups, and the subscript -1 denotes the previous generation, the population size is normalized to 1, and the size of each group is λ , for blacks, and $1-\lambda$, for whites.

The opportunities for each group are defined as Σ^N for blacks and Σ^B for whites. Under a system without quotas, the opportunities for the disadvantaged group would be zero, then, $\Sigma^N=0$. Additionally, all of the opportunities would be for the white group: $\Sigma^B = \Sigma / 1 - \lambda$.

However, under a system of quotas and satisfying the constraint, the opportunities would be:

$$\Sigma^N > 0 \quad (3)$$

$$\Sigma^B = \frac{\Sigma - \lambda \Sigma^B}{1 - \lambda} \quad (4)$$

The first proposition of Su's work is that with the rise in opportunities for blacks, this would lead to an increase of effort and in the accumulation of human capital within this group. The rise in the probability of entering into the realm of higher education triggers an increase in competition for these places, which leads to greater engagement of students in fundamental and in high school, which in the end it would raise the performance of the black group in the tests for admission.

We can highlight that the cutoff score for admission in higher education without the quota policy is given by:

$$\hat{s} = H^{B,1} + \hat{\varepsilon} = H^{B,1} + G^{-1}\left(1 - \frac{\Sigma}{1 - \lambda}\right) \quad (5)$$

$H^{B,1}$ is the stock of capital accumulated by the white individual during fundamental and high school. At equilibrium the effect of $H^{B,1}$ is null, and $\hat{\varepsilon}$ is an exogenous, random variable and is equally distributed. The effect of the policy will depend on the level of intragroup competition, what can be measured by the probability density of the cutoff grade $g(\hat{\varepsilon})$.

When the implementation of a policy of quotas decreases the level of competition within the white group, that is, $g(G^{-1}(1 - \frac{\Sigma - \lambda \Sigma^B}{1 - \lambda})) < g(G^{-1}(1 - \frac{\Sigma}{1 - \lambda}))$, this would lead to a decrease of effort and a reduction in the stock of human capital for all inside the white group.

The most notable contribution of Su (2005) is that it allows us to understand the role of intragroup competition in determining the impact of quotas on human capital stock.

Considering that $g(\varepsilon)$ is a function, the following equations are true:

$$g'(\varepsilon) > 0, \quad (6)$$

$$g''(\varepsilon) < 0, \quad (7)$$

There exists a value $\tilde{\varepsilon} \in [\underline{\varepsilon}, \overline{\varepsilon}]$, so that $g(\tilde{\varepsilon})$ is the greatest possible value, so, $g(\varepsilon)$ increases for $\varepsilon \in [\underline{\varepsilon}, \tilde{\varepsilon}]$ and decreases for $\varepsilon \in [\tilde{\varepsilon}, \overline{\varepsilon}]$.

If there is a significant shortage of vacancies in the higher education system, that is, $G^{-1}(1 - \frac{\Sigma}{1 - \lambda}) > \tilde{\varepsilon}$, then the introduction of affirmative action policies would excessively decrease the opportunities to the white group, leading to a situation of substantial evasion and low effort. In this case, Su's model shows that if there is a process of reduction in effort by the white group, it could be offset if the number of vacancies at the universities increases ($\uparrow \Sigma$).

Additionally, if the capacity of higher education is not so limited, that is, $G^{-1}(\Sigma - 1 / (1 - \lambda)) < \tilde{\varepsilon}$, the introduction of an affirmative action policy will add pressure to the competition by increasing the effort of the white group to maintain opportunities.

Synthesizing Su's results: on one hand, the rise in opportunities for blacks leads to an increase in their effort and, consequently, a rise in their human capital stock as a group. Nevertheless, on the other hand, a decrease in opportunities for whites can diminish the effort of this group, which leads to a decrease in their human capital stock.

4.2 THE MODEL OF STUDENT EFFORT

Knowing the role of education in productivity increases and, as a result, in future earnings, people are stimulated to pursue education and training. Thus, people search for good schools and universities.

Bishop (2006) aims to explain the role of incentives faced by students and their relation to student behavior and results.

The students' decisions relevant to effort at the institution where they study could be represented by three equations: Learning Function, Learning Earnings Function and the Effort Cost Function.

4.2.1 Learning Function

The stock of accumulated human capital, adapted to the end of graduation, can be represented as:

$$L = AE^{\alpha}(E^m)^{\rho}(IX^m)^{\beta} \quad (8)$$

Where $\alpha + \rho + \beta < 1$;

E is the individual effort of the student, an index of time and energy that the individual i spent to learn;

E^m is the medium effort of all students at the m university;

X^m are the expenses with learning inputs and policies that foster the academic performance at the university m , which do not include the expenses per pupil;

I is a parameter of exogenous efficiency to the inputs used by the university to foster academic activities;

α is the elasticity of human capital of the student $i(L)$ with regard to the effort;

β is the elasticity of human capital of the student $i(L)$ with regard to IX^m ; and

ρ is the elasticity of the human capital of the student $i(L)$ with regards to all other students at the same university.

The major results of the Bishop (2006) are as follows: a) the quality of the institution and the effort of the student move in the same manner. For instance, improving the quality of the professors causes an increase in the effort taken by the students; b) the effort of one student affects the effort of the other students in the same manner, and; c) if the effort of all the students rises by 20% ($E + E^m$) and the quality also increases by the same percentage (X^m), the rise in human capital (L) is less than 20%. (BISHOP, 2006).

4.2.2 Learning Earnings Function

In order to understand the model, we must consider its assumptions. First, the model assumes that young individuals prefer the present to the future. In other words, they have higher rates of temporal preferences. So, to offset the cost to study – which can be considered as an investment – the return (in material or nonmaterial values) must have a positive net present value. Thus, the discounted present value of future payments is highly influenced by the sign of L (human capital), which is accessible to students after graduation.

Beyond that, productivity is a dependent variable of human capital (L), a not easily observed factor by employers. Bishop (2006) considers four main factors that employers and universities employ when predicting the level of individual human capital (L):

- (1) Familiar background;
- (2) Individual results in college compared to the average, or the difference in academic performance compared to the average ($L - L^m$);
- (3) A dummy considering the status of pass or fail in exams;
- (4) A vector of scores obtained in other exams and certifications.

The intrinsic and extrinsic present value of knowledge (material and nonmaterial) is Π , which can be represented as:

$$\Pi = (j + w)L + \theta(L - L^m) + \sigma A \quad (9)$$

Whereas, j is the present value of intrinsic benefits not received by the student i ;

w - the impact of absolute levels of achievement (human capital) at the end of secondary school on the present discounted value of lifetime after-tax earnings and other extrinsic rewards for learning for person i . It also includes the prestige and effects of quality of postsecondary schooling obtained.

$L - L^m$ - difference in knowledge between a student i relative to the average student; can be measured by tests done at the university;

θ - difference in knowledge impact;

σ - familiar background impact (A).

Students will choose the effort, comparing the expected costs to expected benefits. Considering the effort of student I , the benefit (B) will be:

$$B = (j + w)L - \theta(L - L^m) \quad (10)$$

The familiar background impact (σ) was considered invalid by the researcher, which means, the impact of family background did not affect the incentive to study.

Considering the human capital of a representative student as $L^m = A^m(E^m)^{\alpha+\rho}(IX^m)^\beta$, then:

$$B = (j + w + \theta)[AE^\alpha(E^m)^\rho(IX^m)^\beta] - \theta[A^m(E^m)^{\alpha+\rho}(IX^m)^\beta] \quad (11)$$

Considering that studying as a cost – physical energy, opportunity costs, decreased leisure – , it is considered as an increasing function in time. So, the cost (C) is defined as:

$$C = C_0 E^\mu \quad (12)$$

Where $\mu > 1$; in other words, the marginal costs rise when the effort increases.

4.3.3 Effort Cost Function

To obtain the determinants of student effort, we must first define a net benefits of study effort equation, $B - C$, and obtain its maximum by differentiating with respect to E , assuming X^m and E^m are fixed.

$$Max(B - C) = (j + w + \theta)[AE^\alpha(E^m)^\rho(IX^m)^\beta] - C_0 E^\mu \quad (13)$$

Deriving (x) with respect to E for each student:

$$\frac{\partial(B-C)}{\partial E} = \alpha(j + w + \theta)[AE^{\alpha-1}(E^m)^\rho(IX^m)^\beta] - \mu C_0 E^{\mu-1} = 0 \quad (14)$$

$$E = \left\{ \left[\frac{\alpha}{\mu C_0} \right] [(j + w + \theta)[A^m(E^m)^\rho(IX^m)^\beta]] \right\}^{1/(\mu-\alpha)} \quad (15)$$

Applying the natural logarithm to both sides of the equation:

$$\ln E = \left(\frac{1}{\mu-\alpha} \right) [\ln \alpha - \ln \mu C_0 + \ln(j + w + \theta) + \ln A + \rho \ln E^m + \beta \ln(IX^m)] \quad (16)$$

The implications of this model are several. Among them, the main implications for the study proposed are:

- Increase the quality of pairs ($\uparrow E^m$). That is, to study with the best students in the same college and class induces a greater effort.

- Increase the reward of the study ($\uparrow w + \theta$). That is, raise the future wages and earnings for the best students as a way to increase their influence over the others.

To some extent, this model inserts the role of the labor market on the effort. It will be an interesting element of such a study to understand the results. A course with a good market perspective will induce people to better develop their skills.

Implicitly, both Bishop (2006) and Su (2005) models converge on the fact that a group of excluded people who would not enroll in a course without reserved places are induced to make a greater effort.

One of the expected responses in this study is whether the effort was enough to make a difference in the student's education. Since the models explained in this section considered observable and unobservable factors constant in time, the value of the impact will be related by the considerations of these models, such as stress, degree of student selection, future wages, prestige and quality of peers.

5. METHODOLOGY

This section presents the methodology of the difference-in-differences (DD) estimator and the propensity score matching (PSM) approach.

As explained in Heckman, Ichimura and Todd (1997), the ideal situation would be to know the difference between the scores of quota's students and the scores of the same students without the system of quotas. We can represent this difference as:

$$D = E[Y_1/T=1] - E[Y_0/T=1] \quad (17)$$

Considering $T = 1$ the situation in which the student takes part in the treatment group, that is, the student is benefitted by the quotas system. The reverse, $T = 0$, indicates that the student is not in the group of treatment. Y_1 is the potential outcome when the student is in the treatment group, Y_0 is the potential outcome when the course of the student is not in the treatment group.

However, the difference in equation (17) is not observable, and it is:

$$F = E[Y_1/T=1] - E[Y_0/T=0] \quad (18)$$

In other words, it is the difference in the potential outcome of a student who took part in the treatment, i.e., entered the university by quotas, compared with the potential outcome of a student who is not part of the treated group.

The difference between the result in (17) compared to (18) gives us the selection bias:

$$A = D - F = -E[Y_0/T=1] + E[Y_0/T=0] \quad (19)$$

This bias arises when a comparison group is inappropriate: that is, when the students of the treatment group are very different compared to the control group. The possibility of selection bias is substantial, because the condition of quota participants is an outcome of self-selection. On one hand, the student who is benefitted by the quota system chooses inclusion in the policy. On the other hand, the manager of the quota policy is in charge of the process of selection, since individuals are selected based on specific criteria such as income, the condition of a public school student, as well as the way the specific course adopted the quotas.

The estimate of F (equation 18) can be understood as the value added from the impact bias. In this case, the bias can be either positive or negative. If positive, the result of F will be overestimated; if negative, the F value or impact will be underestimated. The origin of the bias is related both as observable and as unobservable. The advantage of the DD estimator can help to overcome the bias caused by unobservable variables.

In order to ease the problem of the counterfactual, reinforcing the hypothesis, the parallel trend related variables are added to the socioeconomic characteristics of the students. The description of the variables included in the model will be described in section 5.2.

5.1 ASSESSING THE IMPACT THROUGH THE DIFFERENCE-IN-DIFFERENCES (DD) ESTIMATOR

The difference-in-differences estimator is one feasible way to estimate a specific intervention or a treatment. Therefore it is a technique to assess the impact of public policies and a well-known econometric tool as well. In general, the method consists of comparing the difference in results before and after the intervention with regard to the affected group and the non-affected group (Lechner, 2011).

Due to methodological reasons, in the cases in which the individual takes part in the policy, he or she is classified as a participant in the treatment group, and otherwise, as a member of the control group. In the next step, we choose a variable of interest Y (as years of education, income, or as in this study, scores from ENADE exam); finally, the observations are captured in two time periods, t_0 and t_1 .

The popularity of the DD estimator comes from its simplicity as well as its feature of overcoming the endogeneity problem when making comparisons among heterogeneous individuals. The DD estimator can also be used in panel data when the analysis unity is available in two time periods (BERTRAND, DUFLO and MULLAINATHAN, 2002).

As stressed by Lechner (2011), an important aspect of the DD estimator, highlighted by many papers, is that it does not always require a strong computational apparatus to calculate the basic estimates. Although this is an interesting fact for a methodology, it is also responsible for some of the weaknesses of the estimator. One of these characteristics is the need for a strong assumption – the assumption of parallel trend – that is, the observable factors need to follow the same trend for the treatment group and the control group. The implications of this assumption will be explored below.

5.1.1 Details on the Difference-In-Differences (DD) Estimator's Implementation

As a requirement to infer the quantitative impact of the implementation of quotas in the average scores of ENADE, we need a control group (nonquota students) to replace the counterfactual, which needs to be similar to the treatment group (quota students). Thus, the control group is the group that was not exposed to any treatment during the two periods, and the treatment group was exposed in both periods (IMBENS and WOOLDRIDGE, 2007).

The database is divided into two periods, represented by the dummy t, whose value is 1 if the student is finishing the course, and 0 if the student is a freshman. Unfortunately, students cannot be tracked over time in the database, which makes it impossible to conduct a panel data analysis.

The equation of this methodology follows the following form:

$$Y_i = \alpha + \beta C_i + \gamma t_i + \delta(T_i \cdot t_i) + \varepsilon_i \quad (20)$$

$I = 1, \dots, N$ and N is the number of students;
 Y_i is the score of student i in the exam;

T is a dummy, which assumes the value 0 if the observation is in the first period, and 1 if the observation is in the second period;

C is the dummy for the treatment group;

α , β , γ , and δ are the unknown parameters to be estimated;

ε is the unobserved random error.

The coefficients to be estimated may be interpreted as:

α = the common intercept for all observations;

β = specific effect of the treatment group (accounts for the differences between groups);

γ = common time trend to both groups;

δ = the average effect of treatment (parameter of interest within the regression, which will provide the average impact of the affirmative action policy);

The expected results by group and by time are presented in Table 4:

Table 4 – Results of interest in group and time

	Result (t_0)	Result (t_1)	Difference
Control Group (non-quota)	α	$\alpha + \gamma$	γ
Treatment Group (quota t_0 , t_1)	$\alpha + \beta$	$\alpha + \beta + \gamma + \delta$	$\gamma + \delta$
Difference	β	$\beta + \delta$	δ

Source: BUCKLEY, JACK & SHANG, 2003

Therefore, the difference in comparing the situation before and after the implementation of an affirmative action policy for the treatment group is subtracted from the difference before and after the policy for the control group. The differences represent the extent to which the treatment group and the control group have changed, respectively. Ideally, the control group did not suffer the impact event, only the change over time, following a parallel trend by the treatment group, thereby respecting the assumption of a parallel trend (GERTLER et al., 2011).

The hypothesis of parallel trend implies that the error is not correlated to the other variables within the equation: $\{cov(\varepsilon_i, T_i)=0; cov(\varepsilon_i, t_i)=0; cov(\varepsilon, T_i \cdot t_i)=0\}$. Moreover, there exist the following assumptions: (a) the model is correctly specified; (b) the error terms have zero as their average; and (c) allowances exist for the deduction that the estimator diff-in-diff does not have bias, $E[\hat{\delta}]=\delta$, in other words, the parameter of interest are effectively estimated (LECHNER, 2011).

However, there is no way to demonstrate that the results of the groups would be parallel in the absence of policy. That is, we cannot observe what would have happened to the treatment group in the absence of the effect of the policy. This issue is known as the problem of the unobserved counterfactual.

5.2 ADDING THE CONTROL VARIABLES

In order to refine the effect of the policy and strengthen the hypothesis of a parallel trend, we must include the effect of all other variables that can cause changes in the variable of interest. This will be accomplished by inserting control variables. Table 5 presents the variables to be used in our estimations.

Table 5 –Control variables used

Civil Status of the Student	Has Work Experience or Not
Number of Siblings	Receives Scholarship or Not
Number of Children	Father's Level of Education
Self-identification of Race	Mother's Level of Education
With Whom the Students Live	Kind of School Attended in High School

Family's Income Range	What Kind of High School Course Concluded
How Many People Live with the Student	English Knowledge Level
Means of Financial Support for the Student	Spanish Knowledge Level
How Many Books the Student Read in a Year	Frequency of Newspaper Reading
Library Attendance	Hours of Study Per Week
Access to the Internet	Main Cultural Activity
Frequency of Computer Use	Student Evaluation of the Physical Condition of the Institution
Participation in Undergraduate Research Project	The Student Regards the Physical Space Suitable to the Number of Students or Not
How the Student Regards Access to the Computer Rooms	

Source: Original Compilation

Even though ENADE's socioeconomic questionnaire includes 115 questions, we selected just 27. The 88 other questions were ignored for several reasons. Some of them only concerned undergraduate programs, while others required greater knowledge about the activities of the college/university, which is likely to affect the responses of beginning students.

Many answers were considered as not vital to the study, among them, the questions about the role of the institution and society, the contribution of the institution to the community, ethical performance and professional perspective. For the matching or pairing, we created dummy variables to measure the probability that the individual is a participant in the treatment group, i.e., a quota participant. Variables were used in the estimation of the probit model, which will be presented later.

Table 6 – Description of the variables used in the probit regression

Variable	Description
Low income	Assumes value of 1 if the student is low income (wages up to 3) and 0 otherwise
If black	Assumes value of 1 if the student is black and 0 otherwise
If public	Assumes value of 1 if the student attended all through high school in a public school and 0 otherwise

Source: Original Compilation

5.3 THE PROPENSITY SCORE MATCHING (PSM) METHOD

As explained before, the problem of the unobserved counterfactual generates selection bias, resulting in an incorrect estimation of the impact of treatment. According to Heckman et al. (1998), the bias can be decomposed into three components: a) lack of a common support – that is, the data processing and control group may not have a reasonable degree of overlap; b) bias from the observable, which is generated by differences in observable characteristics between the groups; and c) selection bias in the variables influencing the results and the receipt of treatment.

Once the hypothesis considered here is the selection by observable by both self-selection (because the students' participation in treatment is done on a voluntary basis) as well as selection of the administrator (university decides the criteria for the students to be admitted), the goal of matching or pairing will find a group for the ideal treatment group comparison, minimizing the problem of selection bias (HECKMAN et al., 1998).

The problem in this method is the definition of "similar." There are several characteristics by which students can be compared, and it is not easy to define by what; with the aggravation of more characteristics, it becomes more complicated to carry out the pairing (RAVALLION, 2005).

The propensity score matching (PSM) technique developed by Rosenbaum and Rubin (1983) helps to increase the number of variables used for matching. The method compares those treated with the control

group by means of the similarity in the probability of receiving treatment, hoping that adjusting the differences between the groups in these variables eases the problem of selection bias.

The hypotheses of the authors to ensure the elimination of bias are:

1. $Y_0, Y_1 \perp T \mid X$ – that is, the hypothesis of independence of potential outcomes regarding treatment in observable characteristics. This hypothesis implies that once controlled by several observable characteristics, two students should have the same probability of being quota participants.
2. Implicit hypothesis of common support, $0 < \Pr(T=1|X) = P(x) < 1$; for each student treated, there is another individual with a similar vector x . This assumption implies the need for each value of x to correspond to individuals in treatment and control groups.
3. $Y_0, Y_1 \perp T \mid p(X)$. If the result is independent of the participation, given X (Hypothesis 1), then the result is also independent of the likelihood of participation, given $p(x)$. This third hypothesis implies that a paired group is homogeneous in the score of probability, and also in the distribution of X .

The identification strategy, under the hypothesis of the presence of selection bias on observable characteristics for the treatment, was to apply propensity score matching to pairing of the students in order to reduce the error of estimation of the impact. We are able to combine that with the DD estimator to control under constant time unobservable characteristics bias.

Based on the variables shown in Table 6, we estimate the propensity scores using a probit model. In pairing, the data are grouped in groups or blocks as the values of the scores. The number of blocks is determined by the algorithm for estimating the propensity score, in order to ensure that the scores are not different in each block. Therefore, we know that students within the same block are likely the same or at least similar in the propensity scores. In this case, the number of blocks is 8, and the balancing of the property mentioned above is satisfied using a sensitivity of 10%.

Finally, the estimate of the impact in the DD estimator is weighted by the weight of the resulting pairing. The weights were assigned inversely proportional to the distance between the propensity scores of the treatment groups and control form.

6. IMPACT ASSESSMENT OF QUOTA IMPLEMENTATION OVER THE ENADE'S 2008 GRADES

In Brazil, the higher education system is evaluated at annual basis. One of the most important evaluations which directly assesses the student's performance is the National Examination Performance of Students (ENADE). The basic data of this review provide the necessary information to calculate the impact of affirmative action policy, such as race, how he/she was accepted at University and a note assessing expertise. In this section the test and the results of the estimators will be presented.

6.1 DATABASE AND THE MAIN DESCRIPTIVE STATISTICS – ENADE 2008

The data used in this study come from the National Survey of Student Performance (ENADE). Applied for the first time in 2004. This examination is the responsibility of the National Institute for Educational Studies Teixeira (INEP), which is under the Ministry of Education's authority.

Potential participants in ENADE are first-year students (freshmen) and final-year students (graduating seniors) in higher education. INEP defines as freshman those who stepped into the institution of higher education in the same year of testing, and seniors as those who have attended a minimum of 80% of the workload of the full course.

The reason for using the data from the ENADE examination is related to the fact that it is the only national survey that measures the knowledge acquired in an institution of higher education in Brazil, and additionally providing the information at the individual level. INEP provides, in addition, information on the socioeconomic characteristics from the application of a questionnaire, with questions about parental education, income, frequency of studies, culture and individual perception of the characteristics of the university. It also includes a questionnaire for the coordinator of each course, which includes questions

about the quality of the library, the educational plan, and various levels of course offerings, seminars, conferences, outreach and monitoring activities.

The test is applied annually. However, not all higher education courses are evaluated in the same year. Within the period of seven years during which the examination has been applied, the year 2008 was chosen as the primary source of data.

The choice of the 2008 data is justified for two reasons. First, the base year of 2008 is the first which includes the identification of the student as a quota participant. The second reason is the broader base of data from seven years of examination, with 60 courses, compared to 22 in 2009 and 19 in 2010. Also, unfortunately, the questionnaire and the methodology changed over time, preventing pooling of data from two or more years.

Although the number of observations of the ENADE exam 2008 is considered large (825,235 observations), the examination lacks the high degree of dropout. Of those more than 800,000 observations, 513,265 did not respond to the questionnaire, critical to our study; the remaining students, 106,602, did not respond to evidence knowledge effectively. Since the system of quotas refers to the public higher education system, we selected only the students of federal, state and local universities, leaving our working sample with 74,080 observations.

The ENADE's test is divided into two parts: general knowledge and specific knowledge. This paper considers only the score taken in the specific knowledge test, since it represents 75% of the ENADE's test, and because it was the same for freshmen and senior students, which makes it possible to compare the differences in knowledge between these students.

6.2 RESULTS OF PROBIT MODEL: INITIAL EVIDENCE

The first step in calculating the propensity score is to estimate the probit model. For this we use the variables in Table 6, measuring the probability that the student is a member of the treatment group. In a second step, we classify them and put them together with respect to the scores of sensibility. Pondering the DD estimator with scores, individuals can be compared at least in the item selection to treatment category.

It is usual that for the PSM results, several attempts are required in order to achieve a specification that satisfies the hypothesis of equilibrium (balancing hypothesis) between the variables included in the model; however, this difficulty has been reduced because we have reduced the calculation of probit only to characteristics related to the selection process of the quota participant.

This specification is also justified for another reason: the greater the number of variables included, the better the pairing – that is, the more similar the individuals in control groups and the treatment. However, it also poses a problem for the calculation of regression – since groups already showed before pairing a similar distribution of grades – and when it includes more by the similarity matching, the problem of omission by collinearity coefficient of desired variable becomes commonplace. Table 7 presents the results from the propensity score estimations.

Table 7 – The probit model

Variable	Coeficcient	Standard Error	z	P> z	Confidence interval of 95%	
Low income	0.3556	0.01047	33.85	0.000	0.334	0.375
If black	0.2195	0.01382	15.88	0.000	0.1924	0.2466
If public	0.4925	0.01284	38.36	0.000	0.4674	0.5177
_cons	-1.4561	0.01135	-128.2	0.000	-1.4783	-1.4338

Source: Original Compilation from ENADE's 2008 data

All of the control variables were significant at 1% and had signs as were expected. If the student is low income (up to three times the minimum wage for a monthly family income), is black and attended high

school in a public school, the greater the likelihood of the student in joining an institution of higher education as a quota student.

The next section presents and analyzes the impacts of the quotas by the grades of ENADE exam. One of the estimators is the combination of the propensity score method with the difference-in-differences method.

6.3 IMPACT ASSESSMENT OF QUOTA IMPLEMENTATION

The results of the estimated impact on the performance of the students of public higher education institutions over the specific component of ENADE's exam are shown in detail in the Appendix. In addition, other features related to the socioeconomic level of the student, library attendance, internet use, and cultural issues have been inserted.

For each course, the result was shown based on three estimators: difference-in-differences (DD), difference-in-differences with the inclusion of covariates (DDC) and difference-in-differences after matching with the inclusion of covariates (DDMC).

As shown previously (Section 5), the proposed techniques (DD estimator and others) can be used to capture the impact of the implementation of quotas in the average grade of ENADE, interpreted as an exogenous shock. Knowing this and seeing the results, we realized that they had opposite signs, with 25 courses positive and 25 negative for the DD estimator; and DDC for the estimator of 23 positive, while 20 were negative. Interestingly, the results had a similar distribution of signals, preventing a satisfactory conclusion when considering the total sample, and justifying the separation of courses within the analysis.

When we consider only the statistically significant results, negative results were prominent because the DD estimator showed five negative and two positive, while the DDC showed four negative and one positive.

To better measure the impact, we included Table 8, which provides the impacts (DD, DDC, DDMC), the average grades, standard deviation, and the number of observations of the courses that showed significant results.

Table 8 – Course, impact, average grade, standard deviation and number of observations

Course	DD	DDC	DDMC	Average Grade	Standard Deviation	N
Veterinary Medicine	13.04**	5.45	3.57	26.83	23.65	506
Math	-2.21	-2.48	-3.21***	36.34	18.57	3606
Language	-2.73*	-1.41***	-1.2	34.98	18.11	15201
Physics	-6.42*	-6.54*	-6.19*	37.08	17.52	1231
Agronomy	9.46**	8.56***	9.15**	37.62	15.7	398
Pedagogy	-2.04*	-1.99*	-2.00*	36.41	17.73	13482
History	-5.03*	-4.06**	-4.18**	33.58	15.86	2226
Geography	-2.66**	-2.13	-1.91	36.27	17.14	4015
Mechanical Manufacturing Technology Degree	51.47**	57.05	61.65	35.71	16.61	40

Note: *significant at 2%, ** significant at 5%, *** significant at 10%.

Source: Original Compilation from ENADE's 2008 data

The impact on Language degree was negative and significant for the DD estimator and the DDC, and the impact by the DD estimator was -2.73, compared with the average course grade value, which

corresponds to 7.80. When we insert the control variables (Table 5), the value drops to -1.41, which corresponds to 4.03% of the average grade. The standardized score value of -2.73 (DD) corresponds to a loss of 5.96% for a student who is the median of the distribution, and the value -1.41 (DDC) represents a loss of 3.18%. However, when we observe the estimate by matching, that is, when compared with their peers, the value remains negative but loses significance. In this case, it can be considered that the previous estimates of observable variables not included in the regression influenced the negative outcome.

The impact on Physics was negative and significant in all three estimations. The values changed minimally, ranking -6.42, -6.54 and -6.19, respectively. If we compare this effect with the average grade of the course, the impact corresponds to around 17%. Using the standardized score, these values correspond to a loss of around 14% to the student who is in the median of the distribution, relatively high for the magnitude of the Physics course.

Considering the course of Pedagogy, it also showed negative and significant estimates for the three estimates, altering very little among them, respectively, they were -2.04, -1.99 and -2.00. Comparing these effects with the average grade of the course, the impact corresponds to around 5.40%. The standardized score of these values corresponds to a loss of around 4.30% for the student, who is the median of the distribution.

In History, the three estimates were negative and significant, also changing very little; respectively, they were -5.03, -4.06 and -4.18. Compared with the average score, the impacts correspond by 14.97%, 12.09% and 12.44%, representing a loss of 12.55%, 9.87% and 10.25%, respectively, for the student who is in the median of the distribution.

For Geography, only the estimate for DD showed a significant result of -2.66%, or 7.33% of the average grade. The impact is a loss of 5.9% for a student who is in the middle. However, when we include observable impacts and the pairing, it did not show significant results.

Among the positive results, the impact on the course of Veterinary Medicine had a positive and significant value for the DD estimator of 13.04. Compared with the average grade that corresponds to 48.60%, well above the expected, and when we consider the standard deviation, the impact is a gain of 49.9% to the student who is in the median of the distribution. A direct interpretation of the results tells us that the quota student is among the top in the course.

At first glance, this positive value estimated by DD contradicts the hypothesis raised by Sowell (2004), which predicts that entry-level students who are less prepared have a negative impact through the quota system. On the other hand, although the results of Veterinary Medicine for the DDC estimator are positive, it is not significant, indicating that when we include the observed variables, the result does not repeat.

The course of Mechanical Manufacturing Technology is similar to the Veterinary Medicine course, having the largest impact in terms of value among courses analyzed. The impact achieved significance only for the DD estimator, and not for others. The value was 51.47, which corresponds to 144% of the average grade.

We believe that the reason for positive, significant and high results compared to the average grade for both the Veterinary Medicine course and the Mechanical Manufacturing Technology course would be the distribution of grades among students in the exams.

We can see from Tables 9 and 10 that for the two courses, quota students had a concentration of grades in a certain range.

Table 9 – Distribution of grades in range and relative frequency on the ranges, for Veterinary Medicine course

Grade in Ranges	Group				Total
	D=0 Control	Relative Frequency on the Ranges (%)	D=1 Treatment	Relative Frequency on the Ranges (%)	(n)
0-9.99	117	64.64	64	35.36	181
10-19.99	27	90	3	10	30
20-29.99	40	85.11	7	14.89	47
30-39.99	72	92.31	6	7.69	78

40-49.99	69	90.79	7	9.21	76
50-59.99	41	83.67	8	16.33	49
60-69.99	23	88.46	3	11.54	26
70-70.99	15	93.75	1	6.25	16
80-	3	100	0	0	3
Total	407	80.43	99	19.57	506

Source: Original Compilation from ENADE's 2008 data

From Table 9, we can observe that the frequency of quota participants in the range from 30 to 39.99 is 7.69%, and it is 9.21% in the range of 40 to 49.99, increasing to 16.33% in the range from 50 to 59.99, while in the range from 60 to 69.99 it is 11.54%. As the distribution of quota participants has increased in intervals of the highest grades, this probably caused the positive impact value.

Table 10 – Distribution of grades in range and relative frequency on the range, for Mechanical Manufacturing Technology course

Grade in Ranges	Group				Total
	D=0 Control	Relative Frequency on the Ranges (%)	D=1 Treatment	Relative Frequency on the Ranges (%)	(n)
0-9.99	3	100	0	0	3
10-19.99	4	100	0	0	4
20-29.99	8	100	0	0	8
30-39.99	9	81.82	2	18.18	11
40-49.99	3	50	3	50	6
50-59.99	4	80	1	20	5
60-69.99	2	100	0	0	2
70-	0	0	1	100	1
Total	33	82.5	7	17.5	40

Source: Original Compilation from ENADE's 2008 data

Looking to the case of the Mechanical Manufacturing Technology course, we can see that the grades of the quota participants were distributed asymmetrically. They were concentrated in the range above 30. Another fact that justifies the high impact value is the small number of observations; the weight of each grade is larger in the regression.

Finally, the only course that showed positive and significant values in the three estimates was the course of Agronomy. The results were 9.46 (DD), 8.56 (DDC) and 9.15 (DDMC), representing, respectively, 25.5%, 22.75% and 24.32% of the average grade. In this case, the results were highly in favor of the treatment group.

This last result requires a closer assessment of the policy adoption, as it opposed the previous results.

Table 11 - Distribution of grades in range and relative frequency on the range, for Agronomy course

Grade in Ranges	Group				Total
	D=0 Control	Relative Frequency on the Ranges (%)	D=1 Treatment	Relative Frequency on the Ranges (%)	(n)
0-9.99	12	92.31	1	7.69	13
10-19.99	33	86.84	5	13.16	38
20-29.99	77	90.59	8	9.41	85
30-39.99	79	88.76	10	11.24	89
40-49.99	74	89.16	9	10.84	83
50-59.99	51	89.47	6	10.53	57

60-69.99	20	86.96	3	13.04	23
70-70.99	10	100	0	0	10
Total	356	89.45	42	10.55	398

Source: Original Compilation from ENADE's 2008 data

The distribution of the results shown in the Table 11 does not seem to explain the reason for the positive and significant results from estimations; rather, it shows a more even distribution of the ranges between the grades.

Table 12 shows the average grades for the four courses with significant results in the three estimates. Each course is divided into four groups: Beginner quota participants and nonparticipants, and graduating quota students and no quota students. In addition to the grades, we can see the standard deviation. The purpose is to show the average of each group at both times.

Table 12 – Average grade and standard deviation of courses divided between treatment and control groups

			Group	
			D=0 Control	D=1 Treatment
Agronomy	Time periods	T=0 Beginner	33.44 (14.19)	27.04 (11.74)
		T=1 Graduating	43.52 (16.03)	46.58 (11.80)
Physics	Time periods	T=0 Beginner	31.98 (15.15)	36.27 (16.15)
		T=1 Graduating	43.05 (14.89)	40.91 (19.09)
Pedagogy	Time periods	T=0 Beginner	31.98 (16.72)	34.20 (16.68)
		T=1 Graduating	39.56 (18.22)	39.75 (17.06)
History	Time periods	T=0 Beginner	29.34 (14.06)	29.00 (13.18)
		T=1 Graduating	38.72 (16.47)	33.62 (16.05)

Source: Original Compilation from ENADE's 2008 data

We notice that the course of Agronomy differed from the others, because among these courses it was the one for which quota students had the largest difference between the times. The difference between a quota student finishing the course with a beginner quota participant was, on average, 72%. Neither of the other courses in Table 12 showed the same variation in performance.

As soon as we combined the method of difference in differences of pairing, we expected observable and unobservable characteristics that are constant over time would not affect the results of the impacts; it remains to explain the results by unobservable characteristics that changed over time.

The theoretical framework probably provides some of these unobservable characteristics. One of them, as explained in the model of Su (2005), is the difficulty of the selection process as a determinant of effort. The lower the degree of selection, the lower the level of effort. A low degree of effort would result in an inability to compensate for the difference in educational background between the treatment and the control groups.

In Brazil, the courses of Physics, History and Pedagogy have, normally, selective processes with low competition. As the basis does not include the level of competition, this led to the hypothesis that courses with this feature would involve input from students with lower levels of stress and poorer academic training.

We also assume that other factors which influence the effort were the determinants of this result. The model of Bishop (2006) includes the role of future wages and quality of peers as determinants of stress.

Assuming that the job market for Agronomy is better than in Physics, Pedagogy and History, this will positively influence the level of effort of quota students. We can also consider the presence of peer effect, i.e., if the quota students do not have good training that can positively influence the quota students, also as theoretically predicted by the Bishop (2006) model.

Considering the course of Agronomy, it seems that the incentives for effort offset a worse schooling of quota students, at the point that the impact showed a positive result.

7. CONCLUSIONS

The economic analysis of education has evolved significantly in recent years. Several studies show strong evidence that education promotes economic growth, facilitates the incorporation of technology, and fosters significant positive externalities within society.

In parallel with this, many researchers have been addressing the issue of inequality in access to education. In the political field, in large part because of pressure from social movements, the issue of inequality in access to education has been addressed through the implementation of a system to facilitate access to higher education. In the Brazilian case, this involves the imposition of racial and social dimensions. In this context, since 2012, Brazilian public universities are obligated by law to reserve 50% of placements for these groups.

The two main papers in the area of analyzing the impact of quotas (BOK and BOWEN, 1998; SOWELL, 2004) have divergent opinions on the effectiveness of this instrument. To analyze the impact of quotas on the average scores of courses in ENADE, we first used the methodology of difference in differences, coupled with the method of matching (propensity score matching). This allowed for a strong estimation, with 27 variables and the elimination of selection bias.

Among the results of this paper, we can highlight that the implementation of quotas impacted negatively and significantly in ENADE's 2008 grades in the courses Pedagogy, History and Physics. Somehow, these results confirm the criticism of Sowell (2004) and D'Souza (1991), who claim that the arrival of the worst students would result in a loss of human capital at the university. We believe that in addition to a worsening educational background, the model of Su (2005) and Bishop (2006) include more explanatory factors. These models consider that factors such as stress, degree of student selection, future wages in the labor market and quality of peers (peer effect) explain the accumulation of human capital, and this in turn explains the estimated value of the impact.

Distinctly from the results of Pedagogy, History and Physics, in the course of Agronomy, the implementation of quotas impacted positively and significantly in the three estimates. It seems that, on average, the quota students showed a better improvement in the ratings compared to the control group.

Assuming that there was a difference between the students who are classified as quota participants in comparison to those students who do not, the effort of the quota's students during the graduation— which is an variable that depends on the degree of selection, expected wages and the quality of their peers – was enough to offset the worse educational background and it also had a positive impact over the grades.

In general, we can state that this study has several limitations. First, the lack of enforcement mechanisms in the administration of ENADE, which is a problem that should be addressed by the government, because the dropout level of the test is high, and in many courses, the number of observations was very low (Appendix 1). Another important problem is the INEP's bureaucracy for providing only some databases, which prevented more detailed and larger numbers of observational studies.

However, despite these limitations, this paper is an interesting contribution to the impact of quotas in higher education, going beyond the analysis of only one course or one teaching institution.

Finally, even though this paper addresses the specific case of Brazil regarding quotas, it can be useful to support the analysis of studies which approach aims to implement or improve affirmative policies worldwide.

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APPENDIX

APPENDIX 1. RESULTS OF THE ESTIMATES OF THE IMPACT OF QUOTA IN PERFORMANCE IN THE ENADE'S EXAM

DEGREE	DD	DDC	DDMC
ADMINISTRATION	0,43	0,28	-0,24
LAW COURSE	7,19	4,55	5,06
VETERINARY MEDICINE	13,04**	5,45	3,57
DENTISTRY	1,23	-2,41	-2,1
MATH	-2,21	-2,48	-3,21***
MEDIA	-13,89	-17,53	-15,11
LANGUAGE	-2,73*	-1,41***	-1,2
MEDICINE	-17,05	-	-
ECONOMIC SCIENCES	6,34	4,11	2,74
PHYSICS	-6,42*	-6,54*	-6,19*
CHEMISTRY	2,12	1,8	1,99
BIOLOGY	-0,47	-0,47	-0,34
AGRONOMY	9,46**	8,56***	9,15**
PSYCHOLOGY	-1,17	0,19	-2,14
PHARMACY	-4,88	-4,5	-1,76
PEDAGOGY	-2,04*	-1,99*	-2,00*
ARCHITECTURE AND URBAN PLANNING	-7,26	-6,63	-4,72
ACCOUNTING SCIENCES	10,44	9,67	8,35
NURSING	0,81	1,3	2,67
HISTORY	-5,03*	-4,06**	-4,18**
DESIGN	-14,95	-	-
FONOAUDIOLOGY	-	-	-
NUTRITION	4,2	7,38	15,74
TOURISM	-19,5	-	-
GEOGRAPHY	-2,66**	-2,13	-1,91
PHILOSOPHY	-0,8	-57,12	51,37
PHYSICAL EDUCATION	-2,29	-1,45	-2,48
PHYSIOTHERAPY	27,43	-	-
SOCIAL SERVICE	-1,14	-0,7	-0,36
THEATRE	-14,07	-	-
COMPUTING	0,89	0,16	-1,11
MUSIC	2,13	1,7	3,74
ANIMAL SCIENCE DEGREE	-4,45	-4,21	-8,49
OCCUPATIONAL THERAPY	-	-	-
SOCIAL SCIENCE	0,7	1,65	1,01
BIOMEDICINE	-	-	-
ENGINEERING (GROUP I)	2,23	2,72	2,03
ENGINEERING (GROUP II)	-2,18	-1,47	-1,29
ENGINEERING (GROUP III)	1,7	1,09	2,27
ENGINEERING (GROUP IV)	-5,9	-2,8	-0,65
ENGINEERING (GROUP V)	14,14	-	-
ENGINEERING (GROUP VI)	0,68	1,21	-1,64
ENGINEERING (GROUP VII)	0,39	0,54	-0,54
ENGINEERING (GROUP VIII)	1,96	2,16	1,37
ARCHIVAL	-	-	-
LIBRARY SCIENCE	-3,84	-	-
EXECUTIVE SECRETARY	-	-	-
RADIOLOGY TECHNOLOGY	-	-	-
AGRO INDUSTRIAL TECHNOLOGY	-	-	-
FOOD TECHNOLOGY	3,72	5,86	5,93
TECH IN SYSTEM ANALYSIS AND DEVELOPMENT	5,06	3,88	4,92
INDUSTRIAL AUTOMATION TECHNOLOGY	7,71	7,2	8,28
BUILDING AND CONSTRUCTION TECHNOLOGY	-6,22	-10,56	-9,51
MECHANICAL MANUFACTURING TECHNOLOGY	-5,74	-3,51	-3,3
MANAGEMENT OF INDUSTRIAL PRODUCTION	51,47**	57,05	61,65

INDUSTRIAL MAINTENANCE TECHNOLOGY	-	-	-
CHEMICAL PROCESS TECHNOLOGY	-	-	-
COMPUTER NETWORKING TECHNOLOGY	-2,06	-1,38	-1,47
ENVIRONMENTAL SANITATION TECHNOLOGY	3,83	3,81	3,37

Note: *significant at 2%, ** significant at 5%, *** significant at 10%. Values not provided due to insufficient number of observations.

Source: Original Compilation from ENADE's 2008 data