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ALINE KRÜGER DALCIN

ESSAYS ON EDUCATION ECONOMICS:
INDIVIDUALS WITH DISABILITIES FROM BASIC EDUCATION TO LABOR MARKET

Porto Alegre
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Tese submetida ao Programa de Pós-Graduação em Economia da Faculdade de Ciências Econômicas da Universidade Federal do Rio Grande do Sul como requisito parcial para a obtenção do título de Doutora em Economia.

Orientador: Prof. Ph.D. Flavio Vasconcellos Comim

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BANCA EXAMINADORA:

Prof. Dr. Flavio Vasconcellos Comim – Orientador

UFRGS

Prof. Dra. Izete Pengo Bagolin

PUCRS

Prof. Dr. Sabino da Silva Pôrto Júnior

UFRGS

Prof. Dr. Sílvio Hong Tiing

PUCRS

À minha família, com amor.

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RESUMO

Esta tese traz três ensaios sobre educação e pessoas com deficiência. Cada ensaio aborda uma etapa escolar diferente. O primeiro ensaio tem como objetivo analisar o impacto que a inclusão de alunos com deficiência nas escolas regulares de Ensino Médio tem sobre o desempenho de seus colegas e analisar o impacto que essa inclusão tem sobre o desempenho dos próprios alunos com deficiência. Os resultados mostram que um ponto percentual adicional na proporção de alunos com deficiência reduz a nota de redação dos colegas em apenas 0,0032 de um desvio-padrão. Além disso, os resultados mostram que as notas médias são maiores em até 48% de um desvio-padrão entre os alunos com deficiência matriculados em escolas regulares em comparação com aqueles matriculados em escolas especiais. Em resumo, a avaliação é que as políticas de inclusão atingem o objetivo de melhorar o desempenho dos alunos com deficiência, mas essas políticas têm um efeito colateral pequeno e adverso. O segundo ensaio tem como objetivo analisar o impacto do Sistema de Seleção Unificada (Sisu) no acesso ao ensino superior para estudantes com deficiência. A centralização do processo de inscrição diminui os custos de mobilidade que são importantes na decisão de indivíduos com deficiência de se inscrever em uma universidade. Os resultados mostram que o percentual de alunos ingressantes com deficiência em instituições que adotaram o Sisu por sete anos foi 0,63 ponto percentual maior do que em instituições que não o adotaram. Esse resultado é significativo, considerando que, em 2016, o percentual de ingressantes com deficiência foi de apenas 0,77%. O último ensaio tem como objetivo estimar os retornos salariais da educação para pessoas com deficiência através do método da taxa interna de retorno (TIR). As taxas internas de retorno à educação para pessoas com deficiência são comparadas às TIRs para pessoas sem deficiência: a TIR para pessoas com deficiência é maior do que para pessoas sem deficiência no primeiro e no segundo ciclo do ensino primário (3,7% versus 3,12% no primeiro ciclo e 2,28% versus 1,53% no segundo), mas menor no nível mais alto de educação (11,06% versus 12,34%). Pelo tipo de deficiência, os trabalhadores com deficiência intelectual têm as menores TIRs para todos os níveis de escolaridade.

Palavras-chaves: Educação. Deficiência. Inclusão. Sisu.

ABSTRACT

This thesis brings three essays on education and people with disabilities. Each essay addresses a different school phase. The first essay aims to analyze the impact that the inclusion of students with disabilities in regular High Schools has on the achievement of their schoolmates and to analyze the impact that this inclusion has on the achievement of the students with disabilities themselves. The results show that an additional percentage point in the proportion of students with disabilities would reduce schoolmates' Writing scores by just a 0.0032 standard deviation. In addition, the results show that the mean scores are up to 48% of a standard deviation higher among students with disabilities enrolled in regular schools compared to those who are enrolled in special schools. In summary, the evaluation is that inclusion policies achieve the goal of improving the performance of students with disabilities but such policies have a small and adverse side effect. The second essay aims to analyze the impact of the Brazilian Unified Selection System (Sisu) on access to higher education for students with disabilities. Centralizing the application process diminishes mobility costs that are salient in the decision of individuals with a disability to apply to a university. The results show that the percentage of entrants with a disability on institutions that have adopted Sisu for seven years was 0.63 percentage point higher than those that have not adopted. This result is sizable considering that, in 2016, the percentage of entrants with disabilities was only 0.77%. The last essay aims to estimate the wage returns to education for people with disabilities through the internal rate of return (IRR) method. The internal rates of return to education for people with disabilities is compared to the IRRs for people without disabilities: the IRR for people with disabilities is higher than for people without disabilities at the first and second cycle of primary education (3.7% versus 3.12% in the first cycle and 2.28% versus 1.53% in the second), but lower at the highest level of education (11.06% versus 12.34%). By the type of disability, workers with intellectual disabilities have the lowest IRRs for every schooling level.

Keywords: Education. Disabilities. Inclusion. Sisu.

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1 INTRODUCTION

The Noble Prize winner Amartya Sen says that “the success of a society is to be evaluated primarily by the freedoms that members of the society enjoy”. Freedoms in the sense used by that economist is related to things that people are actually able to do. In that sense, to enjoy a dignified and just life, a citizen is free when he is included in the society by having effective freedoms and capabilities. When the State simply does not offer accessibility conditions to those in vulnerability and marginalized, effective freedom is absent. In particular, there is a demand for inclusive public policies for people with disabilities in order to allow them to participate fully in society.

An essential element to allow full participation in society is education. Besides the known private returns to education, schooling provides vulnerable individuals with tools to be fully included in society and to demand recognition. Bearing this in mind, this thesis brings three essays on education and people with disabilities. Each essay addresses a different aspect of education: the first essay is about Basic Education, where we draw our attention to children; the second is about accessibility to Higher Education; finally, the last essay is about the returns of human capital of disabled individuals in the formal labor market.

More specifically, the first essay aims to analyze the impact that the inclusion of students with disabilities has on the achievement of their schoolmates and to analyze the impact that this inclusion has on the achievement of the students with disabilities themselves. Our results show that an additional percentage point in the proportion of students with disabilities would reduce schoolmates' Writing scores by a 0.0032 standard deviation. In other subjects, we find weak or none evidence of a significant peer effect. In addition, using Propensity Score Matching methodologies our results show that the mean scores are up to 48% of a standard deviation higher among students with disabilities enrolled in regular schools compared to those who are enrolled in special schools. In summary, our evaluation is that inclusion policies achieve the goal of improving the performance of students with disabilities but such policies have a small and adverse side effect.

In the second essay, we study the effects that a centralized university admission system (Sisu) has on the demographic distribution of students admitted to higher education institutions, with focus on a particular type of disadvantaged group: students with disabilities. Centralizing the application process diminishes mobility costs that are salient in the decision of individuals with a disability to apply to a university. We find that the percentage of entrants with a disability on institutions that have adopted Sisu for seven years was 0.63 percentage point higher than those that have not adopted. This result is sizable considering that, in 2016, the percentage of entrants with disabilities was only 0.77%.

Finally, in the last essay, we estimate the wage returns to education for people with disabilities in Brazil. We do so through the internal rate of return (IRR) method and using Annual Social Information Report (RAIS) data for the years 2011 to 2016. Afterward, we compare them to the IRRs to education with people without disabilities. We find that the IRR for people with disabilities is higher than for people without disabilities at the first and second cycle of primary education (3.7% versus 3.12% in the first cycle and 2.28% versus 1.53% in the second), but lower at the highest level of education (11.06% versus 12.34%). We also estimate the IRRs to the schooling of workers with disabilities by the type of disability. We find that workers with intellectual disabilities have the lowest IRRs for every schooling level. We believe knowledge of IRRs of individuals with disability will help policymakers to target education policies better.

2 LEARNING TOGETHER: THE EFFECTS OF INCLUSION OF STUDENTS WITH DISABILITIES IN MAINSTREAM SCHOOLS

Brazil is far from providing universal access to basic education for the population aged 4 to 17 years with disabilities: according to the Demographic Census of 2010, 16% of the population who cannot hear at all is out of school, 16% of the population who cannot see at all is out of school; 23% of the population who cannot move at all is out of school; and finally, 30% of the population with some permanent intellectual disability is out of school. These numbers are very high, considering that only around 8% of the population without disability aged 4 to 17 years is out of school. According to an Unesco study, 98.7% of individuals without disabilities between 15 and 29 have ever attended school, but that percentage drops to 89.2% for individuals with disabilities – a ratio of 0.9 disabled individuals to every non-disabled individual. The Unesco study shows that Brazil is behind if compared with other South American countries for which data is available. The ratio for Uruguay is 0.95 and 0.97 for Colombia (UNESCO, 2018).

Policies to provide education for children and teenagers with disabilities were carried out until recently preferably through exclusive special education schools. This situation only changed when legislation began to require the inclusion of children with disabilities in the regular school system. The trajectory of Brazilian legislation on inclusive special education began in the 1980s with the Federal Constitution (FÁVERO *et al.*, 2009; MAUCH; SANTANA, 2016). Articles 205, 206 and 208 of the 1988 Constitution affirm that "education, which is the right of all and duty of the State and of the family, shall be promoted and fostered with the cooperation of society, with a view to the full development of the person, his preparation for the exercise of citizenship and his qualification for work", "equal conditions of access and permanence in school" and "specialized schooling for the handicapped, preferably in the regular school system" (BRASIL, 1988).

Two decades later, in 2006, the United Nations (UN) declared the Convention on the Rights of Persons with Disabilities. In Brazil, this Convention was ratified in 2008, thus assuming constitutional status through Legislative Decree 186/2008 and Executive Decree 6.949/2009. The Convention establishes that "persons with disabilities can access an inclusive, quality and free primary education and secondary education on an equal basis with others in the communities in which they live" (BRASIL, 2008). In the same year of ratification of the Convention, the Ministry of Education (MEC) launched the National Policy on Special Education in the Perspective of Inclusive Education. One aspect of both the

Convention and the National Policy on Special Education in the Perspective of Inclusive Education is the defense that all students with disabilities, developmental disorders, and high skills or giftedness should attend regular schools. Besides, the National Policy on Special Education in the Perspective of Inclusive Education indicates that, in addition to the common classes, these students should count on Specialized Educational Assistance, a service whose functions are to identify, elaborate and organize pedagogical and accessibility resources that eliminate the barriers to their full participation (BRASIL, 2010; MAUCH; SANTANA, 2016).

The data show that Brazilian education is actually moving towards inclusion in common classes. In other words, along with the evolution of the Brazilian legislation on inclusive special education, the evolution of percentage of students with disabilities, developmental disorders, and high skills or giftedness enrolled in common classes instead of special classes or specialized schools also occurred. In 2007, according to the Brazilian School Census, only 46.8% of the students with disabilities, developmental disorders, and high skills or giftedness in school studied in common classes; in 2017, this percentage jumped to 84.1%.

However, the mainstreaming of special education was carried out without any impact evaluation. Few studies in the literature evaluate the effects of such inclusion - which may be on students with disabilities or students without disabilities. The results of these studies should be taken into account by policymakers when deciding on the implementation of inclusion policies. If poorly conducted, such policies can produce unwanted effects and waste resources. In this scenario, the objective of this article is to provide results to assist the decision on the implementation of inclusion policies for children and teenagers with disabilities.

More specifically, in this paper, we begin investigating how the inclusion of students with disabilities in regular schools affects achievement of schoolmates. To answer this research question, we explore the natural variation in time in the number of students with disabilities and use data from National Exam of Upper Secondary Education (Enem). The results show that the exposure to students with disabilities creates negative Writing achievement externalities in grade-cohort at end of High School. In other subjects, we find weak or none evidence of a statistically significant peer effect. The results are heterogeneous in quantiles of the achievement distribution and in competencies around which the exam is organized. The negative effect is higher among students in the top percentiles of the grade distribution.

Then, we investigate how the inclusion affects achievement of the students with disabilities themselves. We use Propensity Score Matching methodologies and, again, data from Enem. Our results show that the mean scores are up to 48% of a standard deviation higher among students with disabilities enrolled in last grade of High School in regular institutions compared to those who are enrolled in special schools.

When designing public policy, policymakers need to consider studies that assess the impact of this policy. In the case of the policy of including students with disabilities in mainstream schools, they must take into account the impact on all individuals involved, that is, students with disabilities and their peers in regular schools. There are some studies on the peer effect of students with disabilities[1]. However, there is no study that assesses the impact on both groups. Only by analyzing the impact of the policy on both groups, we can conclude whether the policy is positive or not. For this reason, the present study proposes to fill this gap in the literature by analyzing the impact of the inclusion of students with disabilities on both groups. In addition, this paper contributes to the empirical literature of peer effect with an analysis of the peer effect of students with disabilities per competency. Finally, the article is important given the existence of few articles in Brazil on the topic of education and people with disabilities[2].

This article is divided into five sections after this introduction: Section 2 presents the related literature; Section 3 explains the methodology; Section 4 introduces the data; Section 5 reports the results; and Section 6 brings the final remarks.

2.1 RELATED LITERATURE

This paper relates to two strands in the literature. First, it is related to peer effect studies because it analyses the impact of inclusion of students with disabilities on the achievement of their schoolmates. The second literature related to this paper comprises studies that evaluate the inclusive special education or special education services because it also analyses the impact of inclusion of students with disabilities in regular schools on the achievement of the students with disabilities themselves.

Peer effect studies seek to estimate the influence of schoolmates or classmates on individual achievement, having as greatest concern the self-selection, that is, the fact that the

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[1] See, for example, Hanushek, Kain and Rivkin (2002), Farrel *et al*. (2007), Fletcher (2009, 2010), Friesen, Hickey and Krauth (2010), Gottfried (2014), Ruijs (2017), and Balestra, Eugster and Liebert (2019).

[2] See Guidetti, Zoghbi and Terra (2015), and Salvini *et al*. (2019).

assignment of students to schools and classes are not random, which may make estimates less reliable. In the absence of data sets in which peer group variation arises from random assignment, many studies explore data sets in which peer group variation is natural, that is, whose causes are other than self-selection. For example, they explore variation in peer characteristics in time, across cohorts, within schools such as Hoxby (2000), and Lavy and Schlosser (2011), who explore the variation in gender composition and use school fixed effects to deal with potential self-selection across schools.

There is evidence that suggests that schoolmates and classmates with disabilities affect children's cognitive and non-cognitive abilities through two types of mechanisms. First, there are the mechanisms that generate a positive effect: living with students with disabilities can positively affect the interpersonal skills of other schoolmates by increasing their awareness of individual differences (WILLIAMS; DOWNING, 1998); classes with children with disabilities generally receive additional resources, which can positively affect student performance (HANUSHEK; KAIN; RIVKIN, 2002); indeed, classes with children with disabilities require support professionals, and the presence of more qualified adults can improve the performance of all students (CIPANI, 1995). Second, there are the mechanisms that generate adverse effects: students with disabilities are more undisciplined (DANIEL; KING, 1997) and receive more attention from teachers during classes compared to other classmates (DOWNING; EICHINGER; WILLIAMS, 1997). In these circumstances, classmates with disabilities may negatively affect the performance of those students not subject to disabilities.

The following papers empirically evaluate this relationship between having schoolmates or classmates with disabilities and the children's cognitive or non-cognitive abilities: Hanushek, Kain and Rivkin (2002), Farrel et al. (2007), Fletcher (2009, 2010), Friesen, Hickey and Krauth (2010), Gottfried (2014), Ruijs (2017), and Balestra, Eugster and Liebert (2019). These studies do not present a clear picture. On the one hand, Fletcher (2009, 2010), Gottfried (2014), and Balestra, Eugster and Liebert (2019) find a negative peer effect. In both studies, Fletcher (2009, 2010) document that having classmates with severe emotional or behavioral disorders decreases Reading and Math scores by over 10% of a standard deviation in kindergarten and the first grade. Gottfried (2014) finds that a greater number of classmates with disabilities in elementary school adversely affects children's non-cognitive abilities, decreasing up to 4% of a standard deviation of non-cognitive scales. Balestra, Eugster and Liebert (2019) find that one additional student with special needs in a class of 20 in a secondary school reduces test scores by 2.5% of a standard deviation. On the other hand, Hanushek, Kain and Rivkin (2002) find a positive peer effect. Hanushek, Kain and Rivkin (2002) find that an increase of 10 percentage points in the proportion of students with disabilities in the class increases the achievement of the other students in 1.6% of a standard deviation in elementary school. Finally, Friesen, Hickey and Krauth (2010), Farrel et al. (2007), and Ruijs (2017) find a statistically insignificant peer effect.

In Brazil, to our knowledge, the only earlier empirical investigation of the relationship between having classmates with disabilities and the children's cognitive abilities is Guidetti, Zoghbi and Terra (2015). Using data from a panel of students from the city of São Paulo, gathered from Prova São Paulo, and the method of difference-in-differences, the authors estimate the effect of the presence of students with disabilities in class on the Math performance of the students without disabilities. In general, they find no evidence of the existence of an effect. Only by quantile regression, they see that in some quantiles there is an adverse effect on students without disabilities. These results suggest that the peer effect is heterogeneous in the distribution.

The inclusion of students with disabilities in regular schools also affects their own achievement by two types of mechanisms. On the one hand, the sense of inclusion and belonging to society can positively influence the cognitive and non-cognitive skills of students with disabilities. On the other hand, non-specialized support, insensitive classmates, and the sense of exclusion may negatively affect their abilities (TAPASAK; WALTER-THOMAS, 1999; PEETSMA *et al*., 2001).

As Odom *et al.* (2005) observe, it is difficult to apply quantitative methods to research on special education since the relatively small number of students with disabilities requires large samples to have adequate statistical power to detect effects. Thus, there are rare studies that evaluate inclusive special education or special education services, and most of them are case studies or with qualitative approaches, such as Tapasak and Walther-Thomas (1999), and Peetsma *et al*. (2001). Exceptions are Morgan *et al.* (2010), and Salvini *et al.* (2019). Morgan *et al.* (2010) use propensity score matching techniques to examine the effectiveness of American special education services. Their results indicate that the receipt of special education services has a negative or a statistically nonsignificant impact on Reading or Mathematics skills and a small positive effect on learning-related behaviors. Salvini *et al.* (2010) also use propensity score matching techniques. They evaluate the impact of the Brazilian Specialized Educational Assistance on age-grade distortion. Their results indicate a positive impact of the program for ten among thirteen groups of disability types.

2.2 METHODOLOGY

This paper has two different objectives. Each of the research questions has its specificities, requiring its own methodology. Thus, we use different methodologies to satisfy each of the objectives of this study. Next, we explain both empirical strategies.

2.2.1 Impact of the inclusion on the schoolmates

The first objective of this paper is to analyze the impact of the inclusion of students with disabilities on the achievement of their schoolmates. In other words, we investigate how exposure to special needs students affects peers' achievement. We focus on peer externalities in grade-cohort in a school due to the data limitations, following Hoxby (2000) and Lavy and Schlosser (2011).

For this first objective, our econometric model can be expressed in the following way:

$$Y_{ist} = \gamma D_{st} + \boldsymbol{X'}_{\boldsymbol{ist}}\beta + \boldsymbol{S'}_{\boldsymbol{st}}\delta + \alpha_s + \alpha_t + \alpha_e t + \varepsilon_{ist} \tag{1}$$

where Y_{ist} is the normalized Sciences, Humanities, Languages, Math or Writing score of the student i at school s and year t, and D_{st} is the measure regarding children with disabilities in the last grade of High School at school s and year t. The term $\boldsymbol{X_{ist}}$ is a vector with individual control variables, which includes: sex, race, age, family's real income per capita, and dummies for the mother's education. The term $\boldsymbol{S_{st}}$ is a vector with the school grade averages of individual control variables (proportion of females, proportion of whites and mean age), and total and squared enrollment in the last grade of High School. The model also includes school and year fixed effects, α_s and α_t, respectively, and state linear time trends, $\alpha_e t$.

We explore the natural variation in time in the number of kids with disabilities. Our identification assumption is that, conditional on observed characteristics, time and school fixed effects, the variation of individuals with disabilities within schools across cohorts is exogenous. In other words, the year-to-year change in the composition of individuals with disabilities in schools must be independent of time-varying unobserved characteristics that affect students' grades.

The main reason we assume that within-school variation of students with disabilities cohorts is random is that Brazilian allocation of students in public schools depends on geographical variables. The place of residence is the primary determinant of the school in which he or she enrolls. It is plausible that parents might choose the neighborhood according to some school's characteristics, which could potentially invalidate our identification assumption. We believe, however, that in Brazil - a developing country - this is unlikely to happen. Unlike developed countries, families of low income are the main users of the public school system, and they face high moving costs. Rich and middle class prefer to enroll their children in private schools.

In spite of our hypothesis, we also try to test our identification assumption. We regress the students' characteristics (race, gender, and age) on the proportion of students with disabilities to check if this variable is a predictor. If the percentage of students is uncorrelated with students' characteristics, this would be suggestive evidence that cohort variation within a school is random. We present the results in the Appendix.

2.2.2 Impact of the inclusion on the students with disabilities themselves

The second objective of this paper is to analyze the impact that the inclusion has on the achievement of the students with disabilities themselves. More specifically, this paper aims to calculate the Average Treatment Effect on Treated (ATT) for the students with disabilities who study in regular schools instead of special schools.

Defining Y_{1i} as the outcome (normalized Sciences, Humanities, Languages, Math or Writing score) of student i if he is treated (regular school) and Y_{0i} as the outcome of that student if he is not treated (special school), the Average Treatment Effect (ATE) can be expressed in the following way:

$$E[Y_{1i} - Y_{0i}] \tag{2}$$

The expression above tells us the average effect of the treatment considering individuals that have been treated and individuals that have not. We could also calculate the average treatment only on individuals that receive the treatment. This alternative form is the Average Treatment Effect on Treated. Defining T as an indicator variable that receives a value of 1 if the student is treated, the ATT can be expressed as:

$$E[Y_{1i} - Y_{0i} | T_i = 1] \tag{3}$$

Since we cannot observe the outcome of the student in both situations, we need to estimate the outcome that is missing. If we want to obtain the ATT, we have to find a valid estimate for Y_{0i}.

To calculate the ATT, we use Propensity Score Matching methodologies. The Propensity Score Matching methodologies are based on constructing a control group statistically similar to the treatment group regarding observed characteristics, or rather, regarding the propensity score of being treated, to avoid self-selection bias. Each member of the treatment group has a pair, or a few pairs, in the control group that represents the outcome that he would have obtained if untreated (counterfactual). When comparing the pairs, the only factor that differentiates the outcome is the participation or not in the treatment.

Some assumptions are required to use this method. First, $(Y_{1i};\ Y_{0i})\ \perp T_i|X_i$, that is, the potential outcome is independent of the treatment, conditional on the observed characteristics. Second, $0 < Pr(T_i = 1)|X_i < 1$, that is, there is no value of X for which it can be said with certainty that the student is treated or not. Combining these two assumptions, the following expression also holds:

$$(Y_{1i}; Y_{0i}) \perp T_i|P(X_i) \tag{4}$$

where the propensity score $P(X_i)$ is the probability of participating in treatment given the student characteristics. Then, the Propensity Score Matching estimator for the ATT can be written as:

$$ATT_{PSM} = E_{p(x)|z=1}\{E[Y_1|T = 1, P(X)] - E[Y_0|T = 0, P(X)]\} \tag{5}$$

To estimate $P(X_i)$, we use a probit model and the following covariates: sex, race, age, family's real income per capita, dummies for the mother's education, dummies for Brazilian regions, and dummies for type of disability (hearing or visual impairment, intellectual disability or autism, and physical disability). We also test the balancing property, that is, independent of being treated or not, students with the same propensity score must have the same distribution of observed characteristics. Table 8 in the Appendix shows the probit results, and Figure 3 in the Appendix shows the overlap between treated and control groups.

We use different matching criteria to assign students in the treatment group to students in the control group based on the propensity score: nearest-neighbor matching, stratification matching, radius matching, and kernel matching. In nearest-neighbor matching, each student in the treatment group is matched to the student(s) in the control group with the most similar propensity score. In stratification matching, the impact of the treatment is the weighted average of the intervals impact. In radius matching, each treated student is matched to the untreated students only among propensity scores within a specific range. Finally, in kernel matching, we use a weighted average of all untreated students to construct the counterfactual match for each treated student. We can compare if the findings with different matching techniques are quite consistent to check their robustness.

2.3 DATA

The main source of our data is the National Exam of Upper Secondary Education (Enem). Enem is a non-mandatory exam used as admission instrument to higher education and as an evaluation instrument of the school performance at the end of secondary education[3]. For our analysis, we standardize all test scores to ease interpretation and comparability with other studies. Besides Sciences, Humanities, Languages, Math and Writing achievement, the data include socio-economical questionnaires of the students.

We take data from several years - from 2012 to 2018. From these data, we use the following information about student characteristics: disability, sex, race, age, family's real income per capita, and mother's education. When the student is concluding the High School in the same year that is taking the exam, we are able to identify his or her school. Therefore, we take into consideration only students in the last grade of High School taking the exam.

The Enem database is the only Brazilian *public* database in which we can identify how the students performs and if he or she has any disabilities. There are the data from National Basic Education Assessment, a biannual assessment of Math and Languages learning for 5th and 9th-grade public school students. However, in these data we do not have the information whether the student has any disabilities.

We merge the Enem data with the Census of Basic Education School, an annual administrative dataset that presents information of all basic education institutions in the country, including the number of students with disabilities, developmental disorders, and high skills or giftedness. Through the School Census, we are able to get a measure regarding students with disabilities within grades within schools. Since Enem is a non-mandatory exam, we cannot obtain the exact number of students with disabilities concluding High School by institution through the exam data. We use this information about students with disabilities in our first empirical exercise, as well as the proportion of female students, the proportion of white students, the mean age of the students, and enrollment.

In our sample, we keep only students of public schools. We exclude children in private schools, because the assignment of students to private schools are not random. Differently, allocation of students in public schools depends on geographical variables and we believe that

[3] The fact Enem is non-mandatory raises self-selection concerns. To address this problem, we run the main model restricting the sample to schools where the participation in Enem exam is 80% or higher. Results are consistent with the full sample results.

in a developing country, like Brazil, it is unlikely that parents choose the neighborhood they live according to some school's characteristics.

We make different sample restrictions for each research question due to its specificities. To answer the first question, we restrict our analysis to students without disabilities in regular education schools. We classify a student as disabled if he or she has a hearing or visual impairment, an intellectual disability, a physical disability, or multiple disability. Then, we exclude students with missing data and students with a test score equals to zero or family's real income equals to zero. We also drop outliers, what excludes approximately 5% of the previous sample: small grade-cohorts (that is, grade-cohorts with less than 20 students); students younger than 16 years and older than 24 years (considering that the ideal age to conclude High School is 17); grade-cohorts with a mean age over than 21; and grade-cohorts with a proportion of students with disabilities over than 10% (which represent 0.2% of the sample).

With the restrictions made, our sample consists of 3,268,511 observations of students concluding the last grade of High School between 2012 and 2018. Table 1 reports annual descriptive statistics. Statistics show that the average percentage of students with disabilities in the last grade of High School have increased, rising from 0.42% to 1.17%. This increase is possibly due to the fact that Brazil has sought and still seeks to universalize access to basic education for disabled children. We use this variation to analyze the peer effects of the students with disabilities.

To answer the second research question, we keep in the sample only students with disabilities younger than 16 years and older than 24 years in urban schools. Again, we exclude students with missing data and students with a test score equals to zero or family's real income equals to zero. Thus, our sample then consists of 125 observations of students in the control group and 10,256 observations of students in the treatment group, as Table 2 shows.

Table 1 – Descriptive statistics by year

	2012	2013	2014	2015	2016	2017	2018	Total
Sciences score (standardized)	-0.1833872	-0.1347765	0.1176226	-0.1165023	-0.0837547	0.3591886	0.1172776	0
	(1.065156)	(0.9977679)	(1.002676)	(0.947793)	(0.9463775)	(0.958297)	(0.9582452)	(1)
Humanities score (standardized)	-0.2295557	-0.3078351	0.2226383	0.2540931	-0.0157312	-0.2606676	0.4078572	0
	(1.03991)	(1.017731)	(0.9113144)	(0.9011328)	(0.9172738)	(0.9918263)	(0.9895198)	(1)
Languages score (standardized)	-0.2388075	-0.2614312	0.1410383	-0.0761795	0.2185068	0.0177723	0.2592253	0
	(1.000261)	(1.079902)	(0.9486458)	(0.9861635)	(0.9422673)	(0.8963644)	(0.9958259)	(1)
Math score (standardized)	0.0965546	0.1683886	-0.1856586	-0.339535	-0.1392661	0.1880591	0.3457208	0
	(1.142698)	(0.9708701)	(0.995943)	(0.9194286)	(0.9094463)	(0.9402954)	(0.9134918)	(1)
Writing score (standardized)	-0.1608304	-0.0396766	-0.1428166	0.092992	0.1275472	0.2318269	-0.1052635	0
	(1.041634)	(0.9917346)	(1.073857)	(0.8584768)	(0.8974845)	(0.8993121)	(1.173632)	(1)
Share of students with disabilities	0.0042321	0.0049393	0.0057468	0.0069607	0.0082926	0.0094458	0.0117707	0.0071026
	(0.0081699)	(0.0090727)	(0.0095445)	(0.0108107)	(0.0118086)	(0.0130807)	(0.0143783)	(0.0112155)
Share of students with hearing or visual impairment	0.0019916	0.0021261	0.0021844	0.0024378	0.002711	0.0028891	0.0031518	0.0024618
	(0.0055639)	(0.0053601)	(0.0054697)	(0.0057662)	(0.0060456)	(0.0066164)	(0.0065724)	(0.0058963)
Share of students with intellectual disability	0.0014905	0.0020415	0.0026763	0.0036277	0.0046782	0.0055325	0.0074286	0.0037377
	(0.0046702)	(0.006049)	(0.0065675)	(0.0078742)	(0.0090726)	(0.009971)	(0.0115957)	(0.0082691)
Share of students with physical disability	0.0008873	0.0009638	0.0011913	0.0012715	0.001409	0.0015879	0.0019388	0.0012892
	(0.0031022)	(0.0032792)	(0.0036307)	(0.0037104)	(0.003882)	(0.0042894)	(0.0047213)	(0.0037978)
Share of students with multiple disability	0.0001315	0.0001769	0.0002896	0.0003603	0.0004838	0.0005443	0.0007128	0.0003682
	(0.0012912)	(0.0014491)	(0.0018793)	(0.0020858)	(0.0024103)	(0.0025328)	(0.0031197)	(0.0021417)
Share of males	0.6054441	0.4027076	0.4062466	0.4042117	0.4057652	0.4061298	0.4105258	0.4343926
	(0.4887556)	(0.4904433)	(0.4911321)	(0.4907393)	(0.49104)	(0.4911099)	(0.4919299)	(0.4956771)
Share of whites	0.4957386	0.4764575	0.4707751	0.423154	0.4212214	0.4070218	0.3996935	0.4446309
	(0.4999824)	(0.4994459)	(0.4991457)	(0.4940599)	(0.4937554)	(0.4912796)	(0.489836)	(0.4969249)
Age	17.58453	17.58381	17.55174	17.57573	17.54692	17.55938	17.60917	17.57146
	(1.038184)	(1.029352)	(0.9759247)	(0.9714156)	(0.9635363)	(0.9218652)	(0.8849411)	(0.9752531)
Family's real income per capita	486.1421	479.4477	490.3162	489.9797	485.0799	488.8931	494.1819	487.3871
	(486.8527)	(505.1671)	(512.3905)	(495.8187)	(488.3467)	(513.5954)	(517.122)	(502.2138)
Mother's education: no education	0.0218585	0.0220683	0.0192707	0.019459	0.0194907	0.0175772	0.0172492	0.0197065
	(0.1462216)	(0.1469058)	(0.1374749)	(0.1381319)	(0.1382418)	(0.1314087)	(0.1301986)	(0.1389899)
Mother's education: 5th grade	0.4557295	0.4419933	0.420984	0.3180068	0.3094401	0.2851656	0.2786422	0.3638562
	(0.4980368)	(0.4966243)	(0.4937175)	(0.4657026)	(0.4622633)	(0.4514938)	(0.4483317)	(0.481108)
Mother's education: 9th grade	0.0841709	0.086226	0.0891158	0.1885214	0.1887699	0.183833	0.1772227	0.1398536
	(0.2776443)	(0.2806978)	(0.2849111)	(0.3911284)	(0.3913261)	(0.3873484)	(0.3818576)	(0.3468351)
Mother's education: High School	0.3226606	0.3299978	0.344677	0.3570011	0.3621923	0.3815825	0.3880737	0.3531887
	(0.4674946)	(0.4702124)	(0.4752633)	(0.4791156)	(0.4806345)	(0.4857755)	(0.4873122)	(0.4779608)
Mother's education: University	0.1155804	0.1197146	0.1259526	0.1170116	0.1201071	0.1318417	0.1388122	0.123395
	(0.3197215)	(0.3246278)	(0.3317962)	(0.3214345)	(0.325087)	(0.338319)	(0.3457509)	(0.3288901)
Enrollment	204.2154	197.4405	193.3561	188.697	194.3918	190.7782	189.6008	194.2875
	(148.8163)	(140.974)	(136.3264)	(133.472)	(136.6369)	(138.4943)	(143.4954)	(139.6935)
No. of Obs.	**469,794**	**511,458**	**522,141**	**485,738**	**506,140**	**421,513**	**351,727**	**3,268,511**

Standard errors in parentheses.
Source: Elaborated by the author.

Table 2 – Descriptive statistics by group

	Control group (Special school)	Treatment group (Regular school)
Sciences score (standardized)	-0.3981767 (1.012617)	0.004853 (0.9989166)
Humanities score (standardized)	-0.4558565 (1.025804)	0.005556 (0.9984496)
Languages score (standardized)	-0.4958077 (0.9996944)	0.0060429 (0.9985349)
Math score (standardized)	-0.2428263 (0.8370885)	0.0029596 (1.001493)
Writing score (standardized)	-0.186156 (1.202376)	0.0022689 (0.9971362)
Share of students with hearing or visual impairment	0.768 (0.4238076)	0.5431942 (0.4981551)
Share of students with intellectual disability	0.032 (0.1767083)	0.086681 (0.2813807)
Share of students with physical disability	0.208 (0.4075101)	0.4015211 (0.4902299)
Share of males	0.496 (0.501996)	0.50039 (0.5000242)
Share of whites	0.48 (0.5016103)	0.4726989 (0.4992784)
Age	19.312 (1.696372)	18.49678 (1.600338)
Family's real income per capita	475.5652 (436.5752)	479.6881 (512.9643)
Mother's education: no education	0.024 (0.1536649)	0.024766 (0.1554188)
Mother's education: 5th grade	0.384 (0.4883151)	0.3466264 (0.4759187)
Mother's education: 9th grade	0.152 (0.3604656)	0.1421607 (0.3492319)
Mother's education: High School	0.312 (0.4651743)	0.3423362 (0.4745146)
Mother's education: University	0.128 (0.3354342)	0.1441108 (0.3512191)
No. of Obs.	**125**	**10,256**

Standard errors in parentheses.
Source: Elaborated by the author.

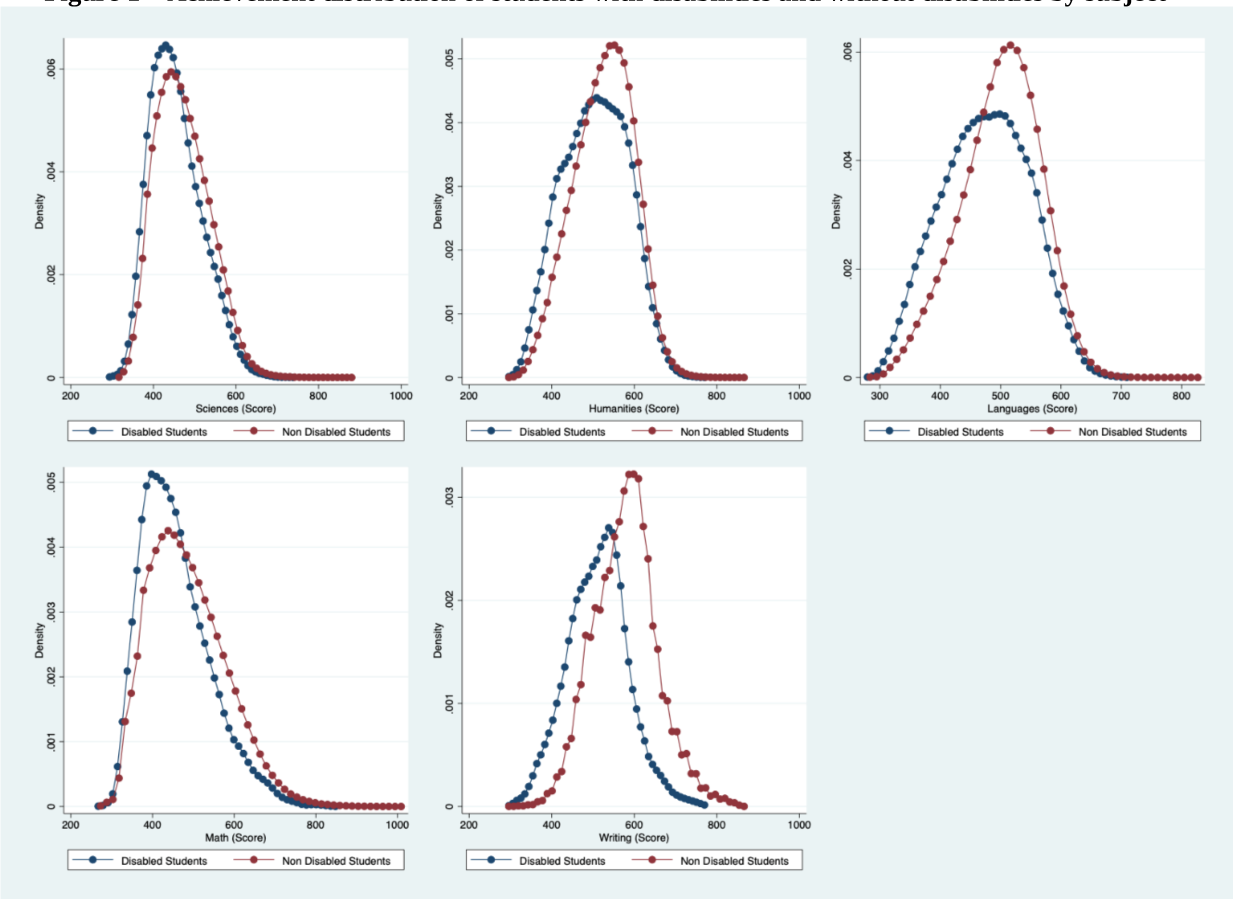
2.4 RESULTS

In this section, we describe our results. First, we present our findings for the impact of the inclusion of students with disabilities in regular schools on the achievement of their schoolmates. Next, we present our findings for the impact that the inclusion has on the achievement of the students with disabilities themselves.

2.4.1 Impact of the inclusion on the students with disabilities themselves

We begin by showing on Figure 1 the achievement distributions of students with disabilities (blue curve) and without disabilities (red curve) for each subject. We observe that the blue curve is more to the left than the red one, that is, students with disabilities perform slightly worse than students without disabilities. This score difference becomes more evident in Languages and Writing. From this figure, we can assume that a large proportion of students with disabilities have learning difficulties. The potential learning difficulties can affect negatively their peers and, for this reason, we may expect an adverse peer effect.

Figure 1 – Achievement distribution of students with disabilities and without disabilities by subject



Source: Elaborated by the author.

In order to investigate this potential adverse peer effect problem, we estimate our main econometric model. We present our first results in Table 3. The table reports the effects of the exposure to peers with disabilities on standardized Sciences, Humanities, Languages, Math, and Writing scores. All regressions include individual covariates, grade averages, school and time fixed effects, and state time linear trends, and standard errors are clustered at the school level. Results show that students tend to perform a little worse in Writing when in schools with a higher proportion of children with disabilities in their grade. In other subjects, we find weak or none evidence of a statistically significant peer effect. The complete table with the coefficients of the control variables is in the Appendix.

We use three different definitions of the treatment variable. The first definition is the percentage of peers with disabilities; the second is the total number of peers with disabilities; and the third is a binary variable that is one if there is at least one peer with disabilities in the school grade and zero otherwise. Results show that an additional percentage point in the proportion of students with disabilities would reduce, for High School 3rd-graders, Writing scores by 0.0032 standard deviation. From the other definitions, we have that an additional student with disabilities would reduce Writing scores by 0.002 standard deviation, and the presence of a student with disabilities would reduce Writing scores by 0.005 standard deviation. All estimates regarding Writing score are statistically significant at the 5% level.

Table 3 – Determinants of student achievement by subject - Impact of students with disabilities

	Sciences	**Humanities**	**Languages**	**Math**	**Writing**
A. First Specification					
Students with disabilities (Share)	-0.0986096 (0.0811)	-0.1034235 (0.0789)	-0.1103299 (0.0765)	-0.0039094 (0.0762)	-0.3217965*** (0.0933)
B. Second Specification					
Students with disabilities (No.)	-0.0011144* (0.0006)	-0.0018910*** (0.0006)	-0.0021819*** (0.0006)	-0.0008613 (0.0006)	-0.0024378*** (0.0008)
C. Third Specification					
Students with disabilities (0 or 1)	-0.0015058 (0.0019)	-0.0032210* (0.0018)	-0.0027758 (0.0017)	-0.0022641 (0.0019)	-0.0046897** (0.0021)
Individual controls	✓	✓	✓	✓	✓
Grade averages controls	✓	✓	✓	✓	✓
School fixed effect	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
State time linear trend	✓	✓	✓	✓	✓
No. of Obs.	3268511	3268511	3268511	3268511	3268511

Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

In our second empirical exercise, we estimate the same model breaking our treatment variable into four variables. We use objective disability categorizations in order to remove the variation from subjective disability designations, which are more likely to be endogenous. The categorizations are: (1) hearing or visual impairment, (2) intellectual disability, (3) physical disability, and (4) multiple disability. Among the four categorizations, just one presents significant results - intellectual disability. Therefore, the results in Table 4 show that students tend to perform a little worse when in schools with a higher proportion of children with intellectual disability in their grade.

Table 4 – Determinants of student achievement by subject - Impact of students with disabilities by type

	Sciences	Humanities	Languages	Math	Writing
Students with hearing or visual impairment (Share)	0.0683788 (0.1519)	0.1263924 (0.1432)	-0.1425421 (0.1398)	-0.0880421 (0.1434)	-0.0350232 (0.1669)
Students with intellectual disability (Share)	-0.2116382^{*} (0.1089)	-0.2757320^{**} (0.1089)	-0.1025426 (0.1059)	0.0944877 (0.0990)	-0.4532622^{***} (0.1273)
Students with physical disability (Share)	-0.1424981 (0.2235)	0.0822321 (0.2177)	-0.0470725 (0.2086)	-0.2705291 (0.2071)	-0.3835794 (0.2436)
Students with multiple disability (Share)	0.3597898 (0.3813)	-0.0030028 (0.3965)	-0.0614884 (0.3857)	0.3596920 (0.3713)	-0.2456671 (0.4521)
Individual controls	✓	✓	✓	✓	✓
Grade averages controls	✓	✓	✓	✓	✓
School fixed effect	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
State time linear trend	✓	✓	✓	✓	✓
No. of Obs.	3268511	3268511	3268511	3268511	3268511
F-test	2212	4131	2873	3088	1705

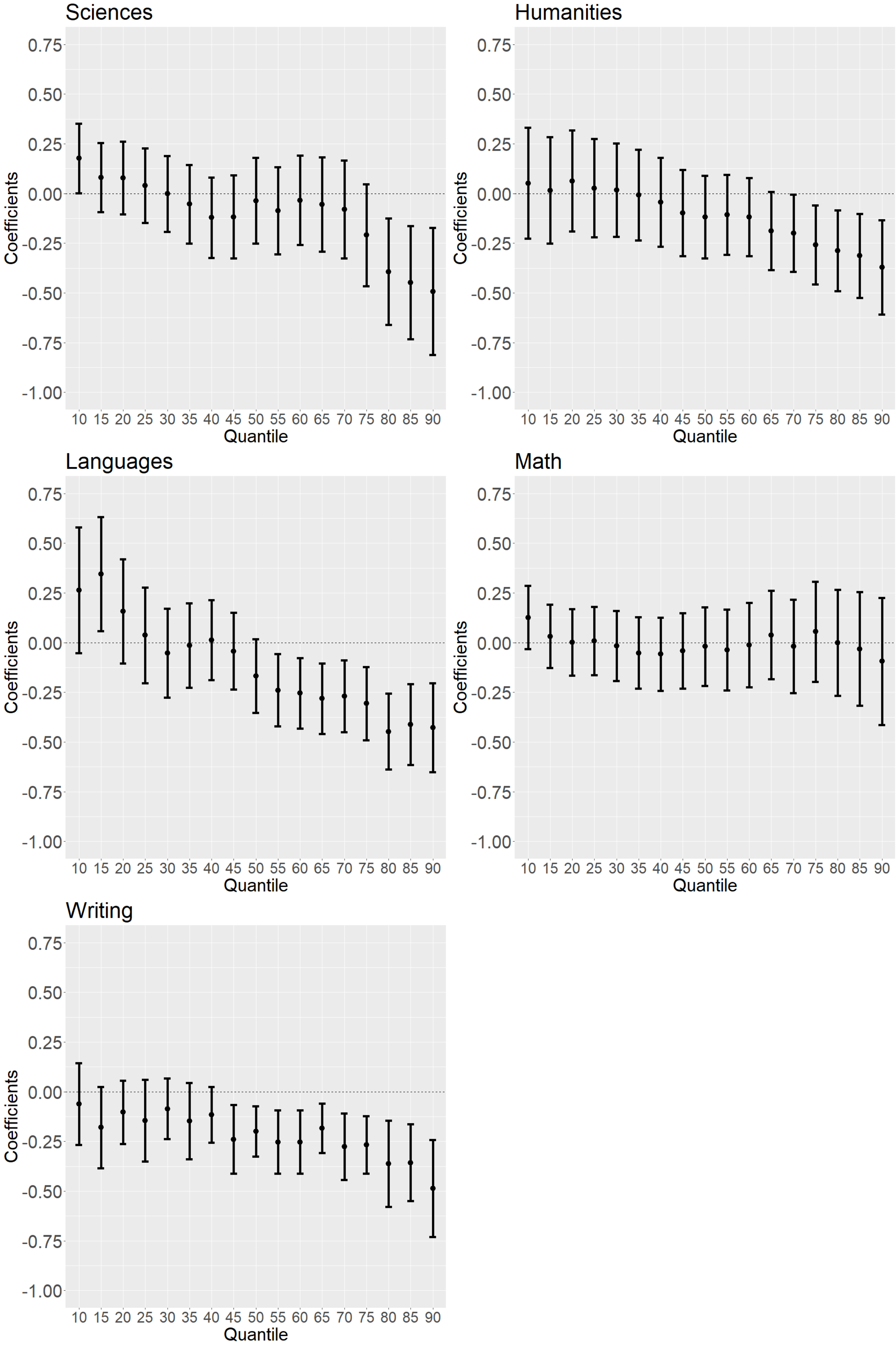
Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

Taking both empirical exercises into account, we find that most of the net negative impact of students with disabilities is small and statistically insignificant. It is possible to conjecture that in Brazil the mechanisms by which schoolmates with disabilities negatively affect children's cognitive abilities are almost entirely compensated by the mechanisms that affect positively. This conclusion corroborates the earlier empirical investigation of the relationship between having peers with disabilities and the children's cognitive abilities in Brazil, Guidetti, Zoghbi and Terra (2015).

The previous empirical exercises give us the average marginal effect. It is plausible that, while the average peer effects of students with disabilities are small, the effect on specific quantiles of the achievement distribution can be larger and more significant. In order to access the possibility of heterogeneous across the achievement distribution, we do a third empirical exercise using unconditional quantile regression approach developed by Firpo, Fortin and Lemieux (2009). The results are shown in Figure 2, which plots quantile treatment effects and the respective 95% confidence intervals for different percentiles of the achievement distribution. We find that high-achieving students are more strongly affected by the proportion of students with disabilities than the low-achieving ones.

More specifically, we find that the peer effect is statistically insignificant at the bottom percentiles, with very few positive exceptions. The effects at top percentiles, in turn, are negative and statistically significant. Only in Math, we do not see any significant result. Castro and Villacorta (2019) show that the productivity of schooling and inputs are a complement to the children's learning only if their complexity exceeds the children's skills. Thus, a possible explanation to our result is that teachers reduce the pace of teaching so that students with disabilities, with greater learning difficulties, can understand the subject, harming students with learning facility.

Figure 2 – Quantile Effects of Peers with Disabilities



Source: Elaborated by the author.

2.4.1.1 Competency assessment

The Enem is composed of 180 multiple-choice questions - 45 questions per subject - plus an essay. All questions are prepared following a reference matrix of competencies and skills. Each question must assess a single skill within a competency. The reference matrix allows us to see in which particular competency and skills the students have struggled more and where they have succeeded. We will use this reference matrix (shown in the Appendix) to investigate further the heterogeneous effects of exposure to disabled students.

Even though we found statistically significant negative peer effects of disabled students on some subjects, we do not know which assessed competencies are responsible for these results. If we knew more specifically which competencies are being affected by exposure to disabled students, we could be able to think about and design policies to correct this adverse peer effect. To achieve this goal, we will regress a measure of student performance *by competency* within a subject. The subjects we have chosen are Writing and Humanities because they were the only subjects where we have found two or more statistically significant effects in our first empirical exercise (see Table 3). Our measure of student performance by competency for Humanities is the student's percentage of correct answers in questions involving the analyzed competency. The measure for Writing is the student's standardized score in each competency[4].

We present the results in Table 5. The table shows the estimated coefficients for each competency in Humanities and Writing of the share of disabled students in the grade. The Humanities exam evaluates six competencies and, of those six, in only two of them (H2 and H3), the peer effect of disabled students is negative and statistically significant. The Writing exam, on the other hand, evaluates five competencies and, of those five, four of them (W2 to W5) are statistically significant.

These results corroborate our initial findings. It seems that, although small, the adverse peer effects of students with disabilities are stronger in Writing than Humanities. The impact in Writing comes through most competencies, while in Humanities, the negative implications occur through only two. Therefore, it might be potentially easier to mitigate the negative effect on the former subject than in the latter.

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[4] The Writing score is calculated differently from the other scores. The essay total score is equal to the sum of the scores in each of the five competencies. The score of each competency ranges from 0 to 200, and, consequently, the Writing score goes from 0 to 1000. Total scores in other subjects are calculated based on the Item Response Theory, and there are no grades per competency. Therefore, for our analysis by competency in subjects with objective tests, we use a different variable, the accuracy rate.

Table 5 – Determinants of student achievement by competency - Impact of students with disabilities

	Humanities					
	H1	**H2**	**H3**	**H4**	**H5**	**H6**
Coefficients	-0.0058377	-0.0307618*	-0.0286785**	0.0112190	-0.0095133	-0.0067305
	(0.0153)	(0.0173)	(0.0144)	(0.0161)	(0.0164)	(0.0163)
No. of Obs.	3267252	3267252	3267252	3267252	3267252	3267252
F-test	2184	1995	2767	7426	2177	2725
	Writing					
	W1	**W2**	**W3**	**W4**	**W5**	
Coefficients	-0.0761314	-0.3489530***	-0.3665280***	-0.0686498	-0.3625994***	
	(0.0771)	(0.0929)	(0.0906)	(0.0859)	(0.1007)	
No. of Obs.	3268511	3268511	3268511	3268511	3268511	
F-test	1947	1537	1723	1621	1296	
Individual controls	✓	✓	✓	✓	✓	✓
Grade averages controls	✓	✓	✓	✓	✓	✓
School fixed effect	✓	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓	✓
State time linear trend	✓	✓	✓	✓	✓	✓

Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

2.4.2 Impact of the inclusion on the students with disabilities themselves

In the previous section, we analyze the effect of including students with disabilities in mainstream schools on their non-disabled peers. For a complete analysis of the inclusion policy, we also need to analyze the effect on students with disabilities themselves. Then, in this section, we present our estimated results of the effect of inclusion on students with disabilities themselves.

Table 6 reports the Propensity Score Matching estimates of the ATT. Our preferred methodology is Kernel Matching. For this Propensity Score Matching methodology, the standard errors are calculated by bootstrapping. We also consider alternative matching criteria to check the robustness of our findings. Results show that students with disabilities tend to perform better when enrolled in regular schools rather than special schools, especially in Humanities and Languages. In our preferred methodology, the differences between the treatment and control groups are all statistically significant at 1%, except in Writing.

More specifically, results show that the mean score on Humanities is 46% of a standard deviation higher among students with disabilities enrolled in regular schools compared to those who are enrolled in special schools. Using the alternative methodologies, the estimates are close to the previous value, going from 33% to 36% of a standard deviation.

Similarly, the mean score on Languages is 48% of a standard deviation higher among the treated students, ranging from 29% to 32% when using the alternative methodologies. The results are smaller for the other subjects and are not significant in the alternative methodologies.

Therefore, we conclude that there is a positive impact of the inclusion of students with disabilities in regular schools on their achievement. This impact is bigger for Humanities and Languages. For these subjects, we find results of considerable size using the Kernel Matching, but also the other alternative matching criteria corroborate our findings. For the other subjects, Sciences, Math, and Writing, our findings are not robust.

Thus, it is possible that students with disabilities enrolled in regular schools develop a sense of inclusion and belonging to society that influences non-cognitive skills and, hence, cognitive skills. It is possible that this impact on cognitive skills is more visible in subjects like Humanities and Languages compared to Math and Exact Sciences. It is also possible that this result is due to peer effect, that is, a student with disability in a regular school may have classmates with better achievement.

Table 6 – Propensity Score Matching estimates of the ATT

Matching	Sciences	Humanities	Languages	Math	Writing
Nearest-Neighbor Matching	0.188	0.356**	0.319**	0.129	0.078
(with replacement)	(0.142)	(0.144)	(0.140)	(0.118)	(0.169)
Stratification Matching	0.127	0.346***	0.292***	0.148	0.117
	(0.106)	(0.115)	(0.106)	(0.110)	(0.115)
Radius Matching (0.001)	0.147	0.334***	0.287***	0.113	0.091
	(0.119)	(0.121)	(0.118)	(0.099)	(0.141)
Epanechnikov Kernel	0.391***	0.464***	0.483***	0.234***	0.164
Matching (bandwidth=0.06)	(0.109)	(0.103)	(0.086)	(0.078)	(0.094)

Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

2.5 FINAL REMARKS

This paper has presented empirical evidence that students with disabilities tend to perform better when enrolled in regular schools rather than special schools, but students in general tend to perform a little worse when in schools with a higher proportion of children with disabilities in their grade. In summary, our evaluation is that inclusion policies achieve the goal of improving the performance of students with disabilities but such policies have a small and adverse side effect. For this reason, when designing inclusion policies, an effort has to be made to minimize this and other potential side effects.

We believe that this paper provides an essential contribution to the still small literature that evaluates the effects of the inclusion of students with disabilities in regular schools. We have shown that the negative peer effect of students with disabilities on students without disabilities concentrates on specific subjects: Writing and Humanities. The effect tends to be higher on students on the top percentiles of the grade distribution. Moreover, we have identified through which competencies within a subject the negative effect comes. The effect seems more widespread in Writing than Humanities. We hope that these findings will help teachers and school principals to guide their resources better to mitigate the small adverse effects of inclusion on students without disabilities.

To continue this line of research, we suggest that the effects of the inclusion on non-cognitive abilities be evaluated.

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APPENDIX

Table 7 – Balancing Test - Regular Schools

	(1) Sex (male = 1)	(2) Race (white = 1)	(3) Age
Students with disabilities (Share)	0.0345562 (0.0299)	-0.0213853 (0.0342)	0.1332370 (0.1030)
Sex (male = 1)		-0.0059430*** (0.0004)	-0.2008487*** (0.0018)
Race (white = 1)	-0.0083679*** (0.0006)		-0.1369402*** (0.0018)
Age	-0.0372750*** (0.0003)	-0.0180496*** (0.0003)	
Enrollment	-0.0000283*** (0.0000)	0.0000027 (0.0000)	-0.0000712 (0.0001)
School fixed effect	✓	✓	✓
Time fixed effect	✓	✓	✓
No. of Obs.	4598919	4598919	4598919
F-test	1404	496	1666

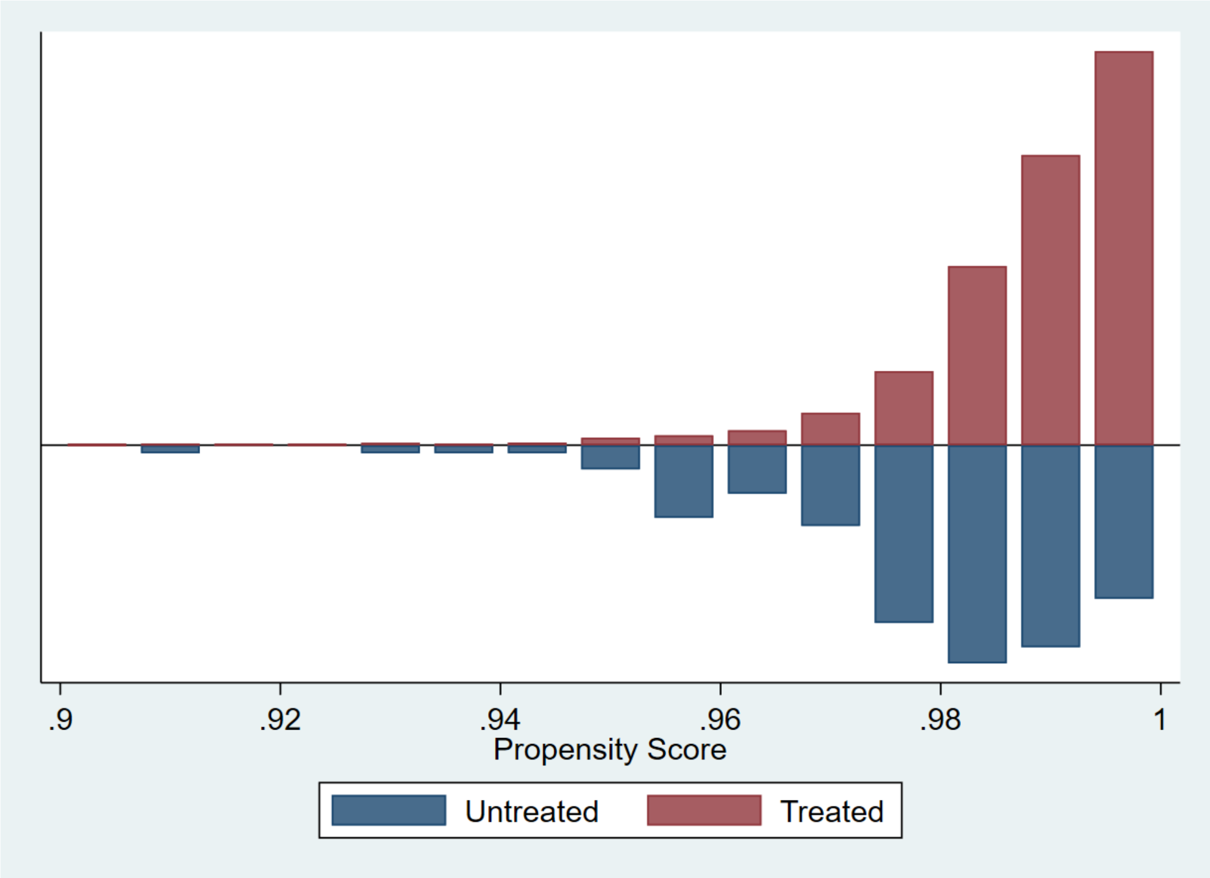
Standard errors in parentheses.
$^{*}p<0.10$, $^{**}p<0.05$ ***, $p<0.01$.
Source: Elaborated by the author.

Table 8 – Probit results

Variables	Coefficients
Students with hearing or visual impairment (Share)	0.2328907
	(0.3574259)
Students with intellectual disability (Share)	0.843765**
	(0.37819)
Students with physical disability (Share)	0.5925421*
	(0.3545666)
Sex (male=1)	0.009886
	(0.0714073)
Race (white=1)	0.0311347
	(0.0761865)
Age	-0.1289442***
	(0.0205354)
Family's real income per capita	0.0000008
	(0.0000796))
Mother's education: 5th grade	-0.0871087
	(0.241064)
Mother's education: 9th grade	-0.1442257
	(0.2525652)
Mother's education: High School	-0.1110518
	(0.2442397)
Mother's education: University	-0.1129966
	(0.2604004)
Brazilian region: Northeast	-0.0499216
	(0.1650231)
Brazilian region: Southeast	-0.3492776**
	(0.1526952)
Brazilian region: South	-0.3924392**
	(0.1699944)
Brazilian region: Middle-West	-0.3718745**
	(0.1703111)
No. of Obs.	10381
LR Chi2	78.19

Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

Figure 3 – Propensity score of observations in common support region



Source: Elaborated by the author.

Table 9 - Determinants of student achievement by subject - Share of students with disabilities

	Sciences	Humanities	Languages	Math	Writing
Students with disabilities (Share)	-0.0986096	-0.1034235	-0.1103299	-0.0039094	-0.3217965***
	(0.0811)	(0.0789)	(0.0765)	(0.0762)	(0.0933)
Sex (male=1)	0.1570085***	0.0916324***	-0.0198449***	0.2212879***	-0.1516631***
	(0.0013)	(0.0012)	(0.0012)	(0.0015)	(0.0013)
Race (white=1)	0.0720220***	0.0648887***	0.0806666***	0.0802763***	0.0537488***
	(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0012)
Age	-0.0904618***	-0.1164287***	-0.1412476***	-0.1216838***	-0.1525981***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)
Family's real income per capita	0.0001680***	0.0001585***	0.0001648***	0.0001818***	0.0001239***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mother's education: 5th grade	0.0281501***	0.0244763***	0.0483653***	0.0569069***	0.0648449***
	(0.0034)	(0.0037)	(0.0038)	(0.0033)	(0.0040)
Mother's education: 9th grade	0.0617204***	0.0626728***	0.0998007***	0.1077714***	0.0986806***
	(0.0037)	(0.0039)	(0.0040)	(0.0035)	(0.0041)
Mother's education: High School	0.1239992***	0.1298441***	0.1720754***	0.1687621***	0.1484860***
	(0.0036)	(0.0038)	(0.0039)	(0.0034)	(0.0041)
Mother's education: University	0.1857458***	0.1826322***	0.2235752***	0.2146722***	0.1921804***
	(0.0040)	(0.0042)	(0.0042)	(0.0039)	(0.0045)
Females (Share)	-0.0499727***	0.0002284	0.1051948***	-0.1106579***	0.2197320***
	(0.0147)	(0.0144)	(0.0139)	(0.0144)	(0.0166)
Whites (Share)	0.0424561***	0.0230895**	0.0121606	0.0298706***	0.0267134**
	(0.0095)	(0.0095)	(0.0088)	(0.0095)	(0.0106)
Mean age	-0.0032065	-0.0097676***	-0.0063828***	-0.0130406***	-0.0062091**
	(0.0025)	(0.0025)	(0.0024)	(0.0025)	(0.0030)
Enrollment	-0.0004746***	-0.0003650***	-0.0003393***	-0.0003500***	-0.0002047***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Squared Enrollment	0.0000003***	0.0000002**	0.0000002**	0.0000003***	0.0000001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
School fixed effect	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
State time linear trend	✓	✓	✓	✓	✓
No. of Obs.	3268511	3268511	3268511	3268511	3268511
F-test	2351	4395	3059	3287	1815

Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

Table 10 - Determinants of student achievement by subject - Number of students with disabilities

	Sciences	Humanities	Languages	Math	Writing
Students with disabilities (No.)	-0.0011144*	-0.0018910***	-0.0021819***	-0.0008613	-0.0024378***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0008)
Sex (male=1)	0.1570068***	0.0916285***	-0.0198496***	0.2212854***	-0.1516651***
	(0.0013)	(0.0012)	(0.0012)	(0.0015)	(0.0013)
Race (white=1)	0.0720242***	0.0648926***	0.0806711***	0.0802780***	0.0537537***
	(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0012)
Age	-0.0904616***	-0.1164288***	-0.1412477***	-0.1216842***	-0.1525970***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)
Family's real income per capita	0.0001680***	0.0001585***	0.0001648***	0.0001818***	0.0001239***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mother's education: 5th grade	0.0281444***	0.0244660***	0.0483532***	0.0569016***	0.0648339***
	(0.0034)	(0.0037)	(0.0038)	(0.0033)	(0.0040)
Mother's education: 9th grade	0.0617108***	0.0626579***	0.0997837***	0.1077656***	0.0986575***
	(0.0037)	(0.0039)	(0.0040)	(0.0035)	(0.0041)
Mother's education: High School	0.1239927***	0.1298323***	0.1720616***	0.1687561***	0.1484732***
	(0.0036)	(0.0038)	(0.0039)	(0.0034)	(0.0041)
Mother's education: University	0.1857383***	0.1826193***	0.2235603***	0.2146661***	0.1921642***
	(0.0040)	(0.0042)	(0.0042)	(0.0039)	(0.0045)
Females (Share)	-0.0501589***	-0.0003634	0.1044731***	-0.1111140***	0.2197829***
	(0.0147)	(0.0145)	(0.0139)	(0.0144)	(0.0166)
Whites (Share)	0.0426450***	0.0234566**	0.0125906	0.0300691***	0.0270498**
	(0.0095)	(0.0095)	(0.0088)	(0.0095)	(0.0106)
Mean age	-0.0032021	-0.0097087***	-0.0063076***	-0.0129790***	-0.0062852**
	(0.0025)	(0.0025)	(0.0024)	(0.0025)	(0.0030)
Enrollment	-0.0004660***	-0.0003513***	-0.0003236***	-0.0003443***	-0.0001844***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Squared Enrollment	0.0000003***	0.0000002**	0.0000002**	0.0000003***	0.0000001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
School fixed effect	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
State time linear trend	✓	✓	✓	✓	✓
No. of Obs.	3268511	3268511	3268511	3268511	3268511
F-test	2350	4398	3061	3288	1818

Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

Table 11 - Determinants of student achievement by subject - At least one student with disabilities

	Sciences	Humanities	Languages	Math	Writing
Students with disabilities (0 or 1)	-0.0015058	-0.0032210*	-0.0027758	-0.0022641	-0.0046897**
	(0.0019)	(0.0018)	(0.0017)	(0.0019)	(0.0021)
Sex (male=1)	0.1570092***	0.0916321***	-0.0198448***	0.2212866***	-0.1516607***
	(0.0013)	(0.0012)	(0.0012)	(0.0015)	(0.0013)
Race (white=1)	0.0720222***	0.0648892***	0.0806670***	0.0802766***	0.0537494***
	(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0012)
Age	-0.0904618***	-0.1164293***	-0.1412480***	-0.1216847***	-0.1525980***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)
Family's real income per capita	0.0001680***	0.0001585***	0.0001648***	0.0001818***	0.0001239***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mother's education: 5th grade	0.0281520***	0.0244792***	0.0483680***	0.0569080***	0.0648512***
	(0.0034)	(0.0037)	(0.0038)	(0.0033)	(0.0040)
Mother's education: 9th grade	0.0617200***	0.0626743***	0.0998015***	0.1077739***	0.0986791***
	(0.0037)	(0.0039)	(0.0040)	(0.0035)	(0.0041)
Mother's education: High School	0.1240010***	0.1298465***	0.1720778***	0.1687628***	0.1484917***
	(0.0036)	(0.0038)	(0.0039)	(0.0034)	(0.0041)
Mother's education: University	0.1857460***	0.1826323***	0.2235754***	0.2146720***	0.1921810***
	(0.0040)	(0.0042)	(0.0042)	(0.0039)	(0.0045)
Females (Share)	-0.0497252***	0.0002937	0.1053426***	-0.1109090***	0.2205663***
	(0.0147)	(0.0145)	(0.0139)	(0.0144)	(0.0166)
Whites (Share)	0.0424175***	0.0230850**	0.0121413	0.0299173***	0.0265826**
	(0.0095)	(0.0095)	(0.0088)	(0.0095)	(0.0106)
Mean age	-0.0032441	-0.0097614***	-0.0063945***	-0.0129808***	-0.0063381**
	(0.0025)	(0.0025)	(0.0024)	(0.0025)	(0.0030)
Enrollment	-0.0004706***	-0.0003578***	-0.0003328***	-0.0003458***	-0.0001919***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Squared Enrollment	0.0000003***	0.0000002**	0.0000002**	0.0000003***	0.0000001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
School fixed effect	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓
State time linear trend	✓	✓	✓	✓	✓
No. of Obs.	3268511	3268511	3268511	3268511	3268511
F-test	2351	4395	3060	3289	1814

Standard errors in parentheses.
* p<0.10, ** p<0.05 ***, p<0.01.
Source: Elaborated by the author.

Table 12 - Reference Matrix of Competencies - Sciences

S1 - To understand natural sciences and technologies associated as human constructions, perceiving their roles in production processes and in social and economic development of mankind.
S2 - To identify the presence and apply the technologies associated with natural sciences in different contexts.
S3 - To associate interventions that result in environmental degradation or conservation to productive and social processes and to scientific-technological instruments or actions.
S4 - To understand the interactions between organisms and environment, particularly those related to human health, connecting scientific knowledge, cultural aspects and individual characteristics.
S5 - To understand methods and procedures pertinent to natural sciences, and apply them in different contexts.
S6 - To appropriate of physics knowledge to, in problem-situations, interpret, evaluate or plan scientific-technological interventions.
S7 - To appropriate of chemistry knowledge to, in problem-situations, interpret, evaluate or plan scientific-technological interventions.
S8 - To appropriate of biology knowledge to, in problem-situations, interpret, evaluate or plan scientific-technological interventions.

Source: ENEM/Inep.

Table 13 - Reference Matrix of Competencies - Humanities

H1 - To understand the cultural elements that make up identities.
H2 - To understand the transformations of geographical spaces as a product of socioeconomic and cultural relations of power.
H3 - To understand the production and the historical role of social, political and economic institutions, association them with different groups, conflicts and social movements.
H4 - To understand technical and technological transformations and their impact on production processes, on the development of knowledge and on social life.
H5 - To use historical knowledge to understand and value the fundamentals of citizenship and of democracy, favoring conscious action of the individual in society.
H6 - To understand society and nature, recognizing their interactions in space through different historic and geographic contexts.

Source: ENEM/Inep.

Table 14 - Reference Matrix of Competencies - Languages

L1 - To apply communication and information technologies at school, at work and in other contexts relevant to life. L2 - To know and use modern foreign language(s) as instrument of access to information, other cultures, and social groups. L3 - To understand and use body language as relevant for life, social integration and identity building. L4 - To understand art as a cultural and aesthetic knowledge, creator of meaning and integrator of world organization and self-identity. L5 - To analyze, interpret, and apply expressive resources of languages, relating texts to their contexts, according to the nature, function, organization, structure of manifestations and within the conditions of production and reception. L6 - To understand and use the symbolic systems of the different languages as a mean of cognitive organization of reality through the constitution of meanings, expressions, communication and information. L7 - To contrast opinions and points of view about different languages and their specific manifestations. L8 - To understand and use the Portuguese language as mother tongue, creator of meaning, and integrator of world organization and self-identity. L9 - To understand the principles, nature, function and impact of communication and information technologies in personal and social life, in knowledge development, associating it with scientific knowledge, languages that support them, the other technologies, the processes of production and the problems they propose to solve.

Source: ENEM/Inep.

Table 15 - Reference Matrix of Competencies - Math

M1 - To build meanings for natural, integer, rational and real numbers. M2 - To use geometric knowledge to perform the reading and representation of reality and act over it. M3 - To build notions of quantities and measures for the understanding of reality and solving everyday problems. M4 - To build notions of variation of quantities for the understanding of reality and solving everyday problems. M5 - To model and solve problems involving socioeconomic or technical-scientific variables using algebraic representations. M6 - To interpret scientific and social information obtained from reading graphs and tables, performing prevision, extrapolation, interpolation and interpretation. M7 - To understand the random and non-deterministic character of natural and social phenomena and use appropriate instruments for measurements, determination of samples and probability calculations to interpret information of variables presented in a statistical distribution.

Source: ENEM/Inep.

Table 16 - Reference Matrix of Competencies – Writing

W1 - To demonstrate mastery of the formal written form of the Portuguese language. W2 - To understand the writing proposal and apply concepts from various areas of knowledge to develop the theme, within the structural limits of the essay-argumentative text in prose. W3 - To select, relate, organize and interpret information, facts, opinions and arguments in defense of a point of view. W4 - To demonstrate knowledge of the linguistic mechanisms required for argumentation construction. W5 - To prepare intervention proposal for the problem addressed, respecting human rights.

Source: ENEM/Inep.

Table 17 – Determinants of student achievement by competency - Impact of students with disabilities

					Sciences				
	S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	
Coefficients	0.0053991	-0.0037261	0.0167843	-0.0116452	0.0328783**	-0.0042065	-0.0079940	-0.0339944	
	(0.0133)	(0.0161)	(0.0152)	(0.0168)	(0.0144)	(0.0135)	(0.0137)	(0.0221)	
No. of Obs.	3267252	3267252	3267252	3267252	3267252	3267252	3267252	3267252	
F-test	1156	1708	1571	737	1950	743	1260	856	
					Humanities				
	H1	**H2**	**H3**	**H4**	**H5**	**H6**			
Coefficients	-0.0058377	-0.0307618*	-0.0286785**	0.0112190	-0.0095133	-0.0067305			
	(0.0153)	(0.0173)	(0.0144)	(0.0161)	(0.0164)	(0.0163)			
No. of Obs.	3267252	3267252	3267252	3267252	3267252	3267252			
F-test	2184	1995	2767	7426	2177	2725			
					Languages				
	L1	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**	**L8**	**L9**
Coefficients	-0.1252338***	-0.0249521**	-0.1069434***	-0.0510183***	-0.0704063***	-0.1112516***	-0.0911499***	-0.1100481***	-0.0935667***
	(0.0225)	(0.0115)	(0.0283)	(0.0187)	(0.0180)	(0.0204)	(0.0204)	(0.0226)	(0.0236)
No. of Obs.	3267103	3267103	3267103	3267103	3267103	3267103	3267103	3267103	3267103
F-test	6928	4245	4032	3624	2404	3139	3536	3230	7001
					Math				
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**		
Coefficients	0.0334743**	-0.0219654	0.0095273	0.0469574***	0.0356244**	0.0764281***	-0.0335796**		
	(0.0136)	(0.0151)	(0.0155)	(0.0164)	(0.0144)	(0.0210)	(0.0136)		
No. of Obs.	3267103	3267103	3267103	3267103	3267103	3267103	3267103		
F-test	1302	2176	1271	2732	1602	1293	1300		
					Writing				
	W1	**W2**	**W3**	**W4**	**W5**				
Coefficients	-0.0761314	-0.3489530***	-0.3665280***	-0.0686498	-0.3625994***				
	(0.0771)	(0.0929)	(0.0906)	(0.0859)	(0.1007)				
No. of Obs.	3268511	3268511	3268511	3268511	3268511				
F-test	1947	1537	1723	1621	1296				
Individual controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Grade averages controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
School fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
State time linear trend	✓	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses.
$^{*}p<0.10$, ** $p<0.05$ ***, $p<0.01$.
Source: Elaborated by the author.

3 UNINTENDED YET DESIRABLE EFFECTS OF CENTRALIZED COLLEGE ADMISSION: MOBILITY COSTS AND COLLEGE ENROLLMENT FOR STUDENTS WITH DISABILITIES

Recently, policymakers have started to pay more attention to particular issues faced by people with disabilities and special needs. In 2007, 160 countries signed the UN’s Convention on the Rights of Persons with Disabilities, which is a treaty designed to protect the human rights of people with disabilities. In addition, the World Bank has recently increased its efforts to promote disability-inclusive development by appointing a disability advisor to the World Bank Group.

In several different countries, in both the developed and the developing world, policies are also being designed with the aim of helping individuals with disabilities to engage in certain aspects of society. Many of such laws focus on regulation regarding the adaptation of facilities to ensure that disabled individuals can access buildings and use public services. Other policies focus on providing conditions for individuals with special needs - and incentives for those who interact with them, such as employers and educational institutions - to make sure that these individuals are able to study and to work.

The rationale behind a large number of these public policies is to reduce costs associated with physical access to buildings. Wheelchair access ramps, information in braille, pathway markers for people with visual impairments are examples of accessibility improvements that are aimed at reducing mobility costs.

Explicit accessibility policies, however, are not the only mechanism capable of lowering mobility costs. Oftentimes, these costs change as a byproduct of advances information technology combined with institutional changes that alter the way information is produced, stored, processed, and shared. Policies that reduce the overall necessity of dislocation might have an unintended yet desirable effect of helping people with disabilities, even if they have not been explicitly designed with that goal.

With that in mind, we study the impact of the Brazilian Unified Selection System (Sisu) on access to higher education for students with disabilities. Sisu centralized the college admission process, unifying entrance exams across participating institutions around a single exam named National Exam of Upper Secondary Education (Enem).

Sisu’s implementation dramatically reduced mobility costs of a college application. Before, students that wished to apply to several universities across the country could only do so by taking the specific admission exams of those institutions. The need to travel to several cities provided barriers for low-income individuals who did not have resources to pay for expenses, but also to special needs individuals who require special attention to travel and thus have lower mobility.

Our empirical strategy is based on an intention-to-treat analysis. By lowering mobility costs, Sisu has affected disproportionately individuals for which the transportation costs to take multiple admission exams are large. Therefore, we expect an increase in the number of college applications from individuals with disabilities through the Sisu, but also, ultimately, an increase in the share of entrants with special needs on these institutions. Our results show that exposure to the Sisu by an institution-degree pair has a significant and sizable effect on the share of entrants with disabilities. Institution-degree pairs that have been exposed to seven years of Sisu have a share of entrants with disabilities 0.63 percentage point higher than institutions-degree pairs that have not been exposed. This is a sizable effect considering that the total percentage of entrants with disabilities in 2016 was on average 0.77%.

This paper is divided into six sections after this introduction: (1) related literature; (2) institutional background; (3) data; (4) empirical strategy; (5) results; (6) final remarks.

3.1 RELATED LITERATURE

This paper relates to two different branches of the literature. First, it is in line with the studies on the effects of the adoption of the Sisu system. In this literature, Machado and Szerman (2017) and Li (2016) investigate the impacts of Sisu on migration, student sorting, enrollment, and college dropout. Machado and Szerman (2017) find that higher education institutions under a centralized system can attract students that score one-third of a standard deviation higher and that interstate mobility of admitted students increases by 2.5 percentage points. Li (2016) finds that, with a centralized admission method, interstate mobility of students increases by 2.9 percentage points, but intrastate mobility decreases by 4.0 percentage points. She also finds that the college dropout increases by 4.5 percentage points. Our paper also relates to Machado and Szerman's (2017) results because the authors investigate if the composition of students changes with the adoption of Sisu. They test to see if individuals with disabilities have a higher probability of entering university programs that use Sisu as the admission system. They find some evidence of this effect. However, their paper only studies the short-run effects of Sisu and not long-run effects[5]. In our empirical

[5] There exists well-known literature concerning adjustment costs in a variety of settings that justify our hypothesis that the impact of Sisu might only fully develop in the medium to long run. Students graduating

exercise, we test and explore the presence of heterogeneous effects of different length of exposure to the Sisu. Our main contribution to this literature is, thus, to investigate the role of Sisu in explaining the rise in the share of students with disabilities in higher education in recent years.

Second, our paper relates to the literature concerning students with disabilities and the policies oriented to increase their achievement, inclusion and ultimately success. For example, Hanushek, Kain, and Rivkin (2002) argue that classes with children with disabilities might receive additional resources which can positively affect student performance. Seeking to empirically evaluate this relationship between peers with disabilities and the cognitive abilities of their classmates, Hanushek, Kain and Rivkin (2002) find that an increase of 10 percentage points in the proportion of students with disabilities in the class increases the achievement of other students in 1.6% of a standard deviation in elementary school.[6]

3.2 INSTITUTIONAL BACKGROUND

In this section, we describe the institutional background. First, we describe what are the Enem Exam and the Sisu System. Next, we present data about people with disabilities in Higher Education in Brazil.

3.2.1 The Enem Exam and the Sisu System

The National Exam of Upper Secondary Education (or Enem) is currently the main access instrument to ascend to Brazilian public higher education, which consists of around 275 institutions (federal, state and municipal) that do not charge tuition fees but offer a limited number of seats.

Enem was created in 1998 as a tool to evaluate school performance at the end of secondary education. From its first edition until 2008, the Enem was held annually with the

high school in the year of SISU implementation have already chosen the pre-application investments in human capital (Bodoh-Creed and Hickman, 2017). That choice can have an impact on their application decisions and their likelihood of success (Bodoh-Creed and Hickman, 2017). In contrast, students of later cohorts can adjust more easily to SISU by, for instance, investing more in their human capital while in high school. Another explanation is dynamic learning: The fraction of students that are aware of the changes in the system is likely to be increasing over time. These factors could explain why the effect of the policy takes a couple of years to be apparent.

6 Friesen, Hickey, and Krauth (2010), Fletcher (2009, 2010) and Gottfried (2014) also evaluate this relationship between having a peer with disabilities and the (cognitive or non-cognitive) abilities of the other classmates.

application of a single test composed of 63 interdisciplinary questions. During this period, some higher education institutions began to use it as an entrance examination to select their students.

In 2009, a reform took place to boost Enem's use as an admission exam: the number of questions increased to 180. These questions were divided into four groups encompassing the fields of knowledge around which basic education is organized in the country (languages, mathematics, social sciences, and natural sciences), plus an essay. Soon after, the government started to nudge institutions to adopt it as an admission instrument. The Enem then began to be used by most public higher education institutions.

Before these reforms, the *vestibular* was the most popular access instrument. Students applied directly to the desired institutions and took the specific exam *vestibular* of each one. Candidates with the best scores in the *vestibular* exam, stratified by major, were offered seats[7]. Importantly for our later analysis, the admission was decentralized across institutions. That is, if a student were to apply to, say, ten different institutions, he would have to take ten different exams and would likely have to travel to several different cities in the process.

After Enem's reform, the exam took the role previously played by the *vestibular* entrance exams. The difference, however, is that the same score became the criteria of admission across different institutions. The Enem has since become one of the main access instruments to ascend to Brazilian public higher education, a change that centralized and unified the admission system.

In 2010, the admission system centralized even further with the creation of the Unified Selection System (called Sisu), an online platform through which public higher education institutions offer seats to students that are selected based on their score obtained in the last Enem exam. Students choose, in order of preference, up to two institutions among the options offered by the participating institutions of the Sisu system. Seats are then offered on the basis of the students' rankings among the applicant pool[8,9].

---

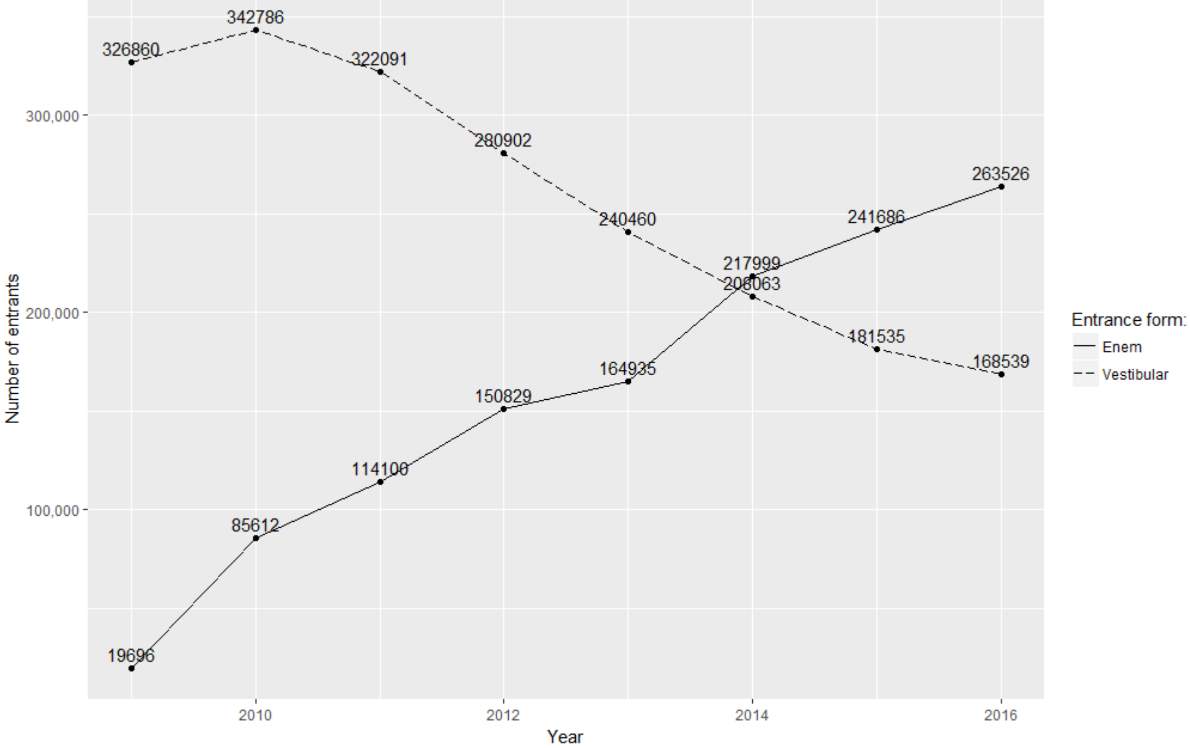
7 Different from college admissions in North America, majors are chosen at the time of application. Another feature is that admission decisions are made solely based on the outcome of the entrance exam. Thus, extracurricular activities, faith, family ties to the university, non-academic skills such as musical talent, none of these factors are taken into account when institutions make admission choices. In a large number of cases, the admission exams are graded in a double-blinded manner, so the individuals grading the exam cannot know the identity of the student being evaluated. These features are mostly unaltered until today, with the notable exception of student demographic characteristics such as race which affect admission choices through the affirmative action reserved seats (known as "quotas").

8 Institutions are free to decide the number of seats offered through the Enem exam. Also, they can use the Enem in different ways for student selection: 1) Enem scores through the Sisu system; 2) Enem scores without the Sisu system, and 3) some combination of Enem and *vestibular* scores.

9 Machado and Szerman (2017) provide further details about the Sisu platform.

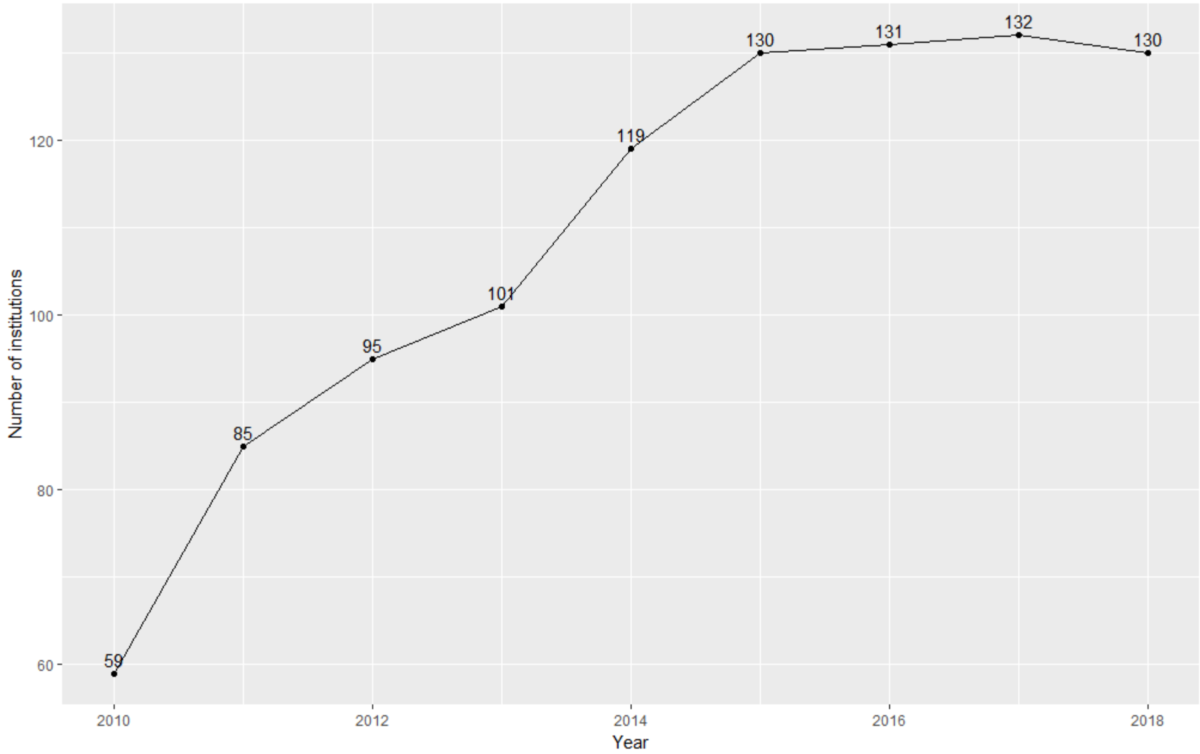
The number of students who entered through the Enem in undergraduate degrees (excluding online education) attended by the public institutions increased from around 20 thousand in 2009 to over 250 thousand in 2016, as shown in Figure 4. In 2014, the Enem passed the *vestibular* and became the main access instrument to enter Brazilian public higher education. Much of this result was due to the Sisu: the number of institutions participating in the Sisu went from 59 in the first edition, in 2010, to 130 in 2018 (see Figure 5). As a result, it is also noticeable that the number of Enem inscriptions grew rapidly, reaching 8,627,367 in 2016, more than twice as many as in 2008 (see Figure 6).

Figure 4 – Evolution of the number of entrants by the Enem and the *vestibular*



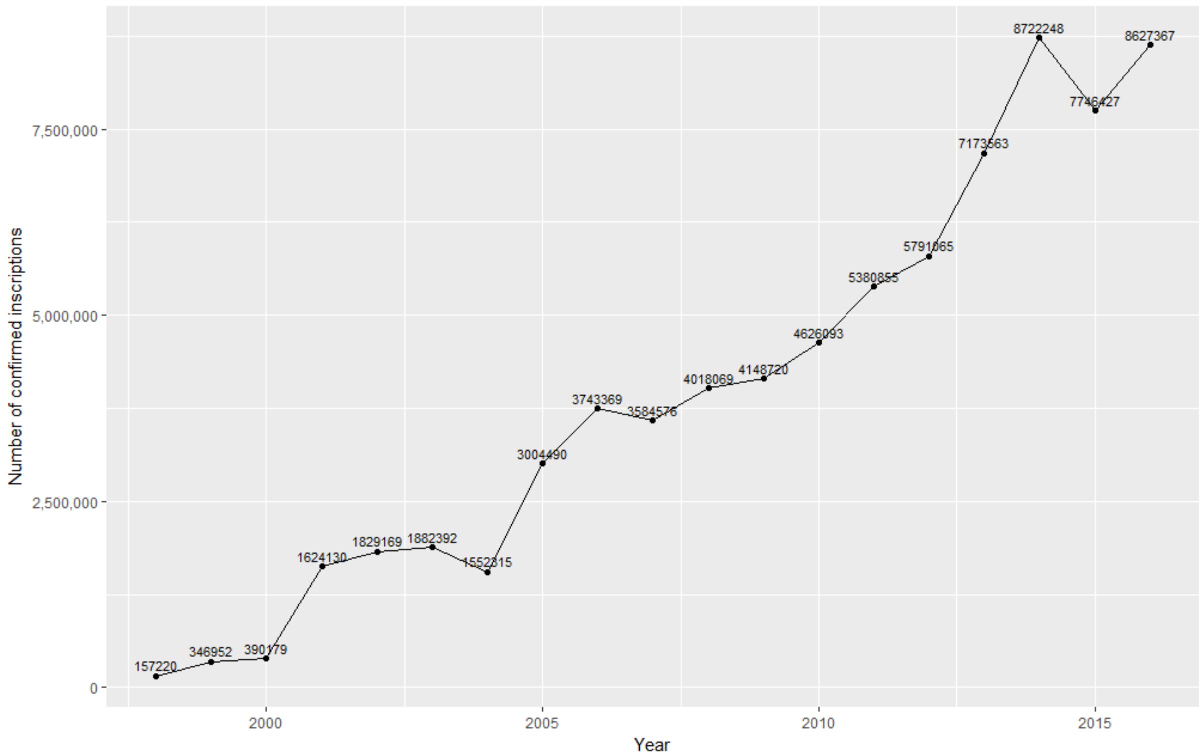
Source: Elaborated by the author, based on data from Inep.

Figure 5 – Evolution of the number of institutions participating in the Sisu



Source: Elaborated by the author, based on data from MEC.

Figure 6 – Evolution of the number of students taking the Enem.



Source: Elaborated by the author, based on data from Inep.

3.2.2 Disabilities and Higher Education in Brazil

According to the Demographic Census of 2010, in Brazil, there are approximately 4 million people (around 2% of the population) with some serious disability (people that are unable to see, hear, move or with any intellectual disability). Access to education for this group is yet a great challenge for the country. For example, only 6.7% of people with disabilities aged over 15 have completed higher education compared to 10.4% of people without disabilities aged over 15, and less than 1% of students enrolled in higher education have any form of disability.

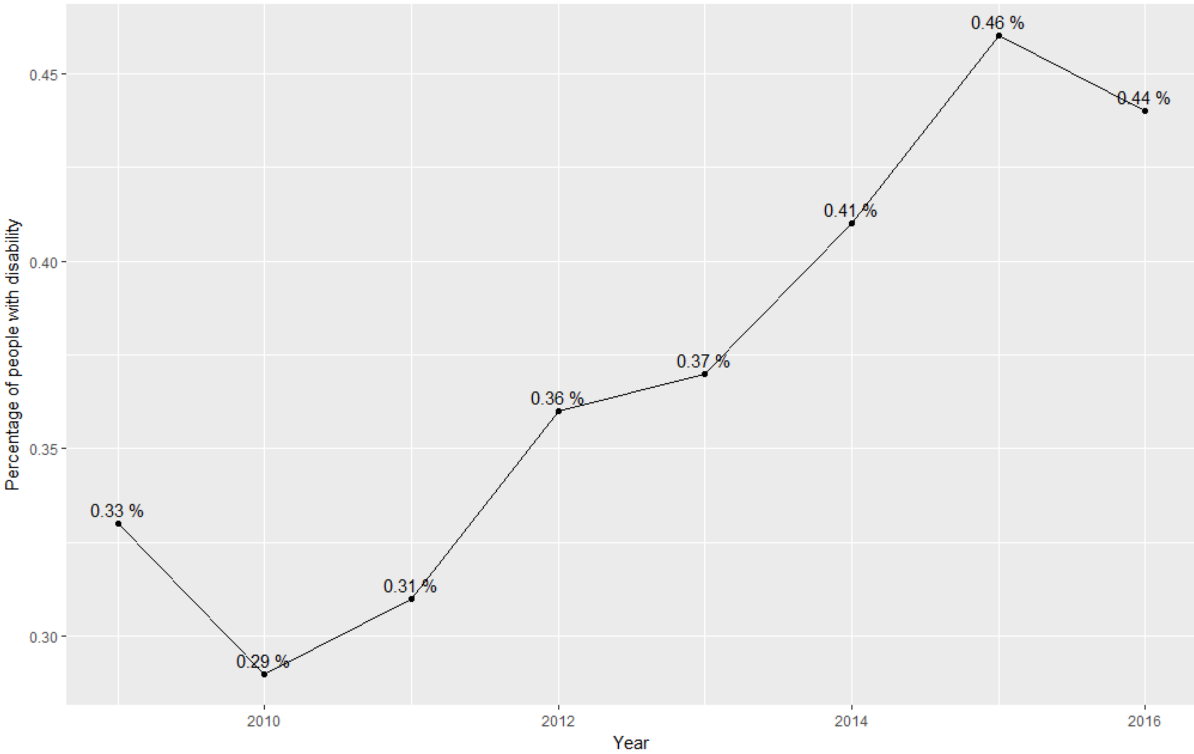
Between 2009 and 2016, the total number of people with disabilities in higher education rose substantially (see Figure 7), from 16,911 in 2006 to 28,725 in 2016. This represents an increase of 70%. For comparison, the growth in overall enrollment in the same period was only 28%. As a result, the fraction of people with disabilities in higher education increased from 0.33% to 0.44% (see Figure 8).

During this period, there was also some progress in terms of policies aimed at providing access to education for people with disabilities. Along with the Federal Constitution of 1988, the National Policy on Special Education in the Perspective of Inclusive Education of 2008, and other documents that aim to ensure the right to education (both primary education and higher education) to people with disabilities, public policies explicitly focused on higher education emerged. In this sense, the *Programa Incluir* and affirmative action policies for people with disabilities stand out:

a) The *Programa Incluir*, created in 2005, proposes actions that aim to guarantee the access and permanence of people with disabilities in federal higher education institutions in Brazil. Among the main actions of the program, there are the creation and consolidation of accessibility centers that guarantee the removal of architectural and communication barriers, fulfilling the legal requirements of accessibility.

b) The Law 13,409/2016, in force since the academic year of 2017, establishes that people with disabilities must be included in the affirmative action policies of federal institutions of higher education, which already included students from public schools, low-income students, black students, and indigenous students. The number of affirmative actions seats (or “quotas”') set aside for people with disabilities in federal institutions must be proportional to the presence of this group in the census of each state[10].

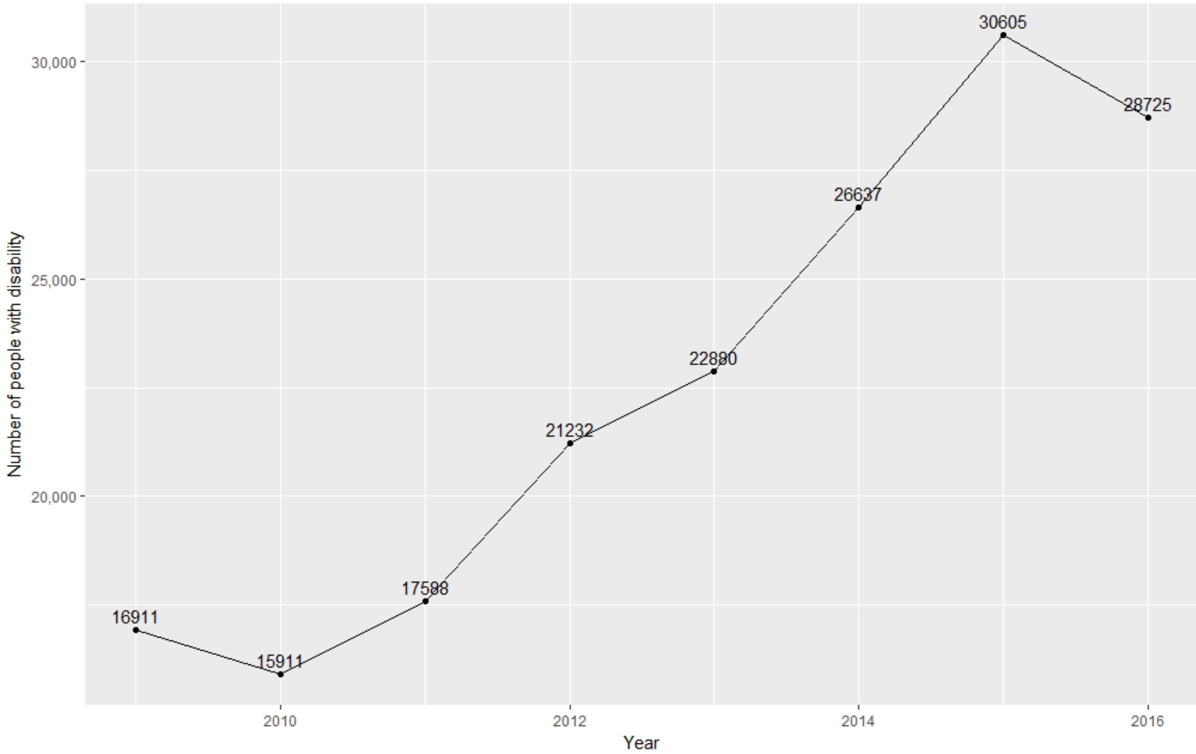
Figure 7 – Evolution of the number of people with disability in Brazilian higher education



Source: Elaborated by the author, based on data from Inep.

[10] In addition to this law valid for federal institutions, some states have previously created laws that are valid for state institutions, and some institutions have established quotas for people with disabilities on their own initiative.

Figure 8 – Evolution of the percentage of people with disability in Brazilian higher education



Source: Elaborated by the author, based on data from Inep.

3.3 DATA

We use the Brazilian Higher Education Census from the years 2009 to 2016, an annual administrative dataset. It contains information of all higher education institutions in the country, including details about majors and characteristics of the student body.

We make some sample restrictions in the data. Since private and municipal institutions cannot participate in the Sisu system, we keep in the sample only federal and state institutions. We consider only information about on-campus degrees and entrant students. In addition, we exclude degrees with less than ten entrants. We also excluded federal institutes from our sample. Established by federal law in 2008 (Lei 11.892/2008), their creation is contemporaneous to the establishment of the Sisu admission system. For that reason, we exclude degrees of federal institutes from our sample so our results are not driven by the changes associated with enrolment in these institutes[11].

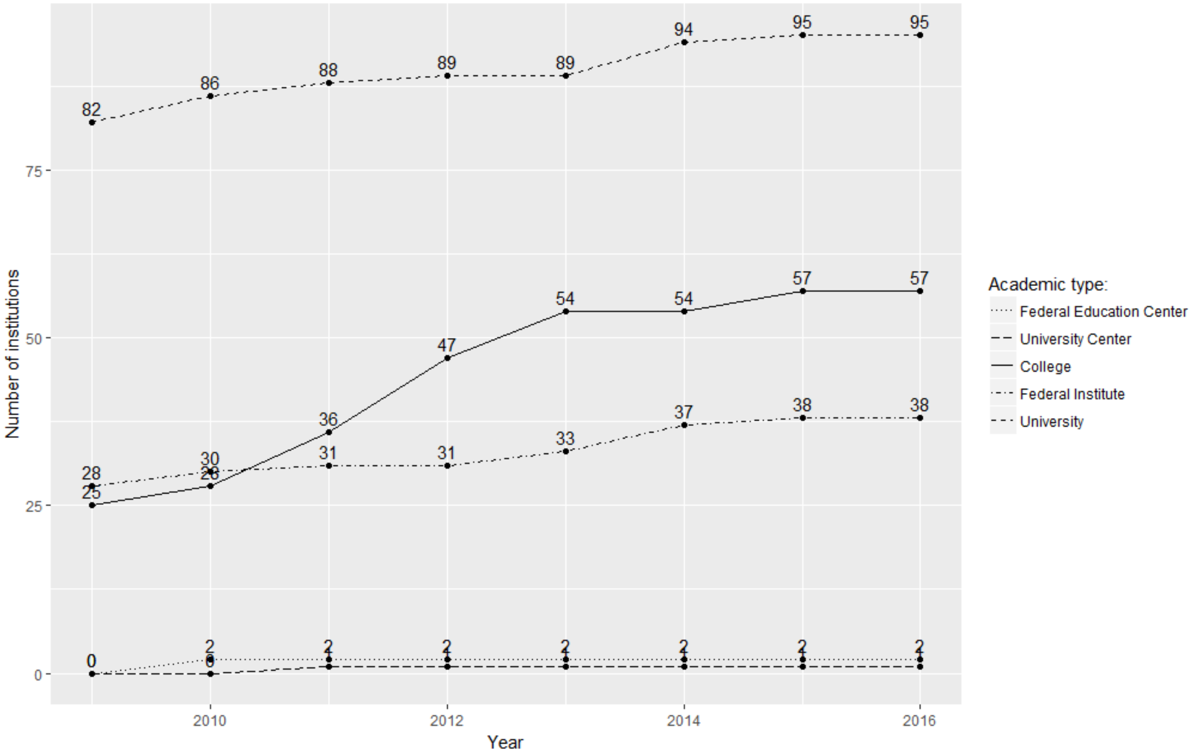
[11] Higher education institutions consist of five groups: universities, university centers, colleges, federal education centers, and federal institutes. Figure 9 shows that the vast majority of higher education institutions are universities.

To the census data, we add to our sample the information, provided by the Ministry of Education, on *whether* and *when* institutions joined Sisu. This transition is made voluntarily by each institution and, most importantly, there are institutions that use the Sisu system for certain majors and *vestibular* for others. Therefore, the variable of our interest varies at the institution-major-year level, which allows us to control for a wide range of unobservables that are constant over time across institutions.

Our interest lies in the following variables: a dummy variable indicating if the entrant is a student with disabilities in an institution-degree pair; student's gender and age; dummy variables indicating the time of exposure of that institution-degree pair to Sisu; the General Index of Evaluated Degrees of the Institution (GIC) (a quality indicator that evaluates Brazilian higher education institutions); a dummy variable indicating if that institution-degree pair offers accessibility conditions for people with disabilities; and dummy variables indicating the institution's length of exposure to affirmative action policies.

Our sample consists of 2.932 million observations of entrant students in federal or state public institutions' degrees between 2009 and 2016 (see Table 18). Table 19 reports annual descriptive statistics. The percentage of entrants with disabilities has increased considerably, almost doubling in seven years. In the same period, we also saw a rapid increase in the share of institutions using Sisu as an admission method, quotas for people with disabilities and a growing number of degrees offering accessibility accommodations. These three factors are possible candidates that might help explain the increasing share of entrants with disabilities in college rises from 0.40% to 0.77% in a few years.

Figure 9 – Institutions by academic type



Source: Elaborated by the author.

Table 18 – Descriptive Statistics

	Obs	Mean	Std Dev	Min	Max
Entrants with disabilities	2932633	0.0061269	0.0780345	0	1
Age	2932633	22.8657	6.814003	12	95
Sex (male =1)	2932633	0.4818908	0.499672	0	1
Participation in the Sisu	2932633	0.4749885	0.4993741	0	1
Exposure time to the Sisu	2932633	1.495935	2.008635	0	7
GIC	2932633	3.246023	0.5855563	0.565132	4.686605
Share degrees with accessibility	2932633	0.6495231	0.4771194	0	1
Quotas policy	2932633	0.2172287	0.4123596	0	1
Exposure time to quotas policy	2932633	0.7530833	1.680662	0	7
ENADE	2112787	2.938169	0.478998	0.6461	4.7846

Source: Elaborated by the author.

Table 19 – Descriptive Statistics by Year

	2009	2010	2011	2012	2013	2014	2015	2016
Entrants with disabilities	0.0039961 (0.0630881)	0.0048664 (0.0695896)	0.0034055 (0.0582573)	0.0047608 (0.0688339)	0.0056103 (0.0746917)	0.0084221 (0.0913848)	0.0091091 (0.0950063)	0.0077443 (0.0876601)
Age	22.4902 (6.28249)	22.66975 (6.537309)	22.68533 (6.61587)	22.99103 (6.905879)	22.78366 (6.820741)	23.15084 (7.146458)	23.15268 (7.098802)	22.85826 (6.848494)
Sex (male =1)	0.4739359 (0.4993211)	0.4660392 (0.498846)	0.4715483 (0.4991905)	0.467597 (0.4989496)	0.4803278 (0.4996135)	0.4870345 (0.4998325)	0.4989945 (0.4999996)	0.5037127 (0.4999868)
Participation in the Sisu	0 (0)	0.2119958 (0.4087225)	0.4266178 (0.4945864)	0.4158339 (0.4928658)	0.4707392 (0.4991437)	0.6299767 (0.4828112)	0.7085297 (0.4544402)	0.76852 (0.4217789)
Exposure time to the Sisu	0 (0)	0.2119958 (0.4087225)	0.5987538 (0.76454)	0.9794006 (1.210405)	1.44493 (1.657245)	2.002089 (1.991882)	2.644519 (2.299514)	3.403278 (2.581916)
GIC	3.12069 (0.621143)	3.213146 (0.6383521)	3.253245 (0.5696176)	3.22483 (0.5679835)	3.269418 (0.555152)	3.27087 (0.5899431)	3.275334 (0.5735525)	3.304432 (0.5605336)
Share degrees with accessibility	0.3045805 (0.4602303)	0.5676449 (0.4954037)	0.6343927 (0.4816007)	0.6606683 (0.4734831)	0.6688846 (0.4706151)	0.7318297 (0.4430073)	0.7479206 (0.4342072)	0.7777823 (0.4157372)
Quotas policy	0 (0)	0.1299421 (0.3362402)	0.1912538 (0.3932889)	0.2008348 (0.4006252)	0.2474343 (0.4315218)	0.2827409 (0.4503321)	0.2946112 (0.4558683)	0.3204768 (0.4666605)
Exposure time to quotas policy	0 (0)	0.1299421 (0.3362402)	0.3118944 (0.6752027)	0.5285593 (1.080013)	0.7515491 (1.434472)	1.032164 (1.834684)	1.318862 (2.230341)	1.615133 (2.622573)

Standard errors in parentheses.
Source: Elaborated by the author.

3.4 EMPIRICAL STRATEGY

In this section, we describe the methodology of our empirical exercise. Our main specification is

$$D_{icst} = \sum_{j=1}^{8} \gamma_j DES_{cst}^{j} + \boldsymbol{X'}_{\boldsymbol{icst}}\delta + \alpha_{cs} + \alpha_t + \alpha_e t + \varepsilon_{icut} \quad (1)$$

where D_{icst} is one if the student *i* enrolled in major *c* at institution *s* and year *t* has a disability and zero otherwise. The dummy variable DES_{cst}^{j} assumes the value one if the degree *c* at institution *i* at time *t* has been exposed to the Sisu admission system for *j* years (and zero otherwise). We allow for the impact of adopting the Sisu admission system on the entrance of individuals with disabilities to take time to emerge. The term $\boldsymbol{X_{icst}}$ is a vector with control variables. We include in the vector of controls two student's characteristics: (1) the student's age and (2) gender. We also include characteristics of the institution and of the degree: (1) the General Index of Evaluated Degrees of the Institution (GIC) and (2) a dummy variable that assumes the value one if the degree provides accessibility accommodations for people with disabilities. Finally, we also include dummy variables indicating the institution's exposure time to affirmative action policies in the same way as the Sisu admission dummies. The model also includes institution by degree fixed effects (α_{cs}), time fixed effects (α_t), and state linear time trends, $\alpha_e t$, where e is the state.

We explore the time variation in the length of exposure to Sisu in order to identify the impact of the adoption of the Sisu and the existence of possible heterogeneous effects as a function of the length of exposure. Our identification assumption is that, conditional on control variables, time and fixed effects and state linear time trends, the path of the proportion of entrants with disabilities in degrees that have adopted Sisu would be identical to the ones that have not adopted Sisu, if the system were not implemented[12].

Institution by degree fixed effects control for characteristics of distinct majors that do not vary over time and might be related to the dependent variable and to the adoption of the Sisu. Year fixed effects control for common shocks in each year that affect all institutions and degrees at the same time. Lastly, state linear time trends control by state characteristics that vary over time.

We also try a specification in which we do not allow for heterogeneous effects of Sisu over time. In this case, we substitute the element $\sum_{j=1}^{8} \gamma_j DES_{cst}^{j}$ by a dummy D_{cst} which is one if the degree c in the university s was participating of Sisu at time t.

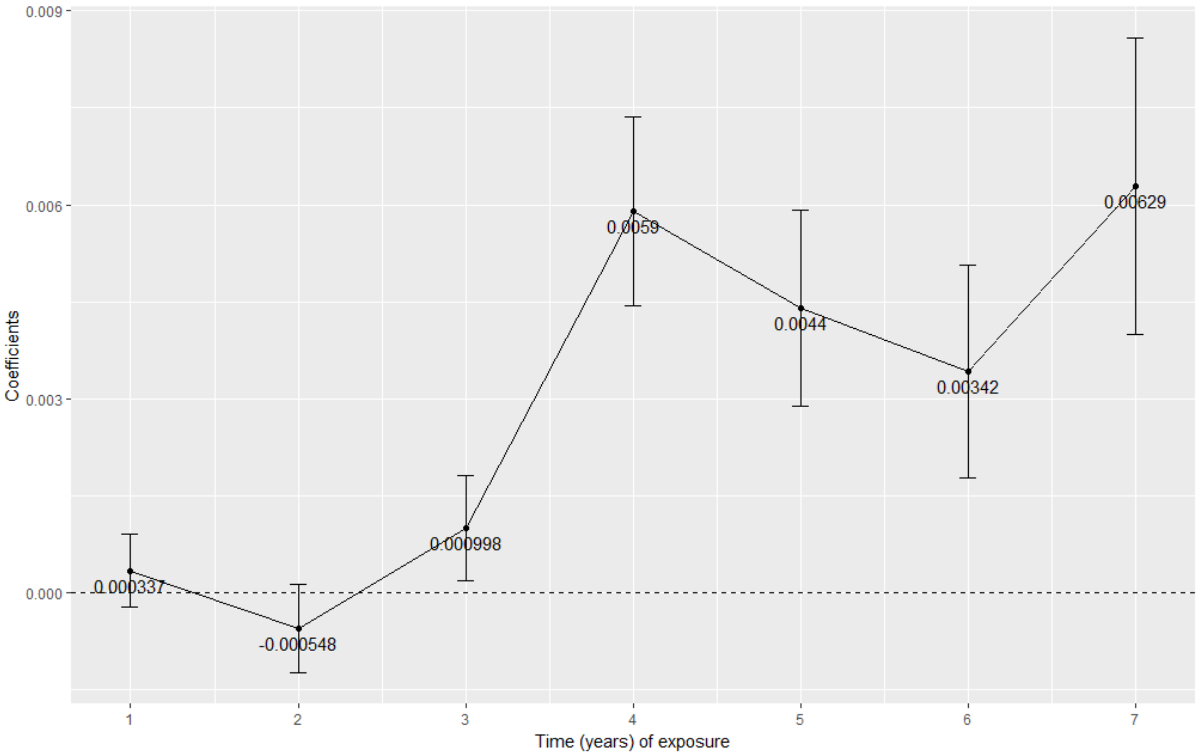
3.5 RESULTS

We present our results in Tables 20 to 22. In the Table 20, we present four different regression results. Our main model is (6), where our variables of interest are dummy variables indicating the time of exposure to Sisu, and institution-degree pair and year fixed effects and state linear time trends are present. The effect is not statistically significant in the first two years of adoption. After the second year of adoption by a degree, the percentage of entrants with disabilities increases by 0.01 percentage point. Considering that the fraction of entrants with disabilities is on average 0.61% (see Table 18), this implies a relative increase of 1.6%. The effect increases in the fourth year of exposure to 0.59 percentage points and remains above 0.3 percentage points afterwards. As expected, Table 20 shows that the presence of accessibility accommodations has a positive impact on the fraction of students with disabilities.

[12] As a placebo test, we ran regressions for the year 2009 (before the adoption of Sisu) with D_{icst} on a dummy that is 1 if the degree will adopt Sisu in some time in the future and 0 if it will never adopt. When we controlled for institutions fixed effects, the Sisu dummy had no statistically significant impact.

In Figure 10, we plot the heterogeneous effects over time. The impact of exposure to Sisu rises over the years exposure. This result is consistent with the hypothesis that the impact of Sisu takes time to affect the share of entrants with disability. A back of the envelope calculation shows that the impact of a seven-year exposure to Sisu represents roughly eighty percent (80%) of the proportion of entrants with disabilities in 2016 (see Table 19), a sizable increase.

Figure 10 – Heterogeneous effects as a function of the time of exposure



Source: Elaborated by the author.

Table 20 – Main Results

	(1)	(2)	(3)	(4)
Sisu	0.00000668 (0.978)	-0.000373 (0.150)		
Quotas policy	0.000626 (0.159)	0.000239 (0.569)		
One year in the Sisu			0.000459* (0.082)	0.000337 (0.243)
Two years in the Sisu			-0.000494 (0.105)	-0.000548 (0.117)
Three years in the Sisu			0.000705** (0.042)	0.000998** (0.016)
Four years in the Sisu			0.00530*** (0.000)	0.00590*** (0.000)
Five years in the Sisu			0.00351*** (0.000)	0.00440*** (0.000)
Six years in the Sisu			0.00228*** (0.002)	0.00342*** (0.000)
Seven years in the Sisu			0.00300*** (0.001)	0.00629*** (0.000)
One year with quotas policy			0.000584 (0.153)	0.0000478 (0.905)
Two years with quotas policy			0.00131** (0.013)	0.000726 (0.152)
Three years with quotas policy			0.00115* (0.062)	0.000413 (0.496)
Four years with quotas policy			0.000743 (0.217)	-0.000191 (0.740)
Five years with quotas policy			-0.000449 (0.529)	-0.000730 (0.299)
Six years with quotas policy			-0.00148** (0.044)	-0.00154* (0.050)
Seven years with quotas policy			0.00147* (0.053)	0.00109 (0.264)
Age	0.000249*** (0.000)	0.000249*** (0.000)	0.000248*** (0.000)	0.000248*** (0.000)
Sex (male = 1)	0.00141*** (0.000)	0.00140*** (0.000)	0.00141*** (0.000)	0.00140*** (0.000)
GIC	0.00145** (0.019)	0.00222*** (0.000)	0.00208*** (0.002)	0.00288*** (0.000)
Degree with accessibility	0.00464*** (0.000)	0.00345*** (0.000)	0.00435*** (0.000)	0.00314*** (0.000)
State linear time trends	NO	YES	NO	YES
N	2932633	2932633	2932633	2932633
F	84.64	43.72	48.30	34.70
r2	0.0451	0.0462	0.0453	0.0464

Cluster-Robust Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All regressions are controlled for institution-degree pairs fixed effects and time fixed effects;
Source: Elaborated by the author.

The structure of our dataset - containing the information of disability status for individuals that *entered* college - allows us to investigate whether the presence of Sisu changes the proportion of individuals with a disability. Sisu, however, does not induce any student to acquire a disability; the causality lies in the opposite direction. Here we discuss how to interpret the effects on the changes on the proportion of students with disabilities in terms of components related to the effects that Sisu induces on the choices made by students with disabilities and the ones without them.

An application of the Bayes' rule shows that the changes in the proportion of students with disabilities associated with Sisu can be decomposed into three components: One associated with the differential effect of Sisu on the likelihood on applying to college across individuals with disabilities and individuals without it. The second component is associated with the differential effect of Sisu on the likelihood of a successful application across students. Lastly, a third component associated with the differential effect of Sisu on the likelihood of entrance.

Together, these three terms add to the total change in the proportion of students with disabilities across schools that use the Sisu system and the ones that do not. With a richer dataset[13], we could hope to separately identify the terms of this decomposition, that is, to disentangle both where in the chain of events the Sisu effects are larger, but also to what extent the changes are happening in the set of students without disabilities as well.

We can draw two conclusions from this decomposition: the first is that for the proportion of students with disabilities to change when Sisu is introduced, it is not enough that students with disabilities will be more likely to apply, be accepted, and ultimately enter. It must be the case that these changes are larger than the effects that the system has on the students that do not have a disability. For example, if the only change that the system induces is to increase by 10% the likelihood that a student will apply, and this effect also occurs in the population of students with no disability, then although the system does have a positive effect on the probability of applying to college, the fraction of students with disabilities in college will remain the same after the policy is implemented.

Thus, the effects we capture here should be interpreted as changes relative to the changes that the system induces in the set of students with disabilities, as compared to students without them. In conclusion, although we can only obtain estimates of the change in

[13] The ideal setting would be a dataset in which we observe all students (regardless of whether they entered college), their disability status, whether they apply to college, whether they apply through Sisu, and whether they were accepted and which institution they ultimately entered.

the proportion of students with disabilities, the changes in this proportion can be easily mapped into changes in the likelihood of an application, acceptance, and entrance; the outcomes we are ultimately interested on investigating.

3.5.1 Heterogenous Effects on Quality of Institution-Degree pairs

We conjecture that the adoption of Sisu should have heterogeneous effects regarding the quality of the institution and degree. In order to measure the presence of this heterogeneity, we use the ENADE ranking, which grades institution by majors regarding their quality, to divide our data into three subsamples: the bottom third institution-degree pairs, which we label as the third quantile, the middle institution-degree pairs, which we label as the second quantile, and the top third institution-degree pairs, which we label as the first quantile. Results are reported on Table 21 and summarized on Figure 11. The effect of Sisu seems to be greater in the bottom quantile of the quality distribution. In fact, the first quantile institution-degree pairs that have adopted Sisu have, for some years at least, experienced a reduction in the chance of having entrants with disabilities. The effect of Sisu adoption on the middle quantile is positive, but lower than the bottom quantile effect. We warn, however, that the standard errors for these comparisons are large, so the null hypothesis of no difference would not be rejected for several of these different coefficients. A deeper investigation of the heterogeneity of effects across different margins could be a fruitful area for future work.

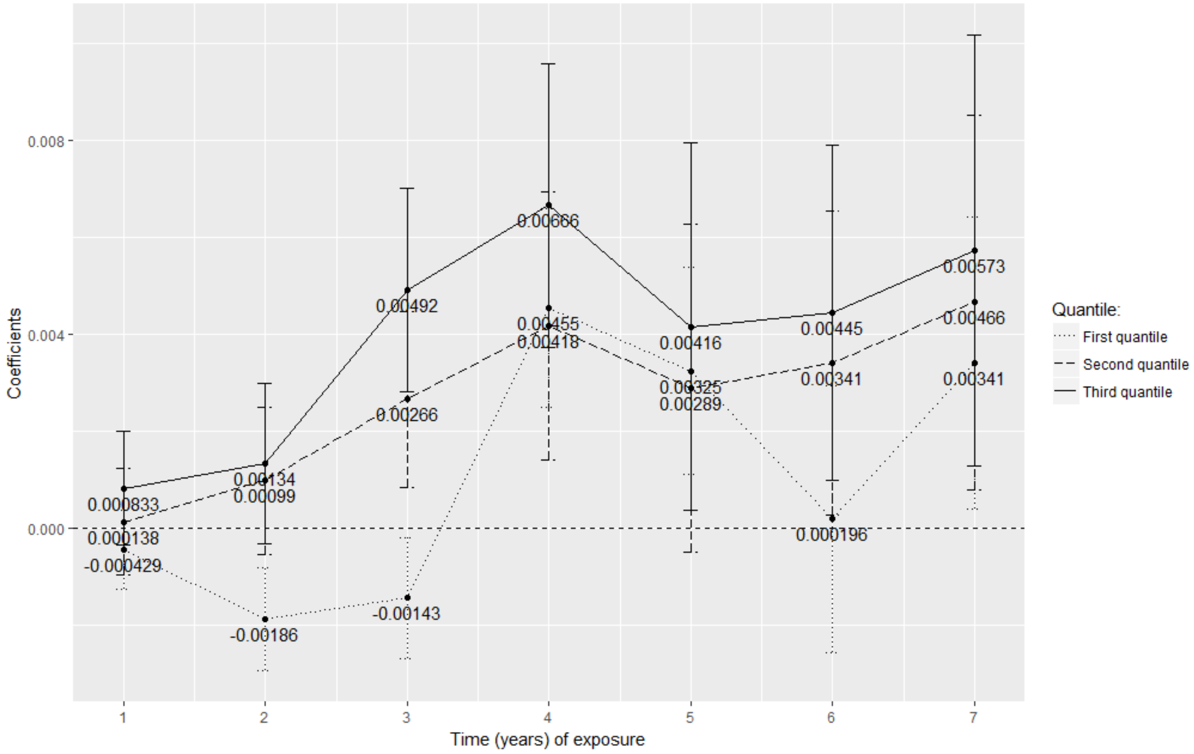
Table 21 – Results by Enade quantiles

	(1)	(2)	(3)	(4)	(5)	(6)
Sisu				-0.00130***	0.000364	0.00119**
				(0.001)	(0.445)	(0.036)
Quotas policy				-0.000581	0.00137*	0.000516
				(0.271)	(0.087)	(0.581)
One year in the Sisu	-0.000429	0.000138	0.000833			
	(0.303)	(0.805)	(0.165)			
Two years in the Sisu	-0.00186***	0.000990	0.00134			
	(0.001)	(0.201)	(0.113)			
Three years in the Sisu	-0.00143**	0.00266***	0.00492***			
	(0.024)	(0.004)	(0.000)			
Four years in the Sisu	0.00455***	0.00418***	0.00666***			
	(0.000)	(0.003)	(0.000)			
Five years in the Sisu	0.00325***	0.00289*	0.00416**			
	(0.003)	(0.094)	(0.032)			
Six years in the Sisu	0.000196	0.00341**	0.00445**			
	(0.889)	(0.033)	(0.012)			
Seven years in the Sisu	0.00341**	0.00466**	0.00573**			
	(0.026)	(0.019)	(0.012)			
One year with quotas policy	-0.000730	0.00117	0.0000819			
	(0.189)	(0.221)	(0.939)			
Two years with quotas policy	0.000155	0.00153	0.00200			
	(0.813)	(0.102)	(0.109)			
Three years with quotas policy	-0.000777	0.00143	-0.000627			
	(0.299)	(0.122)	(0.645)			
Four years with quotas policy	-0.000880	0.000313	-0.000845			
	(0.288)	(0.761)	(0.623)			
Five years with quotas policy	-0.00150	-0.0000597	-0.000611			
	(0.146)	(0.966)	(0.738)			
Six years with quotas policy	-0.00163	-0.00173	-0.00268			
	(0.169)	(0.243)	(0.210)			
Seven years with quotas policy	0.00175	-0.000482	-0.000508			
	(0.279)	(0.767)	(0.844)			
Age	0.000269***	0.000275***	0.000246***	0.000270***	0.000276***	0.000245***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex (male = 1)	0.000888***	0.00213***	0.00166***	0.000895***	0.00213***	0.00166***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GIC	0.00181**	0.00186	0.00305**	0.00136*	0.000921	0.00203
	(0.021)	(0.175)	(0.038)	(0.069)	(0.463)	(0.139)
Degree with accessibility	0.00373***	0.00185***	0.00117**	0.00402***	0.00206***	0.00148***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	1362168	485056	303819	1362168	485056	303819
F	19.25	9.729	6.025	23.64	12.06	6.337
r2	0.0217	0.0169	0.0132	0.0214	0.0168	0.0129

Cluster-Robust Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All regressions are controlled for institution-degree pairs fixed effects, time fixed effects and state linear time trends.

Source: Elaborated by the author.

Figure 11 – Heterogeneous effects as a function of the time of exposure by Enade quantiles



Source: Elaborated by the author.

3.5.2 Placebo

Since Sisu was implemented in 2010, the proportion of *graduating* students with disabilities should only be affected by this system from 2014 onwards, when the students that entered in higher education in 2010 began to graduate. Thus, as a placebo check, we repeated our analysis using as the outcome variable the percentage of graduating students with disabilities for the years 2009 to 2013. Table 22 describes the results of this exercise. The results show, as expected, that the Sisu did not consistently affect the percentage of graduating students with disabilities for those that applied and entered the institutions before the system was implemented.

Table 22 – Results – Placebo

	(1)	(2)	(3)	(4)
Sisu	-0.000637 (0.152)	-0.000348 (0.542)		
Quotas policy	0.00124** (0.028)	-0.000654 (0.317)		
One year in the Sisu			-0.000196 (0.639)	0.0000222 (0.964)
Two years in the Sisu			-0.00191*** (0.000)	-0.00168** (0.016)
Three years in the Sisu			-0.000240 (0.811)	-0.0000458 (0.974)
Four years in the Sisu			-0.00440*** (0.000)	-0.00363*** (0.004)
One year with quotas policy			0.000661 (0.249)	-0.00120* (0.093)
Two years with quotas policy			0.00229*** (0.003)	-0.000198 (0.812)
Three years with quotas policy			0.00156* (0.096)	-0.00134 (0.199)
Four years with quotas policy			-0.00184* (0.070)	-0.00533*** (0.000)
Age	0.000119*** (0.000)	0.000118*** (0.000)	0.000120*** (0.000)	0.000119*** (0.000)
Sex (male = 1)	0.000815*** (0.000)	0.000825*** (0.000)	0.000812*** (0.000)	0.000822*** (0.000)
GIC	-0.00177** (0.014)	0.00124* (0.086)	-0.00211*** (0.004)	0.000856 (0.233)
Degree with accessibility	0.0000132 (0.965)	-0.000106 (0.734)	0.0000421 (0.891)	-0.000166 (0.593)
State linear time trends	NO	YES	NO	YES
N	747448	747448	747448	747448
F	18.46	8.234	12.42	7.580
r2	0.0324	0.0331	0.0326	0.0333

Cluster-Robust Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All regressions are controlled for institution-degree pairs fixed effects and time fixed effects.

Source: Elaborated by the author.

3.5.3 The Enem effect

Before Sisu, students could use their Enem exam score to apply for some universities. Even though the main entrance instrument was the vestibular exam in most universities, it is possible that Enem had a similar effect of reducing application costs. Therefore, it is relevant to disentangle the impact of Enem exam alone from that resulting from the Sisu admission system. Table 23 sheds light on this problem. The table shows the share of students with and without disabilities by entrance method from 2009 to 2016. Before Sisu, when students could use the Enem exam in a few universities, about 5.6% of students without disabilities have accessed higher education through Enem, in contrast with only 0.65% of students with disabilities.

In 2010, after Sisu's implementation, the Enem score became much more relevant as an admission method. The reason is that now using Enem allowed students to apply through the Sisu system. Table 23 shows that the share of students without disabilities that access higher education through Enem rose to 20.2%, about four times greater than in 2009. The increase, however, was much more significant when considering students with disabilities. The share of students with a disability that accessed higher education rose from 0.65% in 2009 (before Sisu) to 10.16% in 2010, increasing by 15 fold. Moreover, the rate of increase through the following years was faster for students with disability.

This fact means that accessing a higher education institution using Enem became much more relevant after Sisu. The centralized admission process was crucial to nudge students to start using their Enem Score and not taking the Vestibular exam. That was especially true for students with disabilities because their sensitivity to Sisu implementation was much higher.

To capture the effect, we run a simple diff-in-diff regression with two groups: individuals with and without disabilities. We run the following regression:

$$\ln\left(E_{d,t}\right) = \alpha S_{d,t} + \beta D_{d,t} + \gamma S_{d,t} D_{d,t} + \sigma_t + \varepsilon_{d,t}$$

Variable $\ln(E_{d,t})$ is the log of the number of entrants that have used Enem at time t and belong to group $d \in \{0, 1\}$ where $d = 1$ for the group of students with disability and zero for the groups of students without disability. $S_{d,t}$ is a dummy indicating if at t Sisu existed, D is a dummy indicating if the group has disabilities or not, and σ_t is time fixed effects.

This simple model illustrates what could be inferred from Table 23. Results (Table 24) shows that the effect of Sisu implementation on the number of students with disabilities that accessed higher education through Enem was higher than students without disabilities.

Table 23 – Share of Students that have accessed a University using Enem (%)

Year	Students with disabilities	Students without disabilities
2009	5.67	0.65
2010	20.19	10.17
2011	25.63	17.53
2012	32.33	34.13
2013	36.11	35.90
2014	47.09	62.27
2015	50.55	64.90
2016	54.91	63.34

Source: Elaborated by the author.

Table 24 – Results - The Enem Effect

	(1)	(2)
Sisu	2.075**	-
	(0.870265)	
Disabilities	-7.718***	-7.718***
	(1.151253)	(0.676135)
Interaction	2.520*	2.520**
	(1.230741)	(0.722818)
2010		1.002
		(0.599329)
2011		1.248*
		(0.599329)
2012		1.921**
		(0.599329)
2013		2.064**
		(0.599329)
2014		2.706***
		(0.599329)
2015		2.823***
		(0.599329)
2016		2.763***
		(0.599329)
N	16	16
F	72.34	73.11
r2	0.948	0.991

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Elaborated by the author.

3.6 FINAL REMARKS

We study the effects of centralizing the college admission process on human capital investment decisions by individuals with disabilities. The evidence suggests that the decrease in the marginal costs of college applications associated with moving towards a centralized admission process would have a disproportionally larger effect for the populations that these costs are larger.

We find that the change to a centralized admission system led to an increase in the proportion of students with disabilities (compared to the control group) for the institutions that participate in the centralized mechanism. This result suggests that, on top of other documented benefits of such a system (Machado and Szerman, 2017), an unintended but positive consequence of such an admission system is to substantially improve access to higher education for individuals with special needs.

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4 MEASURING THE INTERNAL RATE OF RETURN TO SCHOOLING FOR WORKERS WITH DISABILITIES IN BRAZIL

Over the past few decades, efforts have been made to increase accessibility and participation of people with disabilities in all aspects of life. However, individuals with disabilities still have lower employment rates, lower levels of schooling, and lower wages. Efforts to increase the participation of people with disabilities in Brazil's work force began over 30 years ago[14]. In spite of Brazilian government's inclusion policies, people with disabilities represent only 0.91% of the country's formal labor force.

An important aspect that influences employment, wages and other labor market conditions is the worker's human capital. With that in mind, our work analyzes the role that education plays in the lives of disabled people in Brazil. In particular, we estimate their wage returns to education, examining linkages between disability and the returns and also compare them with returns to education for people without disability. In addition, we also estimate returns to education for individuals according to five types of disabilities: physical, visual, hearing, intellectual and multiple disabilities.

Unlike previous works that estimate mincerian equations, we measure the wage returns to education through the internal rate of return (IRR), which was introduced as a central concept of human capital theory by Becker (1964). According to Becker (1964), individuals decide to invest in education by comparing their costs and benefits, and the IRR is the discount rate that equals them. In a regression of log earnings on years of schooling, the coefficient on schooling (the mincerian coefficient) is often called an IRR. However, this coefficient is a growth rate of earnings for each year of schooling and not an IRR - except under the specific conditions of the Mincer model (1958, 1974)[15]. Since such conditions seldom apply[16], our objective in this paper is to calculate the IRRs for people with disabilities using nonparametric estimates of wage function, following Heckman, Lochner, and Todd

[14] Law 8213/1991 established employment quotas in companies with 100 or more employees.

[15] The conditions that would make the mincerian coefficient an IRR are as follows: risk-neutral agents that maximize the present value of expected income over the life cycle; the total working time throughout the life cycle is the same for all individuals regardless of schooling level; the only costs incurred are opportunity costs; there is no uncertainty; agents enter the labor market one period after the end of their studies; the agents do not work during schooling; there are no imperfections in the credit market; after obtaining a job, the agents do not return to education; the functional form of income must be (in log) linear on education and multiplicatively separable between education and experience (parallelism).

[16] Hungerford and Solon (1987), Bound, Jaeger, and Baker (1995), Jaeger and Page (1996), Heckman, Layne-Farrar, and Todd (1996), and Heckman, Lochner, and Todd (2006) performed linearity and parallelism tests for United States and rejected the hypothesis about the functional form of earnings, which is crucial for interpreting the mincerian coefficient as IRR. Moura (2008) performed the same tests for Brazil and also rejected the hypothesis about the functional form.

(2008) and Moura (2008). This method accounts for nonlinearities and nonseparabilities, unlike OLS based on Mincer equation.

To estimate the IRR on schooling for people with disabilities, we rely on Brazilian administrative data from 2011 to 2016. We use the RAIS database, which provides comprehensive information regarding the employment characteristics in the formal market. Results show that the IRR for disabled individuals is higher than for the nondisabled individuals at lower levels of schooling. In particular, the return for completing the first cycle of primary level is 18% higher for disabled individuals. However, the return for completing higher education is lower. Individuals with disability receive 11% less for completing higher education than individuals without disabilities. We also show that the higher returns in lower levels of schooling are mainly driven by hearing impairments.

After this introduction, this article is divided into more five sections: (1) related literature; (2) Brazilian labor market for people with disabilities; (3) data and methodology, (4) results; (5) final remarks.

4.1 RELATED LITERATURE

The starting point for all analyses of returns to education is the Mincer equation (1958, 1974) and the internal rate of return introduced by Becker (1964). There is a vast literature that seeks to estimate wage returns to education based on these works. Even in the case of people with disabilities, there are many studies on returns to education, like Johnson and Lambrinos (1985), Baldwin and Johnson (1994), Baldwin and Johnson (2000), and DeLeire (2001). More recently, Hollenbeck and Kimmel (2008), Lamichhane and Sawada (2013), Baldwin and Cohe (2014), and Henderson, Houtenville, and Wang (2017) also estimate wage returns for disabled workers. Currently, the focus of this literature is to find methodologies that reduce endogeneities, relax functional restrictions, and enable heterogeneities, as we can observe in these three more recent works.

Hollenbeck and Kimmel (2008) estimate the returns to education for males by disability status and age of disability onset using an endogenous switching model. They find that workers with early-onset disability have no statistically significant return to education that may be the result of the failure of special education programs to prepare for employment. They also find that workers who experience disability onset after reaching adulthood have substantial wage returns to education, much higher than the returns for the non-disabled ones

(21.1% against 10.2%). Thus, education protects workers against potential adverse wage effects of becoming disabled.

Lamichhane and Sawada (2013) estimate the returns to education for people with disabilities in Nepal using the instrumental variable method. They find very high rates of returns, ranging from 19.4% to 33.2%. The coexistence of high returns to education and limited years of schooling indicates that supply-side constraints in education to accommodate people with disabilities or there are credit market imperfections.

Baldwin and Cohe (2014) do a decomposition exercise of the wage gap between disabled and nondisabled individuals. They use a different version of the traditional Oaxaca-Blinder decomposition to investigate what percentage of the wage differential can be attributed to discrimination. In addition to new method, the authors incorporate in the model measures of job requirements. They argue that occupations differ with respect to physical requirements and therefore individuals with disabilities would tend to be, on average, less productive than individuals without disabilities. They find that even after controlling for job requirements, male disabled individuals earn 10% less and females 20% less. That unexplained gap can be attributed to discrimination.

Henderson, Houtenville, and Wang (2017) estimate the distribution of returns to education for people with disabilities using nonparametric estimation techniques to relax functional restrictions and enable heterogeneities. Their mean nonparametric estimates range from 9.4% to 12.3% and differ by the type and timing of disability. They also construct a measure of the returns to education considering risks, which indicates substantially larger returns to educational investment than that for those for other financial assets. Finally, they conduct stochastic dominance tests whose results indicate that the returns to distribution are better for workers without disabilities than for workers with disabilities and that labor market conditions may have worsened even more for workers with disabilities.

To our knowledge, there is no study on returns to education for people with disabilities in Brazil. However, there are works on other aspects of the labor market for people with disabilities. For example, while Castro, Moreira, and Silva (2017) and Becker (2018) aims to analyze the effect of disability on wages, Thomasi *et al*. (2017) aim to analyze the employability of people with disabilities in the labor market.

4.2 BRAZILIAN LABOR MARKET FOR PEOPLE WITH DISABILITIES

The Brazilian government has developed public policies to increase the inclusion of people with disabilities in the labor market. The law 8213/1991 established that a company with 100 or more employees must fill 2% to 5% of their positions with people with disabilities. However, only the ordinance 1199/2003 made it possible to inspect and punish the companies that do not comply with the provisions of this law. In addition, the decree 3298/1999 established a 5% quota for people with disabilities in civil service jobs.

In the current decade, according to the Annual Social Information Report (RAIS) from the Ministry of Labor and Employment, we can observe that indeed the total number of workers with disabilities in Brazilian formal labor market jumped from 324,000 in 2011 to 419,000 in 2016 (Figure 12). As a consequence, the percentage of workers with disabilities in the labor market presented a similar trajectory, jumping from 0.70% in 2011 to 0.91% in 2016 (Figure 13)[17]. The most common disability among workers is physical disability, followed by hearing and visual impairments (Figure 14).

The difference in average wages between disabled and non-disabled workers has also increased. In 2011, the average wage (in constant prices for 2016) of disabled workers was R$ 2,467.90, which was 96% of the average wage of workers without disabilities. In 2016, this 4% differential increased to 11%: in this year, the average wage of disabled workers was R$ 2,421.87, while the average wage of workers without disabilities was R$ 2,734.45 (Figure 15).

This wage differential may be due to two factors: productivity and discrimination. Castro, Moreira, and Silva (2017) and Becker (2018) analyzed if this differential is predominantly due to differences in individual characteristics and lower productivity or if it is predominantly due to discrimination. The authors find that, depending on the wage quantile, sex, and severity of disability, discrimination may not exist. However, discrimination can be the primary determinant for a few groups.

A major individual characteristic that influences productivity and, consequently, one’s wage is schooling. As shown in Figures 16 and 17, workers with disabilities have, on average, fewer years of study. For example, by 2016, only 15% of disabled workers had completed higher education, while that percentage was 20% among non-disabled workers. Therefore,

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[17] For comparison, according to the Demographic Census of 2010, 23% of the working-age population has some type of disability. This percentage drops to 7% when we do not account for minor disabilities. Considering only severe disabilities, this percentage drops to 2%.

education can be one of the determinants of the wage differential between workers with and without disabilities.

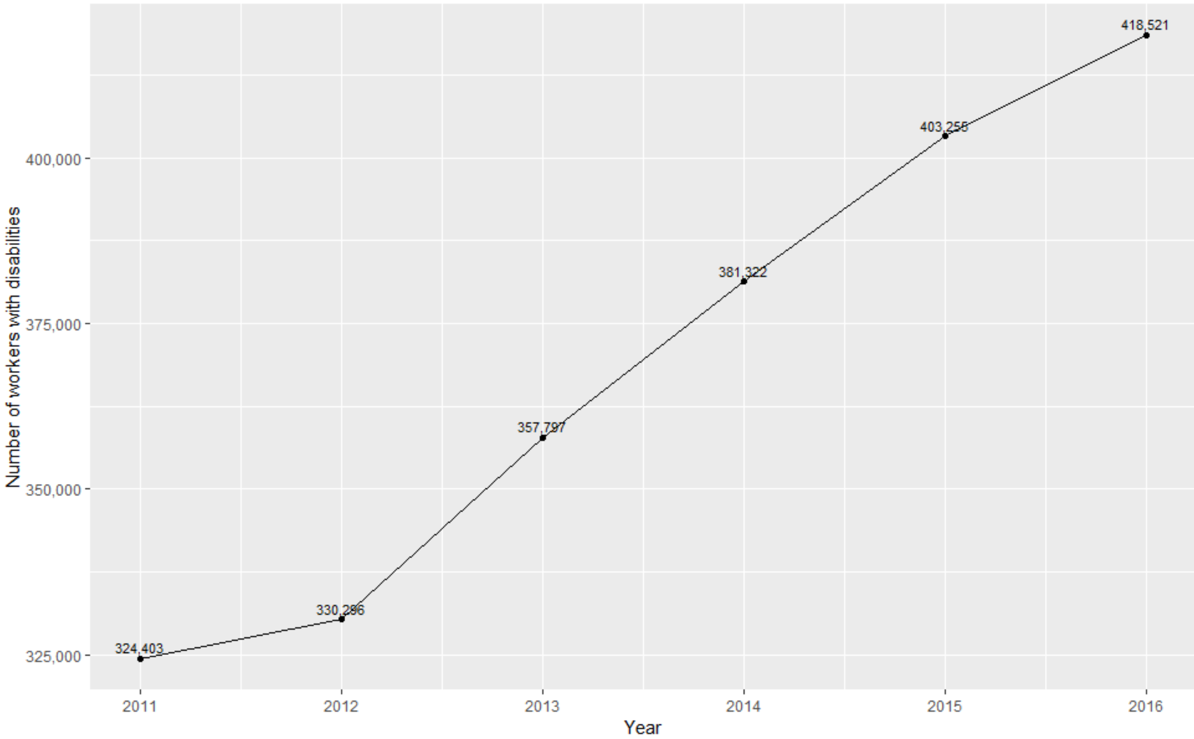
The central basis of the demand for education is the private return in the form of higher wages. An individual decides whether or not to invest in education by comparing their costs and benefits. Disabled workers have on average fewer years of study than non-disabled workers. One possible explanation is that their returns to education are lower because the education received by these individuals is not serving them well on finding productive jobs. In this case, low returns to education may be related to both fewer years of study and lower wages.

Wages also vary according to the occupation of the worker. For example, managers and professionals are more valued occupations and, consequently, have higher wages. There are proportionally fewer workers with disabilities in these occupations compared to workers without disabilities. As Figure 18 shows, while only 2.1% of workers with disabilities work as managers, 5.1% of workers without disabilities work in this occupation. Similarly, only 6.1% of workers with disabilities work as professionals, compared to 11.2% of workers without disabilities.

The highest percentage of disabled people work as clerical support workers (32.0%), service and sales workers (21.9%) or craft and related trades workers (20.3%). While 32.0% of disabled workers work as clerical support workers, only 19.4% of workers without disabilities work in this area. It is possible to attribute this difference to the public sector quotas, since many of the employees in that sector are classified as clerical workers. However, this difference remains when we look only at the private sector (Figure 19).

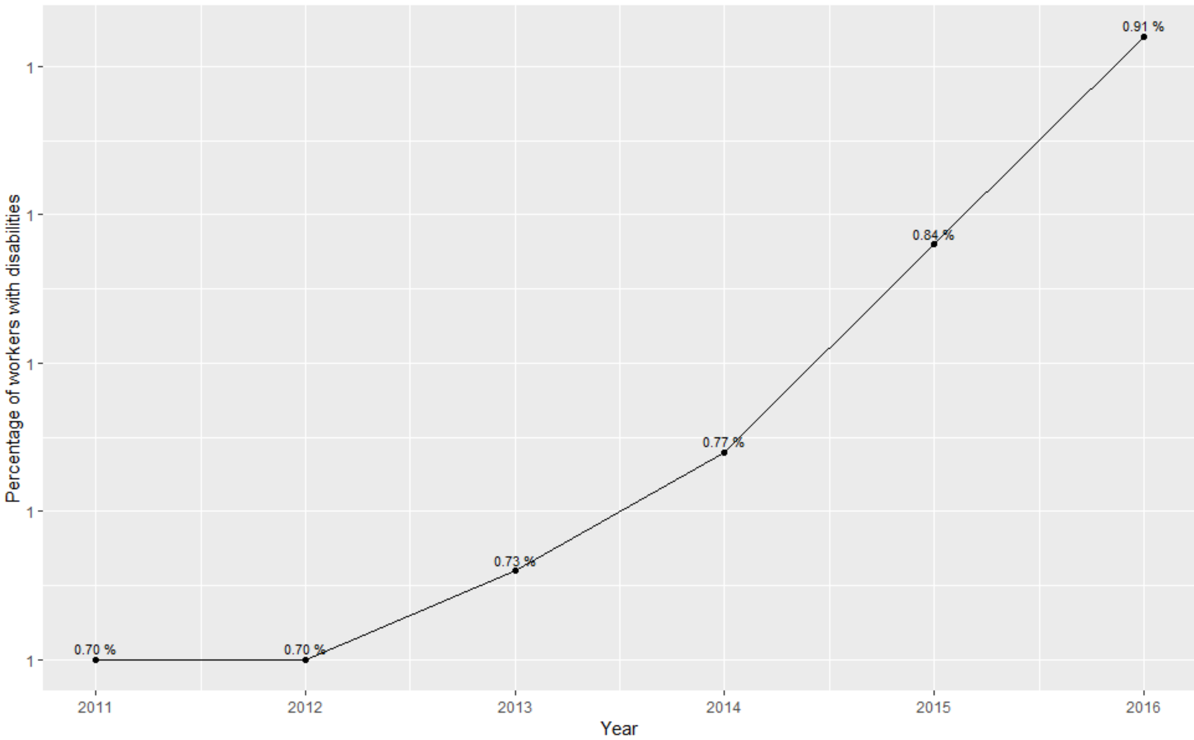
Figures 20 and 21 present other individual characteristics that influence wage returns: age (a proxy of experience) and the number of contracted working hours in a week. There is not much difference between workers with and without disabilities in these two characteristics. Workers with disabilities are slightly older than workers without disabilities. For example, in 2016 the mean age of workers with disabilities was 38.9 versus 37.4 for workers without disabilities. Workers with and without disabilities work on average around 40 and 41 hours a week, respectively.

Figure 12 – Evolution of the number of workers with disabilities in Brazilian formal labor market



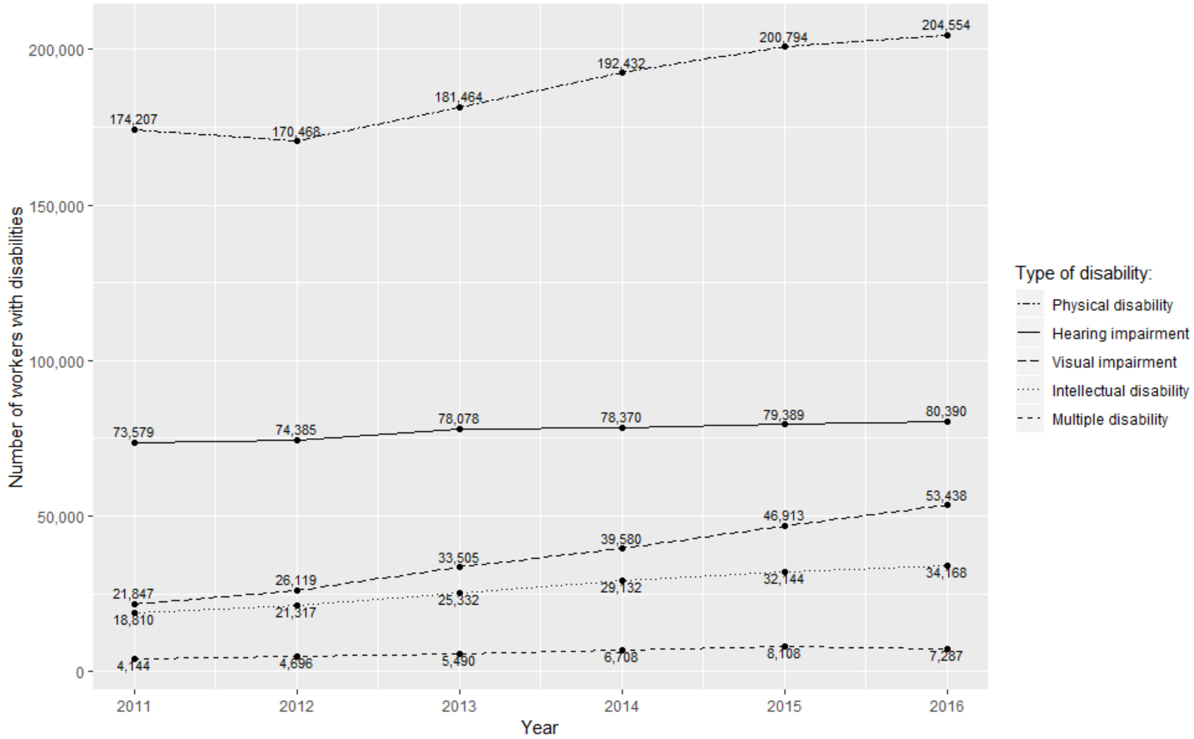
Source: Elaborated by the author, based on data of RAIS.

Figure 13 – Evolution of the percentage of workers with disabilities in Brazilian formal labor market



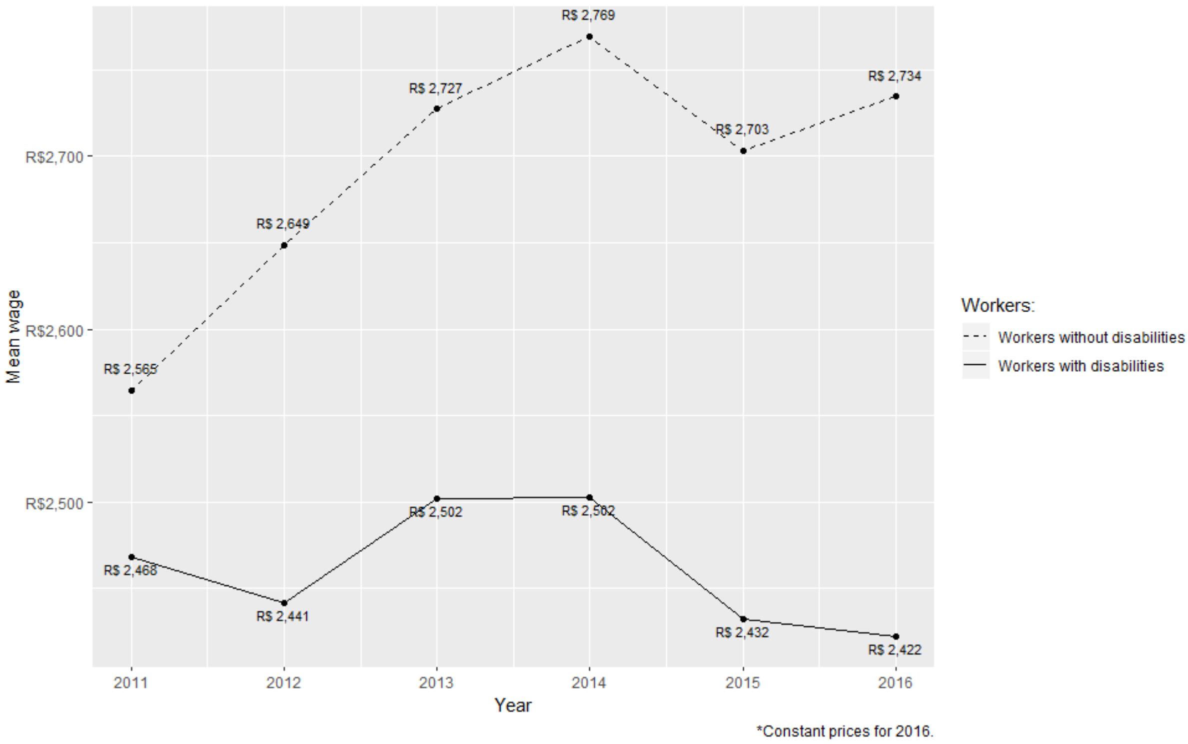
Source: Elaborated by the author, based on data of RAIS.

Figure 14 – Evolution of the number of workers in Brazilian formal labor market by type of disability



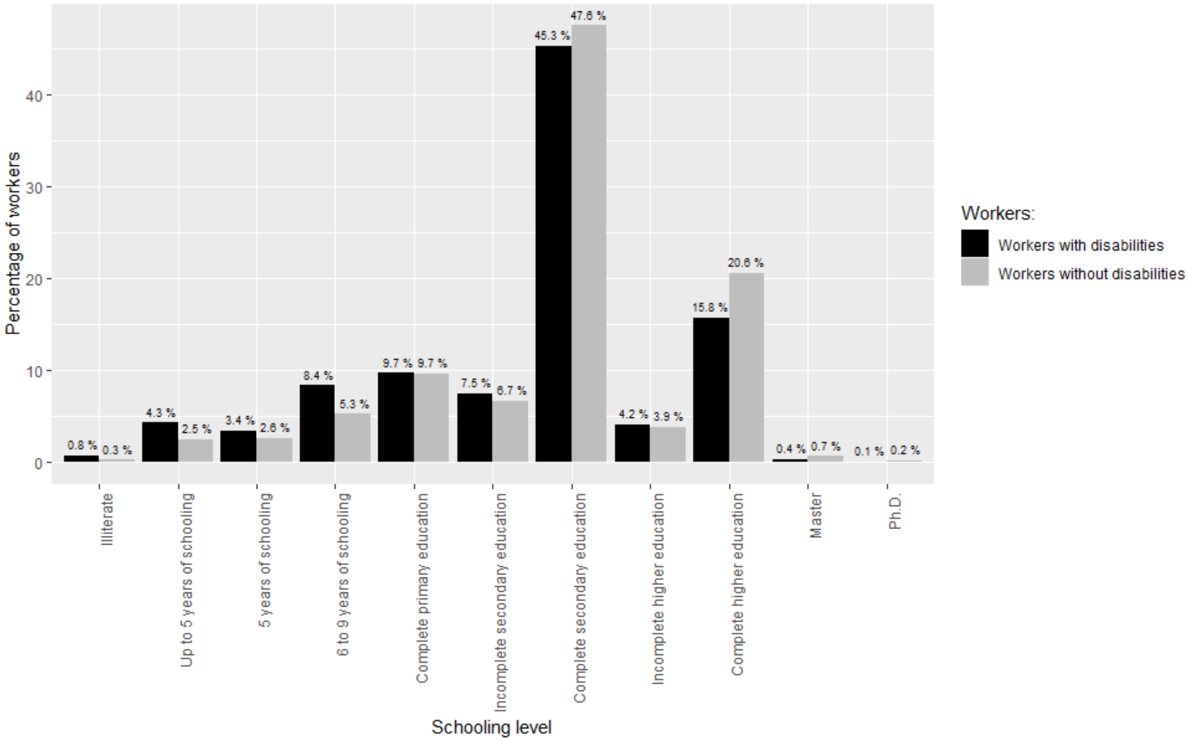
Source: Elaborated by the author, based on data of RAIS.

Figure 15 – Evolution of the mean wage* of workers with and without disabilities in Brazilian formal labor market



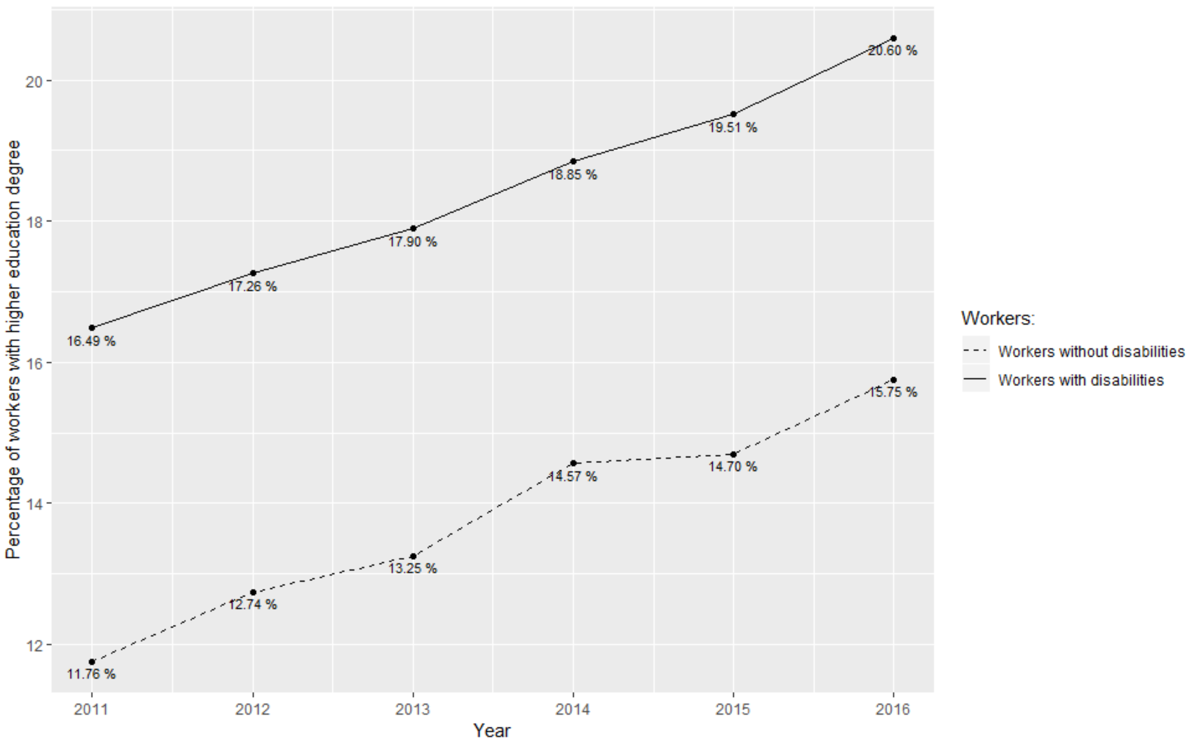
Source: Elaborated by the author, based on data of RAIS.

Figure 16 – Percentage of workers by schooling level in Brazilian formal labor market – 2016



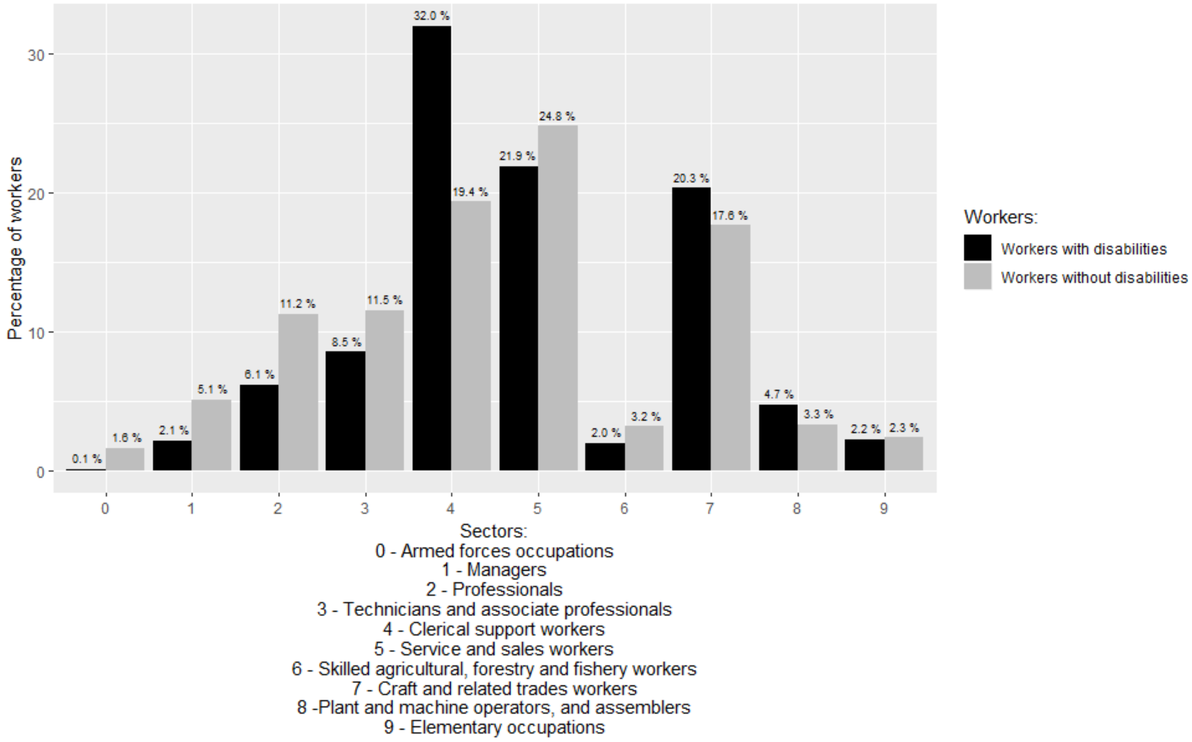
Source: Elaborated by the author, based on data of RAIS.

Figure 17 – Percentage of workers with higher education degree in Brazilian formal labor market



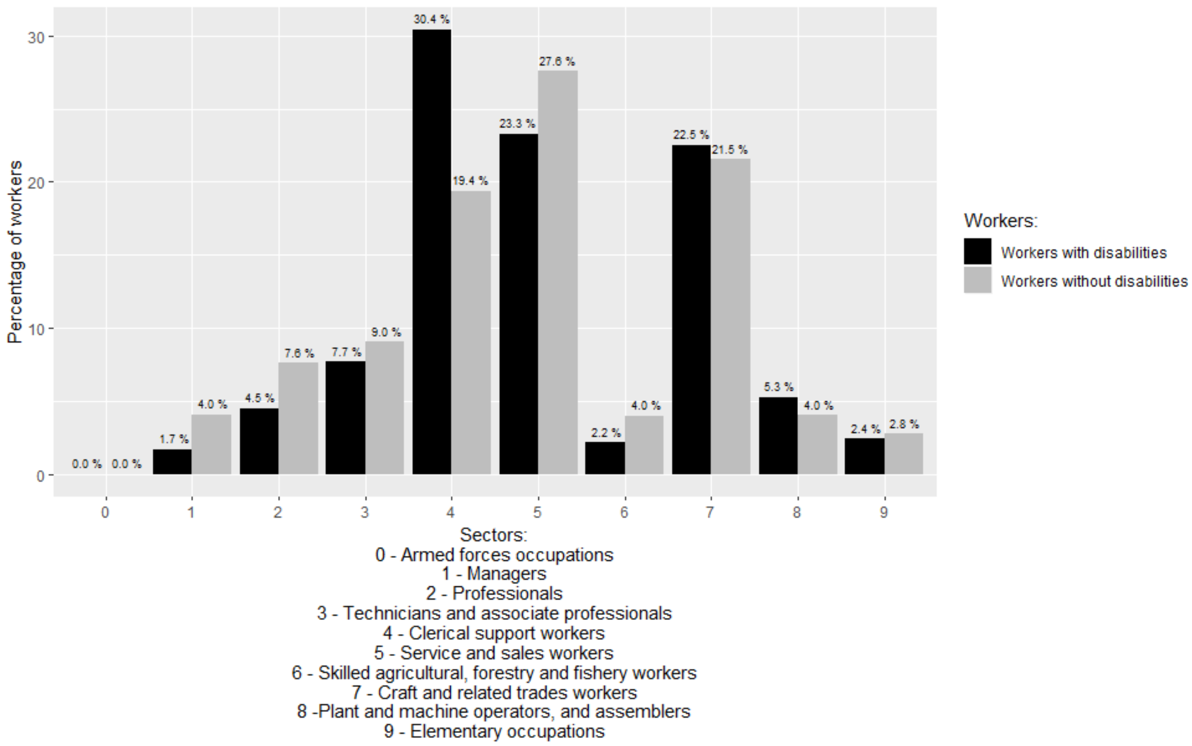
Source: Elaborated by the author, based on data of RAIS.

Figure 18 – Percentage of workers by sector in Brazilian formal labor market – 2016



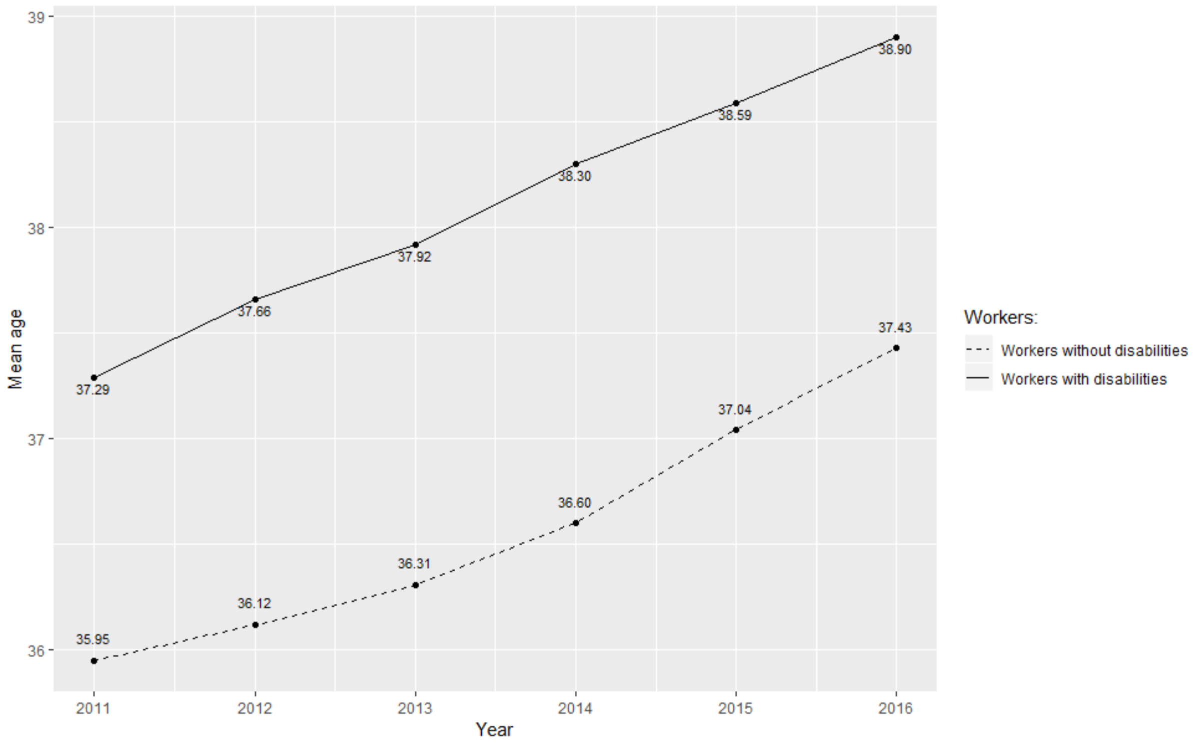
Source: Elaborated by the author, based on data of RAIS.

Figure 19 – Percentage of workers by sector in Brazilian private formal labor market – 2016



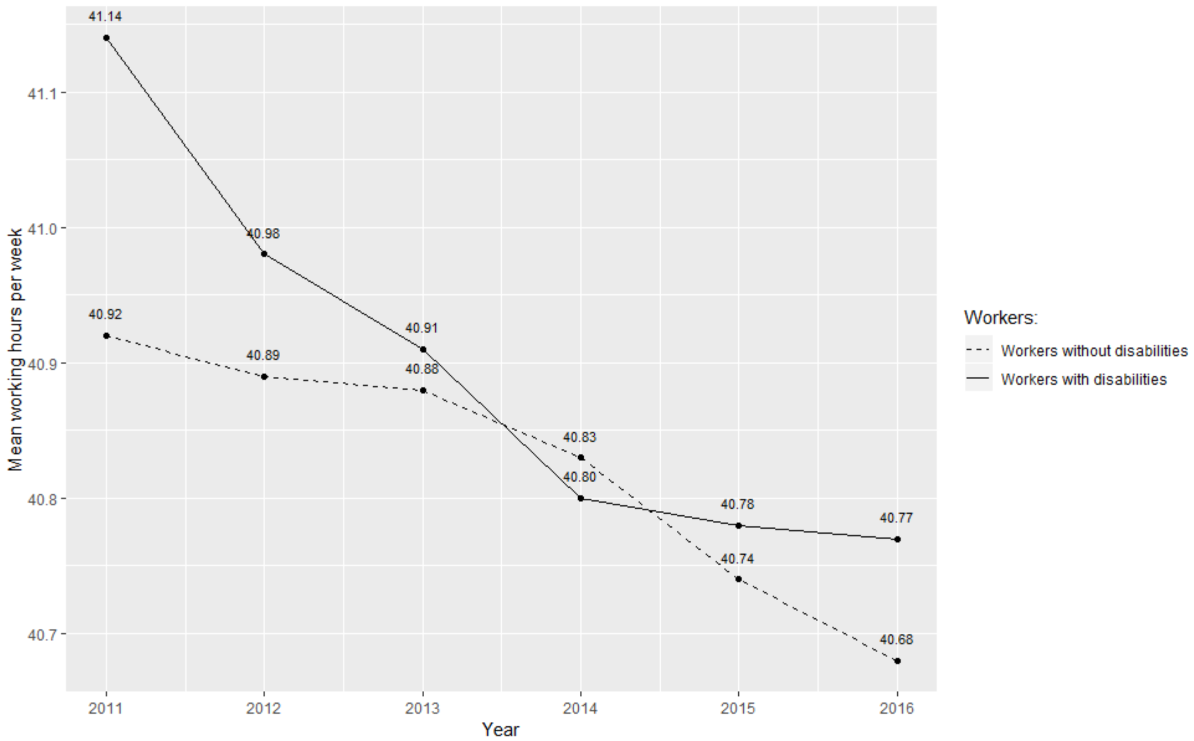
Source: Elaborated by the author, based on data of RAIS.

Figure 20 – Evolution of the mean age of workers with and without disabilities in Brazilian formal labor market



Source: Elaborated by the author, based on data of RAIS.

Figure 21 – Evolution of the mean working hours per week of workers with and without disabilities in Brazilian formal labor market



Source: Elaborated by the author, based on data of RAIS.

4.3 DATA AND METHODOLOGY

We use microdata from the Annual Social Information Report (RAIS) from 2011 to 2016. The RAIS consists of an annual administrative dataset that presents information on the entire formal labor market in Brazil. In this paper, we restrict our sample to working age individuals (between 15 and 64 years) with a full-time job (with a working week of more than 36 hours and less than 44 hours).

Our methodology follows Heckman, Lochner, and Todd (2008) and Moura (2008), who calculate the IRRs for all workers in United States and in Brazil, respectively. So, using the data described above, we calculate the IRR by the following equation:

$$\sum_{x=0}^{l}\frac{\hat{Y}(x,s+h)}{(1+r)^{s+h}} - \sum_{x=0}^{l}\frac{\hat{Y}(x,s)}{(1+r)^{x}} = 0 \qquad (1)$$

where the first expression represents the present value of the benefit of the investment in more h years of study, and the second expression represents the present value of the cost of the same investment. $\hat{Y}(.)$ is the adjusted value of the nonparametric estimation by local linear regression in which the natural logarithm of the wage is the dependent variable and the age (experience proxy) is the independent variable. Therefore, x is the age, s and $s+h$ are the two schooling levels that we compare, and r is the IRR.

We compute the local linear regression estimator for the conditional expectation $E[Y_i|x_i = x_0]$ from the following minimization problem:

$$min_{a,b}\sum_{i=1}^{n}(Y_i - a - b_1(x_i - x_0))^2 K(\frac{x_i - x_0}{h_n}) \qquad (2)$$

where K(.) is a kernel function and $h_n > 0$ is a bandwidth which converges to zero as n → ∞, that is, the estimator of the conditional mean $E[Y_i|x_i = x_0]$ is $\hat{a}$. We can write this local linear estimator as a weighted average:

$$\sum_{i=1}^{n} Y_i W_i(x_0) \qquad (3)$$

where $W_i(x_0) = \frac{K_i\sum_{j=1}^{n}K_j^2 - K_i\sum_{k=1}^{n}K_k}{\sum_{k=1}^{n}K_k\sum_{j=1}^{n}K_j^2 - (\sum_{k=1}^{n}K_k)^2}$ (HECKMAN; LOCHNER; TODD, 2008). Thus, in this paper, the local linear estimator is given by $\widehat{m}(x_0) = \sum_{i=1}^{N} Y(x_i)\, W_i(x_0)$, where $Y(x_i)$ represents the logarithm of the wage of the individual with x years and N represents the number of observations. We use the Gaussian kernel function and we calculate the optimal bandwidth by cross-validation method.

In the Tables 25 and 26, we can see the number of observations in each schooling level in our dataset after the restrictions made. We calculate the IRRs for four comparisons between schooling levels: 0-5, 5-8, 8-11, and 11-15. In order to obtain standard deviations for our estimates, we use the bootstrap method, resampling and re-estimating the returns 50 times. Since process we used to estimate the IRRs is very time consuming given the computational capacity of our hardware, estimating the return for every single schooling level with the full sample was not possible. To solve this problem, we use a random sample of 12,000 observations in the IRR calculation. Just for the IRRs by type of disability, we use the entire sample.

Table 25 – Number of observations

Schooling level	People with disabilities	People without disabilities
0	14,002	830,727
5	74,970	8,199,384
8	195,798	27,755,741
11	814,978	116,977,895
15	226,085	35,559,156

Source: Elaborated by the author.

Table 26 – Number of observations by type of disability

Schooling level	Physical disability	Hearing impairment	Visual impairment	Intellectual disability	Multiple disability
0	3,945	3,212	858	4,942	471
5	33,050	21,522	5,601	6,355	1,556
8	90,572	49,591	15,875	15,852	3,466
11	432,999	163,696	85,341	36,985	11,513
15	128,670	41,878	28,858	2,494	3,105

Source: Elaborated by the author.

4.4 RESULTS

In this section, we describe our results for the IRRs estimates that are in Tables 27 and 28. Table 27 presents the IRRs estimates for people with disabilities versus people without disabilities. Two aspects call attention in these results.

Table 27 – Internal return rates

Measure	People with disabilities				People without disabilities			
	Comparisons between schooling levels				Comparisons between schooling levels			
	0-5	5-8	8-11	11-15	0-5	5-8	8-11	11-15
Mean	3.70%	2.28%	4.39%	11.06%	3.12%	1.53%	4.11%	12.34%
SD	0.08	0.24	0.41	0.60	0.14	0.33	0.48	0.46

Source: Elaborated by the author.

First, for both groups, the returns increase along with the schooling level, and the highest return is at higher education. For all schooling levels but complete higher education, the IRR is lower than 5%. For workers with complete higher education, however, the IRR exceeds 10%. This result is in line with Moura (2008), who calculated the IRRs for all workers in Brazil and also found higher IRRs for higher levels of education. Brazil still has a relatively low supply of high skilled labor, which means the return to schooling at higher levels of education are still very high.

Second, there is a statistically significant difference between the IRRs of workers with and without disabilities, and this difference is higher at lower schooling levels. In the first two comparisons between schooling levels ("no schooling" *versus* "five years of schooling", and "five years of schooling" *versus* "complete primary education"), the difference between the IRRs is around one or a half percentage point higher for disabled workers. These results mean that the wage gain for individuals with disabilities that complete primary education in comparison to individuals with disabilities that do not complete primary school is higher than the same comparison but considering individuals without disabilities.

In the third comparison between schooling levels ("complete primary education" *versus* "complete secondary school"), the IRRs are almost the same. Lastly, comparing "complete secondary education" *versus* "complete higher education", the highest rate is for non-disabled workers. An explanation for this phenomenon is that the abilities required for occupations at low schooling levels are sensory abilities. Individuals with hearing and sight might have more significant difficulties in performing such tasks and therefore, will face low demand for their labor. However, primary education enables individuals with disabilities to be qualified to perform jobs that rely more on cognitive abilities than physical ones. Primary education *increases* the marginal productivity of the worker with disabilities *more* than that of workers without disabilities.

Table 28 – Internal return rates by type of disability

People with disabilities			
Comparisons between schooling levels			
0-5	**5-8**	**8-11**	**11-15**
Physical disability			
3.21%	1.61%	4.22%*	11.18%*
Hearing impairment			
3.69%	2.71%	4.18%	9.36%
Visual impairment			
3.07%	2.04%	4.68%	11.01%
Intellectual disability			
1.53%	0.97%	2.27%	6.86%
Multiple disability			
3.76%	0.26%	3.54%	10.12%

Source: Elaborated by the author.

Table 28 shows the IRRs to schooling levels by types of disability, and they contain a few noteworthy results. First, if we compare Tables 27 and 28, we see that the only type of disability that follows a similar pattern to individuals with disabilities in Table 27 is Hearing Impairment. Disabled individuals have a higher return than the nondisabled in the lower levels of schooling, but they have a lower return at higher education. Second, individuals with physical disabilities have IRRs that are very similar to individuals without disabilities. It possible that adaptations to enable accessibility of workers with physical disabilities are easier to implement. Once they are in place, workers can perform most occupations at all levels of schooling, as opposed to individuals with hearing or visual disabilities. Baldwin and Choe (2014) document the empirical relevance of this hypothesis. They show that “physical job demands” help to explain a significant share of the wage differential between disabled and nondisabled individuals. Lastly, workers with intellectual disabilities have the lowest IRRs for every schooling level and are especially lower at higher levels of education. A possible explanation for this fact is that intellectual disability affects negatively their ability to perform cognitive tasks, which are present in most occupations that require college degrees.

4.5 FINAL REMARKS

We have estimated the wage returns to schooling for workers with disabilities in Brazil using the internal rate of return method. Overall, we find that IRR is higher for individuals with disabilities than individuals without disabilities when looking at lower schooling levels, but lower at higher schooling levels. We speculate that this phenomenon occurs because primary education enables individuals with disabilities to access occupations that are less dependent on sensory abilities, which they are, to different degrees, lacking. Therefore, schooling at lower levels increases their marginal productivity to a higher degree relative to individuals without disabilities.

We believe our findings provide valuable information to policymakers concerned with improving the lives of individuals with disabilities. Our findings can help policymakers to target specific education policies to individuals with disabilities at the more effective schooling levels.

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