POTENTIAL HETEROGENEOUS TREATMENT EFFECT OF EDUCATION IN PUBLIC FEDERAL SCHOOLS: AN ANALYSIS OF BRAZILIAN HIGH SCHOOL[1]

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In Brazil, the debate about the influence of different types of schools on the academic performance of students is fundamental, as it is immersed in the apparent low quality of Brazilian education, a nation lacking economic and social development. In this context, this paper aims to estimate the potential heterogeneous effects of studying in federal public high schools in Brazil on academic performance. As an empirical strategy, the causal forest method was used to estimate the effect of heterogeneous treatment and, as an indicator of academic performance, the scores of the National High School Exam (Enem) carried out in 2019, for a set of 565,759 students were used. It was found that, controlling for the 10 economic and social variables specified in the model, federal public schools achieve better results in terms of student performance than state public schools in all subjects. In addition, it was possible to verify a heterogeneous effect, that is, a higher level of performance, but with different amplitudes, for students from federal public schools in different states of the federation and with different levels of family income.

Keywords: academic performance; causal forest; causal inference; education economics.

POTENCIAL EFEITO HETEROGÊNEO DO TRATAMENTO DA EDUCAÇÃO NAS ESCOLAS PÚBLICAS FEDERAIS: UMA ANÁLISE DO ENSINO MÉDIO BRASILEIRO

No Brasil, o debate sobre a influência dos diferentes tipos de escolas no desempenho acadêmico dos alunos é fundamental, pois está imerso na aparente baixa qualidade da educação brasileira, uma nação carente de desenvolvimento econômico e social. Nesse contexto, este artigo tem como objetivo estimar os potenciais efeitos heterogêneos de estudar em escolas públicas federais no Brasil sobre o desempenho acadêmico. Como estratégia empírica, foi utilizado o método da floresta causal para estimar o efeito do tratamento heterogêneo e, como indicador de desempenho acadêmico, foram avaliadas as notas do Exame Nacional do Ensino Médio (Enem) realizado em 2019, para um conjunto de 565.759 alunos. Verificou-se que, controlando as 10 variáveis econômicas e sociais especificadas no modelo, as escolas públicas federais obtêm melhores resultados em termos de desempenho dos alunos do que as escolas públicas estaduais em todas as disciplinas. Além disso, foi possível verificar um efeito heterogêneo, ou seja, maior nível de desempenho, porém com amplitudes distintas, para alunos de escolas públicas federais de diferentes estados da federação e com diferentes níveis de renda familiar.

Palavras-chave: desempenho acadêmico; floresta causal; inferência causal; economia da educação.

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EFECTO POTENCIAL HETEROGÉNEO DEL TRATO EDUCATIVO EN LAS ESCUELAS PÚBLICAS FEDERALES: UN ANÁLISIS DE LAS ESCUELAS SECUNDARIAS BRASILEÑAS

En Brasil, el debate sobre la influencia de los diferentes tipos de escuelas en el rendimiento académico de los estudiantes es fundamental, ya que está inmerso en la aparente baja calidad de la educación brasileña, una nación carente de desarrollo económico y social. En este contexto, este artículo tiene como objetivo estimar los posibles efectos heterogéneos de estudiar en escuelas secundarias públicas federales de Brasil sobre el rendimiento académico. Como estrategia empírica se utilizó el método de la causal forest para estimar el efecto del tratamiento heterogéneo y, como indicador del rendimiento académico, se tomaron los puntajes del Examen Nacional de Enseñanza Media (Enem) realizado en 2019, para un conjunto de 565.759 estudiantes. Se encontró que, controlando por las 10 variables económicas y sociales especificadas en el modelo, las escuelas públicas federales logran mejores resultados en términos de desempeño estudiantil que las escuelas públicas estatales en todas las materias. Además, se pudo verificar un efecto heterogéneo, es decir, un mayor nivel de desempeño, pero con amplitudes diferentes, para estudiantes de escuelas públicas federales en diferentes estados de la federación y con diferentes niveles de ingreso familiar.

Palabras clave: rendimiento académico; bosque causal; inferencia causal; economía de la educación.

JEL: I280; I210; H430; H750.

1 INTRODUCTION

Although Constitutional Amendment 59 of 2009 instituted free and compulsory basic education for everyone at an appropriate age, in Brazil, half of the population aged 19 or over (about 50.1% in 2018) did not complete basic education (elementary school). In addition, the discussion about the quality of education in Brazil is constant, intense and extremely important, since it is a country lacking economic and social development. Regarding the quality of education in a country, it is worth noting what Hanushek (2006) says about the evidence of a strong and direct link between quality of education and individual earnings, productivity and economic growth.

In Brazil, there is a tangled system of educational governance, which, in terms of the type of administrative dependence, can be public or private. At the public level, the school can be administered by the federal government, the state government, or the municipal government. The municipal government is generally responsible for elementary education. The central theme of this research is to estimate possible differences in the academic performance of students in secondary schools,[3] which are administered by the federal government or the state government.

In terms of the differentials of federal schools, one can cite the fact that, mostly, they are institutions which offer professional courses at all levels and modalities, from basic education to postgraduate education. In addition, professors are guaranteed

3. Throughout the text the term *secondary school* is used as a synonym for *high school*.

a portion of their total workload for research, with incentives for applied research involving students and the development of patents, for example (Pacheco, 2010; Deitos and Lara, 2016). That characteristic brings the position of a professor in a federal school much closer to the position of a university professor.

According to Weller and Horta Neto (2020), schools in the federal education system have more funding and better pay their teachers compared to other systems, which, in conjunction with trained teachers, attracts young people, including the middle-class incomes. Therefore, most students from federal schools do not work as technicians, but continue their studies at the best universities, given that they perform better than the students of public state schools or even that the majority of private schools.

Therefore, this research aims to estimate the potential heterogeneous effects on National High School Exam[4] (Enem) scores of studying in federal schools in Brazil. To do this, the analysis is divided in order to answer the following questions.

1) Does studying in federal schools improve student achievement in Enem scores in Brazil when compared to state schools? And what is the effect when compared to private schools?

2) Is the possible effect of higher performance of students from federal schools heterogeneous across states when compared to state schools? And between different levels of household income?

The literature that provides evidence on the influence of the type of administrative dependence of the school and that, at the same time, also identifies associated influence of family income on school performance is vast, and can be seen, for example, in Jimenez, Lockheed and Paqueo (1991), Vandenberghe and Robin (2004), Duncan and Sandy (2007), Moraes and Belluzzo (2014), Sobreira et al. (2019) or Feijó and França (2021). Regarding the possible influence of the state on school performance, evidence is rarer, but can be found, for example, in Carmo et al. (2015), Almeida, Araújo Júnior and Ramalho (2016), Soares, Soares and Santos (2020) and Alves et al. (2020). The fact that in Brazil, state governments are responsible for elementary school II (final years of elementary school) and high school, each one can even adopt different public policies also reinforces the hypothesis of heterogeneous effects between states.

A recurring problem in this type of research is selection bias. Specifically in this case, it is reasonable to believe that students are interested and make their decisions to study in state or federal schools based on their personal characteristics, such as specific abilities and motivations, as well as those of their family. Furthermore,

4. Freely translated from *Exame Nacional do Ensino Médio*, which is equivalent to the American SAT.

if students take a test on these abilities to enter school, as is the case in federal schools, their Enem scores may also be contaminated (Jimenez, Lockheed and Paqueo, 1991; Adelson, 2013). The methodological tools used here seek to mitigate selection bias to estimate only the value added by federal schools.

The causal forest method, a non-parametric, machine learning based estimator, was used as an empirical strategy to estimate the heterogeneous effects of studying in federal schools. It is a method for heterogeneous treatment effect estimation that recovers estimates that are low-bias and yields asymptotic confidence interval (Wager and Athey, 2018; Athey and Wager, 2019). It focuses on estimating heterogeneous effects across different levels of household income and between states of the federation, comparing federal and state public schools, and controlling for observed economic and social variables. Enem scores were used as a measure of academic performance, which evaluates the performance of students at the end of basic education, and also serves as a mechanism for accessing higher education.

The relevance of this paper can be noticed in some aspects. Firstly, for the expansion and qualification of the debate, with empirical evidence, on the influence of the type of school on the quality of education in Brazil. In addition, the importance of this debate can be highlighted when considering the inequalities in terms of learning for students from economically disadvantaged families, a recurring problem in the country. The empirical evidence from this research can also contribute to a possible extrapolation of the results to other developing countries, as these generally face similar problems in educational matters.

Still regarding the relevance of research with themes similar to this paper, Moreira (2015) highlights the importance of evaluating public educational policies, especially with regard to the quality of education, since an improvement in the performance and learning level of students can justify and demonstrate efficiency in the use of public resources. The author also emphasizes that, from the mid-1990s, Brazilian educational policies began to give greater weight to the quality in education. This brought the need for greater processing of educational information, through a more comprehensive national assessment system, with an increasing number of schools and students, covering the different regions of the country. Thus, possible differences in the quality of education between states of the federation must be pointed out, and this paper also contributes to this. Finally, another contribution is the consolidation of recent literature on the use of machine learning in applied econometric studies.

This study is organized as follows: section 2 performs a literature review on the main topics covered. The econometric model and data are presented in section 3. Section 4 describes the main results. Discussion is presented in section 5. Finally, section 6 shows the final considerations.

2 LITERATURE REVIEW

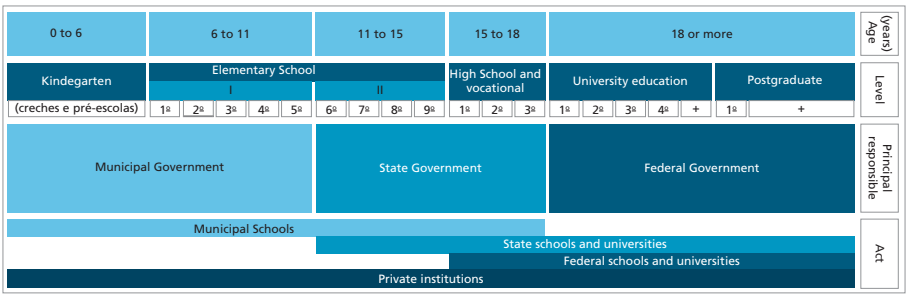
2.1 The Brazilian education system

With 26 states, the Federal District and 5,568 municipalities, Brazil has a complex system of education governance, regulated by several laws that guide its format. There are approximately 40 million students, with 700 schools managed by the federal government, 31 thousand schools by state governments, 113 thousand schools by municipal governments, 40 thousand schools by the private sector (Pinto, 2020).

According to the Brazilian Constitution of 1988 and the Law of Directives and Bases of National Education of 1996 (Brasil, 1996), the federal, state and municipal governments have complementary responsibilities, although different in several aspects. The federal government, for example, is responsible for, in addition to the main responsibility for providing and regulating higher education, the definition of normative guidelines for the formulation of educational policies at all levels, with a distributive, financial and consultative function.

In collaboration with the federal government, the state and municipal governments are responsible for compulsory education for all the population, with the municipality in charge of early childhood education and elementary school I (first years of elementary school), and the state for elementary school II (final years of elementary school) and high school. The figure 1 summarize this system in terms of administrative dependence.

FIGURE 1
Brazilian education system



Author's elaboration.

With the objective of expanding the presence of the federal network of professional education, the Ministry of Education started, in 2005, the Expansion Plan of the Federal Network of Professional Education in Brazil. The intention was to improve the spatial distribution and coverage of federal educational institutions, thus expanding the population's access to Vocational and Technological Education in the country.

The plan was divided into three phases. In Phase I, the priority was the installation of federal educational institutions in states of the federation which had not had such schools yet, as well as the construction of professional education institutions on the outskirts of large centers and municipalities in the countryside. In Phase II, which began in 2007, 150 units of federal education institutions were created in all states of the federation and in the Federal District (Brasil, 2008).

During Phase III, which began in 2011, the goal was to build 208 units of federal education institutions. In 2018, this number reached 660 education units, organized into 38 federal institutes of education, science and technology, a federal technological university, two federal technological education centers, 23 technical schools linked to federal universities and Colegio Pedro II.[5] The public education network covers 58.8% of enrollments in vocational education, and despite the expansion of the federal education network, it is responsible for only 3% of enrollments in high school in Brazil (Inep, 2020).

The implementation of a public policy as complex and comprehensive as this one implied, on the part of the federal government, an important destination of considerable amounts of the public budget. The amount spent on vocational education increased from US$ 0.46 billion in 2007 to US$ 1.96 billion in 2019. Brazil annually spends around 5% of GDP in the education system as a whole; one of the largest expenditures in Latin America.

2.2 Education with a production function

Following what has already been outlined, for example, by Hanushek (1986; 2020), Azevedo et al. (2021) and Grewenig et al. (2021), conceptually, education can be interpreted as a service that is the result of a transformation of inputs into products. This transformation can be expressed through an education production function, as follows.

$$\Delta Y_i = f(A_i, F_{i,} S_i) \quad (1)$$

In expression (1), ΔY_i represents the variation in student *i*'s learning. Although school performance is the result of variations in learning accumulated over time and generally more closely resembles skill acquisition, for the sake of simplification for empirical application, ΔY_i can be approximated as learning for a certain period of the student's time *i*.

Educational output, or school performance, then, can be expressed as a function of student abilities A, the family conditions F, and school conditions S.

5. Available at: http://portal.mec.gov.br/setec-programas-e-acoes/expansao-da-rede-federal. Accessed on: July 8, 2020.

As an example of researches which use family conditions as determining variables for school performance, it can be mentioned, among others, the paper of Tran and Nathan (2010), who found a negative impact of family income in science and mathematics subjects for pre-university engineering students. Sirin (2005) in a review of the literature, found a strong relationship between family background and academic performance. This was also the conclusion of Woessmann (2004) for Western Europe and the USA, and Araújo et al. (2020) for Southeast Brazil.

2.3 Some evidence on differences in proficiency test scores by school type

In the debate on the quality of education, there are analyzes of possible influences of the types of schools on the academic performance of students, and the literature dealing with eventual differences in academic performance in different types of schools is vast in the world.

For instance, it can be seen in Rohm et al. (2021) who analyzed to what extent the development of students' reading achievement in secondary school diverges across different school types, since in Germany, after elementary school, students are separated into different school tracks, with different assessment measures. The authors found no significant differences in reading competence, and demonstrated which variables, if not considered, may indicate differences. Delprato and Chudgar (2018) use measures of competitive pressure, administrative autonomy and staffing practices to explain the private-public performance in Australia, Portugal and Spain, and concluded that those factors do not explain the overall private-public performance gap in the three countries except at the higher-end of the distribution. Driessen, Agirdag and Merry (2016) did not observe significant differences between religious schools and public schools in a study in the Netherlands, except in Islamic schools. Harry (2016), in a study in Trinidad, compared the academic performance of students attending privately managed public elementary schools and traditional public schools, and found no meaningful difference.

Specifically, by comparing public and private schools, Suna et al. (2020) found that in private schools which were socioeconomically stronger in Turkey there are significantly higher academic achievement levels. Frenette and Chan (2015) found that private high school students score significantly higher than public high school students at the age of 15 and have higher levels of educational attainment by the age of 23. Complementary, the authors found out that students who attended private high schools were more likely to have socio-economic characteristics positively associated with academic success. Research of Hahn, Kim and Seo (2014) show that students in private schools have better academic performance than students in public schools in Korea. A study of Alimi, Ehinola and Alabi (2012) revealed no significant differences in academic performance of students in the private and public secondary schools in Nigeria.

In Brazil, in this same field, one can mention the works of Silva Filho and Moraes (2017) who compared the performance of different types of high school and found that federal technical schools add greater proficiency to their students than state and private propaedeutic schools. Sobreira et al. (2019) analyzed the performance in the International Student Assessment Program of Brazilian students from public and private schools and concluded that there was a positive effect of private schools, especially in mathematics. The authors explain that the main tangible factor that explains the difference is the family background. Feijó and França (2021) used Enem microdata to study the differences between students from public and private schools and concluded that there is a positive effect for students from private schools. For the authors, the explanation for this difference depends on how one looks at the distribution of scores and subjects, and can then be explained by the family background, the class background, the characteristics of the teachers and the school. Moraes and Belluzzo (2014), in a study on the difference in school performance between public and private schools, concluded that there is a differential that is favorable to private schools in all quantiles of the distribution. Also, Cavalcanti, Guimarães and Sampaio (2010) and Guimarães and Arraes (2010) analyzed the performance of students from public and private schools in entrance exams at federal universities in Northeastern Brazil, and found that students from public schools perform worse, being this an indication that family income influences school performance. Oliveira, Belluzzo and Pazello (2009) found out that low performance students from public schools would perform even worse in private schools, but in general, private schools perform better.

3 ECONOMETRIC MODEL AND DATA

3.1 Econometric model for estimating the heterogeneous treatment effect

In randomized experiments, in which the assignment or not to treatment is done randomly, the groups are formed by observations with homogeneous characteristics. This allows direct observation and consideration of the difference in means between the two groups of the response variable as the treatment effect (Angrist and Pischke, 2008). This is the simplest case of classic randomized experiments, for which obtaining the estimator for the average treatment effect can be done directly by the difference in the means of the potential results of the observations exposed and not exposed to the treatment (Imbens and Wooldridge, 2009). However, experimental data, arising from random experiments, are generally collected in the laboratory in natural sciences research, being less frequent and difficult to obtain in social sciences. Most found in social sciences research are non-experimental data, also called observational data, which are not collected through controlled experiments (Wooldridge, 2013). In this case, verifying the effect of the treatment is not straightforward, because the same individual cannot

be in both groups at the same time. This would facilitate verification, as the same unit, with identical characteristics, would present values for the analysis variable for both the treated group and the control group (Caliendo and Kopening, 2008; Kang and Schafer, 2007).

Among the particularities of the approach for analyzing causal effects in observational studies, of relevance is the relationship between attribution to treatment and potential results. Rubin (1974) formulated the approach to the problem of evaluation or causal inference, and proposed the comparison of so-called potential outcomes, which are pairs of outcomes established for the same observation, so that an outcome is the unit that was exposed to the treatment and the other outcome of the pair is the unit that was not exposed to the treatment. Thus, models are developed for the pair of potential outcomes, and not just for the observed result (Imbens and Wooldridge, 2009).

In this paper, the Causal Forest[6] (Wager and Athey, 2018) method was used for estimating the heterogeneous treatment effect, which is an adaptation of the random forest algorithm of Breiman (2001).

The formalization of the problem can be done in terms of potential outcomes framework, according to Neyman (1923), Rubin (1974) and Imbens and Rubin (2015). We have access to n independent and identically distributed samples, indexed $i = 1, \ldots, n$. For each observation there is a feature, or covariate, vector $X_i \in \mathbb{R}^p$, where p is the number of features, and a treatment indicator $W_i \in \{0,1\}$. We posit the existence of potential outcomes $Y_i(0)$ and $Y_i(1)$ corresponding to the outcome of the ith subject observed, given the treatment assignment, such that $Y_i = Y_i(W_i)$. The definition of average treatment effect is $\tau = E[Y_i(1) - Y_i(0)]$ and the conditional average treatment effect is $\tau(x) = E[Y_i(1) - Y_i(0)|X_i]$.

Writing $e(x) = P[W_i|X_i = x]$ for the propensity score and $m(x) = E[Y_i|X_i = x]$ for the expected outcome marginalizing over treatment, Athey and Wager (2019) defined an expression for a causal forest with binary treatment to compute the average treatment effect estimate $\hat{\tau}$, based on a double robust correction, reasoned on a variant of augmented inverse-propensity weight (Robins, Rotnitzky and Zhao, 1994). With cluster J, the expression is as follows.

$$\hat{\tau} = \frac{1}{J}\sum_{j=1}^{J} \hat{\tau}_j, \tag{2}$$

6. Implemented in the R package grf.

with

$$\hat{\tau}_j = \frac{1}{n_j} \sum_{\{i:A_i=j\}} \hat{\Gamma}_i, \tag{3}$$

and

$$\hat{\Gamma}_i = \hat{\tau}^{(-i)}(X_i) + \frac{W_i - \hat{e}^{(-i)}(X_i)}{\hat{e}^{(-i)}(X_i)(1 - \hat{e}^{(-i)}(X_i))} \left(Y_i - \hat{m}^{(-i)}(X_i) - \left(W_i - \hat{e}^{(-i)}(X_i)\right)\hat{\tau}^{(-i)}(X_i)\right) \tag{4}$$

In expression (4):

- $\hat{\tau}^{(-i)}(X_i)$ is the treatment effect estimate, and in the potential outcome notation, by definition, is $E[Y_i(1) - Y_i(0)|X_i]$; and
- $\hat{m}^{(-i)}(X_i) - \left(W_i - \hat{e}^{(-i)}(X_i)\right)\hat{\tau}^{(-i)}(X_i)$ is as estimate of the realized mean for subject i. This is by default estimated using a regression forest.

The $(-i)$ superscript indicates that the estimate is uncovered by leaving observation i out, in other words, denotes "out-of-bag", or at least, Y_i is not used to compute $\hat{\tau}^{(-i)}(X_i)$.[7]

In order to identify $\hat{\tau}(x)$, it is necessary to assume unconfoudedness, in other words, the treatment assignment W_i is unconfounded $\{Y_i(0), Y_i(1)\} \perp W_i|X_i$, and in that sense, the treatment assignment is randomized once we control for the features X_i and that the propensities $e(x)$ are uniformly bounded away from 0 and 1 (Rosenbaum and Rubin, 1983).

Briefly, causal forest firstly fit two regression forests to estimate $\hat{m}(.)$ and $\hat{e}(.)$. These two first-stage forests result in makes out-of-bag predictions, which are used to grow a causal forest. The next step is to choose the tunning parameter, in other words, the minimum node size for individual trees, by cross-validation on the R-objective, as indicated by Nie and Wager (2021), or in other words, train causal forests with different tuning parameters, and choose the ones that make out-of-bag estimates of the objective minimized in the R-objective as small as possible.

In order to test for heterogeneity, the approaches suggested by Athey and Wager (2019) were used. In the first approach, it can provide some qualitative insights about the strength of heterogeneity and implicate in dividing and grouping the observations according to whether their conditional average treatment effect (Cate) estimates are above or below the median Cate estimate, and also, it can estimate the average treatment effect in these two groups separately using the equation (2).

7. For a more detailed discussion for estimation with this functional form, see Farrell (2015).

In the second approach, Athey and Wager (2019), motivated by the "best linear predictors" method of Chernozhukov et al. (2018), suggest to create two synthetic predictors, $C_i = \bar{\tau}(W_i - \hat{e}^{(-i)}(X_i))$ and $D_i = (\hat{\tau}^{(-i)}(X_i) - \bar{\tau})((W_i - \hat{e}^{(-i)}(X_i))$, where $\bar{\tau}$ is the average out-of-bag treatment effects estimates, and regress $Y_i - \hat{m}^{(-i)}(X_i)$ against C_i and D_i. In that sense, D_i could be interpreted as the quality of the estimates of treatment heterogeneity. If D_i is 1, the treatment heterogeneity estimates are well calibrated, and the p-value for the coefficient of D_i could be used to test the hypothesis that the causal forest succeeded in finding heterogeneity.

Among its advantages, it can be mentioned that Causal Forest is a non-parametric, machine learning based estimator, that recovers estimates that are low-bias and yields asymptotic confidence interval for the true treatment effect, that is, it allows for a tractable asymptotic theory and valid statistical inference; furthermore, the method has a data-driven way to weight neighboring observations, which is important when working with many covariates or complex interactions among covariates; the trees consider all interactions and polynomials of the covariates included in the model as covariates; it is more robust to confounders; and requires weaker assumptions about unobservables (Wager and Athey, 2018).

3.2 DATA AND DEFINITION OF VARIABLES

The main data source for this paper was the Ministry of Education, through Enem Microdata for the year 2019 made available by the National Institute of Educational Studies and Research, which is the lowest level of disaggregation of data collected through the exam, whose primary objective is to individually assess students' domains and knowledge at the end of high school. The microdata makes available the scores and the questionnaire answered by those enrolled in Enem. This questionnaire includes aspects about the student's socioeconomic level, family, education, and work.[8]

Each student's skill is much more difficult to measure, and even more difficult to be available in large numbers. In this sense, it will not be considered in this study. Despite that, emphasizing that these are not proxies for personal skills, this research uses personal characteristics, namely, the variables sex, skin color and age at table 1. As proxies for family conditions, the variables father's education, mother's education, people in house, income, computer and internet of the table 1 are used.

The family income variable originally, in Microdata, has 17 possible answers. Here, I am reducing it to 13 possibilities, with incomes greater than US$ 1,633.09 being included in the last class of possibilities. The variable having a computer at home originally in Microdata has 5 possible answers, 0 for not having one

8. Available at: https://www.gov.br/inep/pt-br/acesso-a-informacao/dados-abertos/microdados/enem. Accessed on: July 10, 2021.

and 1 to 4 for the number of computers you have. Here, I am using only two possibilities, having or not having a computer. These adjustments did not change the estimation results, as the frequency of observations in the grouped classes, in both cases, was low.

The variable that is used to measure school performance is the score obtained in Enem in the subjects of mathematics, languages and codes, natural sciences, human sciences, and writing.

TABLE 1
Econometric model variables

	Variable	Type	Description	Possibles values
Y	Enem score	Continuous	Score obtained in Enem	Interval [0,1000]
W	School dependence	Categorical	Type of administrative dependence of the school	0 = control (state school); 1 = treated (federal school)
X1	State code	Categorical	School state code	26 states and 1 federal district
X2	Sex	Categorical	Person's sex	0 = female; 1 = male
X3	Skin color	Categorical	Person's skin color	0 = not declared 1 = white 2 = black 3 = brown 4 = yellow 5 = indigenous
X4	Age	Integer	Person's age	Minimum = 0
X5	Father's education	Integer	Father's education	0 = never studied 1 = 4th grade/5th year of elementary school incomplete 2 = 8th grade/9th year of elementary school incomplete 3 = incomplete high school 4 = completed high school 5 = incomplete faculty 6 = completed faculty 7 = completed post-graduate 8 = I don't know

(Continues)

(Continued)

	Variable	Type	Description	Possibles values
X6	Mother's education	Integer	Mother's education	0 = never studied 1 = 4th grade/5th year of elementary school incomplete 2 = 8th grade/9th year of elementary school incomplete 3 = incomplete high school 4 = completed high school 5 = incomplete faculty 6 = completed faculty 7 = completed post-graduate 8 = I don't know
X7	People in house	Integer	People living in the house	Interval [1, 11]. 11 or more, used 11.
X8	Income	Integer	Level of income	Interval [0, 12]. 0 = no income. 1 = until US$ 181.45[1] 2 to 5 = increase US$ 90.73 for each level 6 to 11 = increase US$ 181.45 for each level 12 = more than US$ 1,633.09
X9	Computer	Categorical	To have computer at home	0 = no; 1 = yes
X10	Internet	Categorical	To have internet at home	0 = no; 1 = yes

Author's elaboration.
Note: [1] Rate exchange: US$ 1 = R$ 5.50.

Regarding the conditions of the school where the student finished high school, a school location variable is used, and the variable on which the central research problem of this research is based, which is the potential effects heterogeneous differences in school performance caused by the type of administrative dependency on the school (school dependence in table 1). It is important to mention that this is not a perfect indicator, as a student may have built their entire educational base in primary education at a private school, for example, and secondary education in a federal or state public school. This is a limitation of the available database and may lead to bias in the causal effect.

It is noteworthy that the main purpose of the Federal Network of Technological Education in Brazil does not include improvements in Enem scores. However, in the absence of an indicator of quality and effectiveness of technical secondary education offered by federal institutions, in the present study Enem scores were used as a proxy for the quality of education, and these is the response variable of

the econometric model.[9] Hanushek (1970; 1979) and point out that although in theory it is known that the outputs produced by a school are diverse, including social aspects and conative development, due to the availability of data cognitive development, reflected in the scores obtained from standardized tests, are the most used. Figueirêdo, Nogueira and Santana (2014) for example, also use the Enem score as an output from the educational production function, and argue, based on a theoretical framework, that it can capture effort and a set of characteristics beyond the student's control.

The complete 2019 Enem Microdata database has 5,095,270 observations. Cases were excluded for not attending at least one of the tests, for not indicating the type of administrative dependency of the school where they finished high school, for residing in cities that did not have at least one person who had studied in a federal school or for having secondary education in municipal schools, which in specific cases may occur. After that, 697,696 observations remained, 519,999 from state schools, 45,760 from federal schools and 131,937 from private schools. The main sample for this study focuses on state and federal public schools (565,759 observations). However, in order to better understand the general context, also it is also presented the ATE of federal schools in relation to private schools, and a deeper analysis is made by comparing federal schools only with state schools, both public.

This sample includes people who were finishing high school in 2019, who are attending high school and took the test just to train, or who finished school longer. People who were taking the test just to train and people who finished high school a long time ago, and may have taken other preparatory courses for the Enem, could bias the estimates. As a way of analyzing possible sensitivity to this, an estimation of the treatment effect was carried out by excluding from the sample people who took the test just to train, people under 16 years old and people over 19 years old. The sample was then reduced to 469,733 observations, and the estimation results are in appendix A.

Table 2 presents the averages, with their respective standard deviations, of Enem scores and by type of administrative dependency of the school. Some other descriptive statistics of the variables used in the econometric model are also presented.

9. Enem score calculations are based on Item Response Theory, with a score of 500 representing the average proficiency of those who took the test, with a dispersion of 100 (Inep, 2021).

TABLE 2
Summary statistics for the econometric model variables

School dependency	State		Federal		Private	
	Mean	S. D.	Mean	S. D.	Mean	S. D.
Sample size		519,999		45,760		131,937
Enem's scores						
Math	499.36	88.73	607.73	111.46	630.82	117.33
Languages and Codes	508.95	59.23	560.76	51.57	570.31	52.40
Human Sciences	491.16	72.30	561.64	70.87	575.06	73.49
Natural Sciences	456.90	64.20	533.22	69.74	546.42	74.88
Writing	553.45	177.32	704.07	146.79	739.10	153.53
Personal characteristics						
Age	17.79	1.29	18.00	1.03	17.41	0.69
Sex						
Female	59%		53%		52%	
Male	41%		47%		48%	
Skin color						
Not declared	2%		2%		2%	
White	32%		41%		61%	
Black	13%		12%		6%	
Brown	49%		44%		28%	
Yellow	2%		2%		2%	
Indigenous	1%		0%		0%	
Social characteristics						
Income						
No income	5%		2%		1%	
0 - 181.45	30%		17%		4%	
181.45 - 362.90	28%		21%		9%	
362.90 - 544.35	9%		9%		7%	
544.35 - 725.80	10%		11%		7%	
725.80 - 907.25	4%		5%		6%	
907.25 - 1,088.70	6%		10%		9%	
1,088.70 - 1,270.15	3%		6%		9%	
1,270.15 - 1,451.60	2%		6%		7%	
1,451.60 - 1,633.05	1%		3%		5%	
1,633.05 - 1,814.50	1%		2%		4%	
1,814.50 - 1,995.95	0%		2%		4%	
1,995.95 - 2,177.40	0%		1%		4%	
More than 2,177,.40	1%		5%		25%	
Father's education	4.25	1.89	4.63	1.68	5.46	1.39

(Continues)

(Continued)

School dependency	State		Federal		Private	
	Mean	S. D.	Mean	S. D.	Mean	S. D.
Mother's education	4.37	1.55	4.98	1.42	5.66	1.16
No. people in house	4.14	1.40	3.94	1.21	3.79	1.10
Computer at home	46%		72%		86%	
Internet at home	75%		87%		96%	

Author's elaboration.
Obs.: S. D. – standard deviation.

As it can be seen in table 2, students from private schools have the highest average Enem scores in all subjects. Those from state schools had the lowest average, leaving those from federal schools in an intermediate position. In state schools, three of the five areas of knowledge are close to average proficiency, with proficiency in natural sciences being almost half a deviation below the average and writing a little more than half a deviation above the average. In the five areas that make up the Enem, federal schools showed proficiency above the average, with emphasis on mathematics with one deviation above and writing with approximately two deviations above. This is also the case for private schools, with proficiency immediately higher than federal schools in all five areas.

However, as the characteristics of schools are not the only determinants of school performance, personal and social characteristics can also interfere in these results. As an example, it can be observed, also in table 2, that the income level of the families of private school students is higher, and they also have, in general, more access to computers and the internet.

4 MAIN RESULTS

The causal forest method (Wager and Athey, 2018; Athey and Wager, 2019) was used to estimate the average and heterogeneous treatment effect.[10] In addition to model variables, some arguments can also be specified 500 trees grown in the forest were used, clusters in the state variable where the school is located, equal weight in the forest to each cluster and all tunable parameters are tuned by cross-validation.

4.1 Average treatment effect on Enem's scores

Table 3 reports the estimated ATE results for studying in federal schools. These represent one of the main estimates and results of this paper. In part (a) the ATE of federal schools was compared to state schools. Furthermore, these estimations were made in two ways: using all observations in the sample and using only observations with propensity score in range of 0.05 to 0.95. It can be verified which in both estimations have similar values.

10. Available at: https://CRAN.R-project.org/package=grf.

It is found that, controlling for the 10 variables specified in the model, federal schools achieve better results in terms of student performance than state schools in all subjects, at the 95% confidence level. The subject in which the effect was most prominent was writing, followed by mathematics. The subject with the least effect is languages and codes. In this sense, it is possible to assume that federal schools, in general, are able to produce more quality education than state schools, since through the causal forest method, other observable features are being controlled. In writing and math, the effects estimates are more eloquent.

TABLE 3
Average treatment effect for studying in federal schools

(a) Federal against state schools				
	All observations		Observations with propensity score in range 0.05 to 0.95	
	Cate	95% C. I.	Cate	95% C. I.
Math	68.99	+- 9.7	74.41	+/- 10.3
Languages and Codes	36.36	+/- 4.8	36.79	+/- 4.9
Human Sciences	48.60	+/- 5.1	49.82	+/- 5.8
Natural Sciences	54.19	+/- 4.8	56.23	+/- 5.3
Writing	115.13	+/- 13.5	114.01	+/- 14.2
(b) Federal against private schools				
	All observations		Observations with propensity score in range 0.05 to 0.95	
	Cate	95% C. I.	Cate	95% C. I.
Math	8.94	+/- 11.4	8.94	+/- 11.4
Languages and Codes	4.56	+/- 4.6	4.56	+/- 4.6
Human Sciences	3.41	+/- 6.7	3.41	+/- 6.7
Natural Sciences	3.7	+/- 6.4	3.7	+/- 6.4
Writing	-19.98	+/-16	-19.98	+/-16

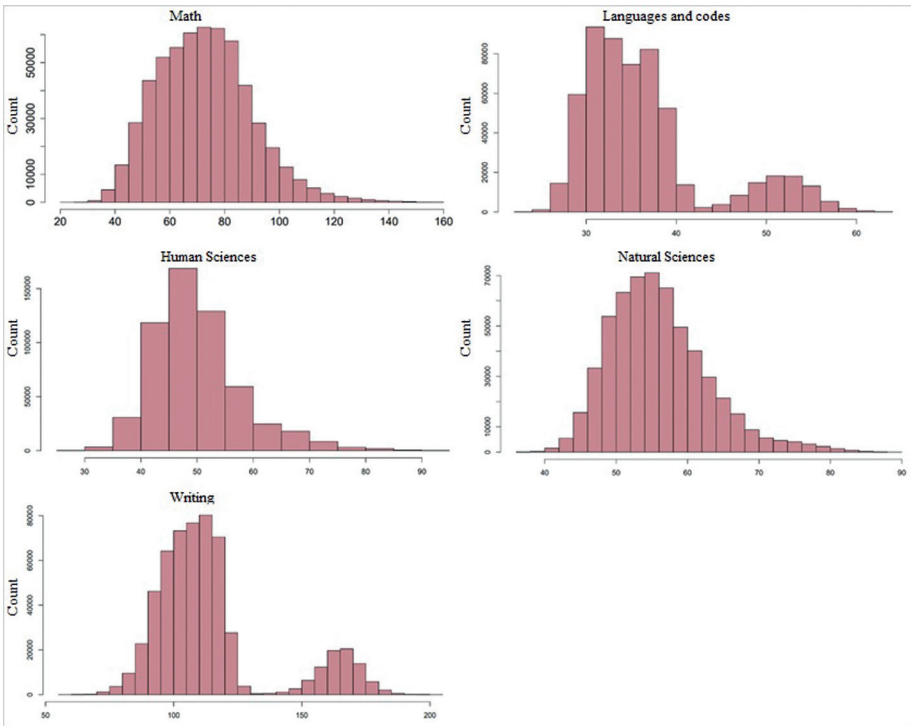
Author's elaboration.
Obs.: C. I. – Confidence interval.

To provide a better understanding of the context, it is also reported the ATE between federal schools and private schools. In this case, it is not possible to observe significant effects in four of the five subjects that make up the Enem. In writing, the effect is negative, which suggests there is a positive effect when studying in private schools compared to federal schools in this regard. Therefore, it is reasonable to conjecture that in general, and controlling for the 10 variables

specified in the model, the two types of schools are able to produce similar results in terms of learning performance, with the exception of writing.

As seen in figure 2, the Cate estimates from federal opposed to state school show variation. Also, in mathematics and writing the range of values of the estimated effects is greater, and consequently the variations are greater. In addition, in all school subjects and all observations, no negative effects were estimated for studying in federal schools.

FIGURE 2
Histogram of Cate estimates from federal opposed to state school



Author's elaboration.
Obs.: Figure whose layout and texts could not be formatted due to the technical characteristics of the original files (Publisher's note).

Even so, it is not possible to say that there is a heterogeneous treatment effect, requiring further analytical analysis for such validation.

4.2 The heterogeneous treatment effect on Enem's scores

In this section, the results for one of the main topics are presented, which are the possible heterogenous effects of treatment on Enem grades. First, in table 4, the results of the approach of the method suggested by Chernozhukov et al. (2018)

to test the hypothesis whether the causal forest succeeded in finding heterogeneity (Athey and Wager, 2019). Specifically, it computes the best linear fit of the target estimated using the forest prediction (on held-out data) as well as the mean forest prediction as the sole two regressors, along with one-sided heteroskedasticity-robust (HC1) SEs.[11]

The coefficient nearby 1 of the mean forest prediction in all Enem subjects suggests that the mean forest prediction is correct. The coefficients of differential forest prediction in all Enem subjects also suggest that the heterogeneity estimates from the forest are well calibrated, because they are close to 1 as well. The *p*-value are significant, which means that the null hypothesis of no heterogeneity can be rejected, and consequently, that the causal forest succeeded in finding heterogeneity in all Enem subjects.

TABLE 4
Best linear prediction

Math					
	Estimate	S. E.	t-value	Pr(>t)	
Mean forest prediction	0.97	0.07	13.73	2.2e-16	***
Differential forest prediction	1.03	0.12	8.19	2.2e-16	***
Languages and Codes					
	Estimate	S. E.	t-value	Pr(>t)	
Mean forest prediction	0.99	0.06	15.68	2.2e-16	***
Differential forest prediction	1.04	0.17	6.00	9.562e-10	***
Human Sciences					
	Estimate	S. E.	t-value	Pr(>t)	
Mean forest prediction	0.97	0.05	18.04	2.2e-16	***
Differential forest prediction	1.12	0.15	7.32	1.2e-13	***
Natural Sciences					
	Estimate	S. E.	t-value	Pr(>t)	
Mean forest prediction	0.98	0.04	21.41	2.2e-16	***
Differential forest prediction	1.19	0.16	7.23	2.314e-13	***
Writing					
	Estimate	S. E.	t-value	Pr(>t)	
Mean forest prediction	1.00	0.06	15.78	2.2e-16	***
Differential forest prediction	0.99	0.14	6.80	5.383e-12	***

Author's elaboration.
Obs.: S. E. – Standard error.

11. Available at: https://CRAN.R-project.org/package=grf.

As suggested for Athey and Wager (2019), another approach to try to detect heterogeneous treatment effect, is to divide and group the observations according to their Cate, and estimate average treatment effect in these two groups separately. This division was made according to whether the estimated Cate was below or above the median of the estimated Cate. After this procedure, the Cate was estimated separately for each subgroup using the doubly robust approach. The results are in the table 5, and it is possible to conjecture that the treatment heterogeneity is present and relatively strong, because the causal forest identifies subgroups with different effects.

TABLE 5
Compared regions with high and low estimated Cates

	Diference in Cate	95% C. I.
Math	26.57	+/- 14.3
Languages and Codes	11.92	+/- 7.4
Human Sciences	12.98	+/- 8.0
Natural Sciences	12.18	+/- 7.0
Writing	29.23	+/- 20.7

Author's elaboration.
Obs.: C. I. – Confidence interval.

Assuming the presence of heterogeneous treatment effect, the next step is to analyze the heterogeneity along specific variables. It was carried out with school localization states and the family income.

For family income levels, initially, the t-test compared high and low estimates Cates income levels. This is a test that seeks evidence regarding heterogeneity in the treatment effects, that is, whether there is heterogeneity in the effects along the family income variable and along the school location variable, at the state level.

As seen in the table 6, there is a significant difference on the effect of studying in federal schools in math, human sciences and natural sciences, when considering family income. In languages and codes, and writing, the difference between high and low estimated Cates is not significant.

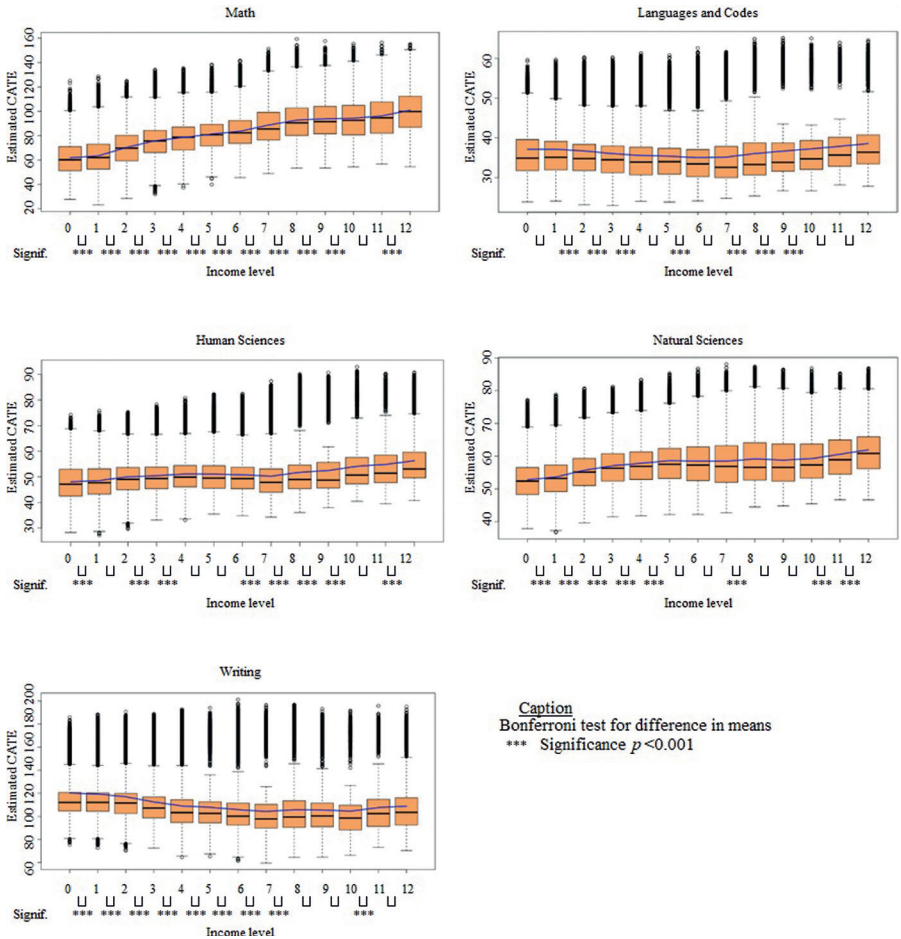
TABLE 6
Compared levels income with high and low estimated Cates

	95% C. I.		t	df	p-value
Math	10.59	34.82	5.70	10.253	0.0001801
Languages and Codes	-1.94	6.25	6.11	14.77	2.121e-05
Human Sciences	1.90	10.23	7.58	13.17	3.68e-06
Natural Sciences	0.58	9.17	4.85	13.44	0.0002862
Writing	-8.6	6.7	4.15	8.53	0.002797

Author's elaboration.
Obs.: df – *t*-distribution curve degrees of freedom.

To deepen the appreciation, Bonferroni test between income sequential income levels of the estimated Cates was performed. The results are shown in the figure 3, which also shows the boxplot of the Cates estimates for each income level. As it can be seen, in math, there is significant difference between all income levels, except between 10 and 11, and the Cate estimates increase as the income level increases. The same happens with human sciences and natural sciences, but with a lower incidence, since there are more spaces without statistical significance difference. In languages and codes, the Cate seems to decrease between 0 to 6 income level, and increase between 6 and 12. In spite of that, not all space has statistical significance. In writing, the perception is that the Cate decreases as the income level increases, at least between 0 and 7 and it stabilizes after that.

FIGURE 3
Estimated Cates and difference in means by levels income



Author's elaboration.
Obs.: 1. The blue line is a cubic smoothing spline, which estimates a functional relationship between the income level and the estimated Cate.
2. Figure whose layout and texts could not be formatted due to the technical characteristics of the original files (Publisher's note).

The t-test was also used for states, which reflects the variable school localization, to compare high and low estimated Cates. The table 7 shows a significant difference in all Enem subjects, which allows us to initially conjecture the presence of heterogeneity in the treatment effect between states.

TABLE 7
Compared states with high and low estimated Cates

	95% C. I.		t	df	p-value
Math	13.21	30.05	8.24	17.91	1.649e-07
Languages and Codes	1.44	2.99	7.08	24.97	2.021e-07
Human Sciences	3.74	6.73	4.92	19.13	9.314e-05
Natural Sciences	2.44	6.32	5.72	15.02	4.058e-05
Writing	3.22	11.09	6.34	24.90	1.239e-06

Author's elaboration.

Also here, it is crucial, for the purposes of the study, to zoom in on these differences. In the figure 4 is possible to observe the estimated Cates by state (boxplot graph), the mean by state (red points), the country's overall Cates (red line) and the matrix of significance for Bonferroni test for difference in means for all possible combinations of state pairs.

As can be seen in figure 4, in mathematics it is possible to deduce the presence of heterogeneous treatment, that is, there is a greater positive effect of studying in federal schools in some states. The largest effects are most notable (looking at the boxplot graph) in the states of Rio Grande do Sul, Santa Catarina, Paraná and Distrito Federal, where the effect averages (red dots) are further from the national average effect line (red line). Furthermore, in the general scenario, the significance matrix for the Bonferroni test for difference in means shows that there is a greater predominance of green squares, which indicates statistical significance in the difference between the means of the effects in the comparison between two states. For the state of Rio Grande do Sul, for example, when compared with the other 26 federative entities, there was only no significant difference in one situation (orange square). This situation refers to the comparison of the effect with the state of Santa Catarina. Thus, in the other 25 comparisons, the difference is significant.

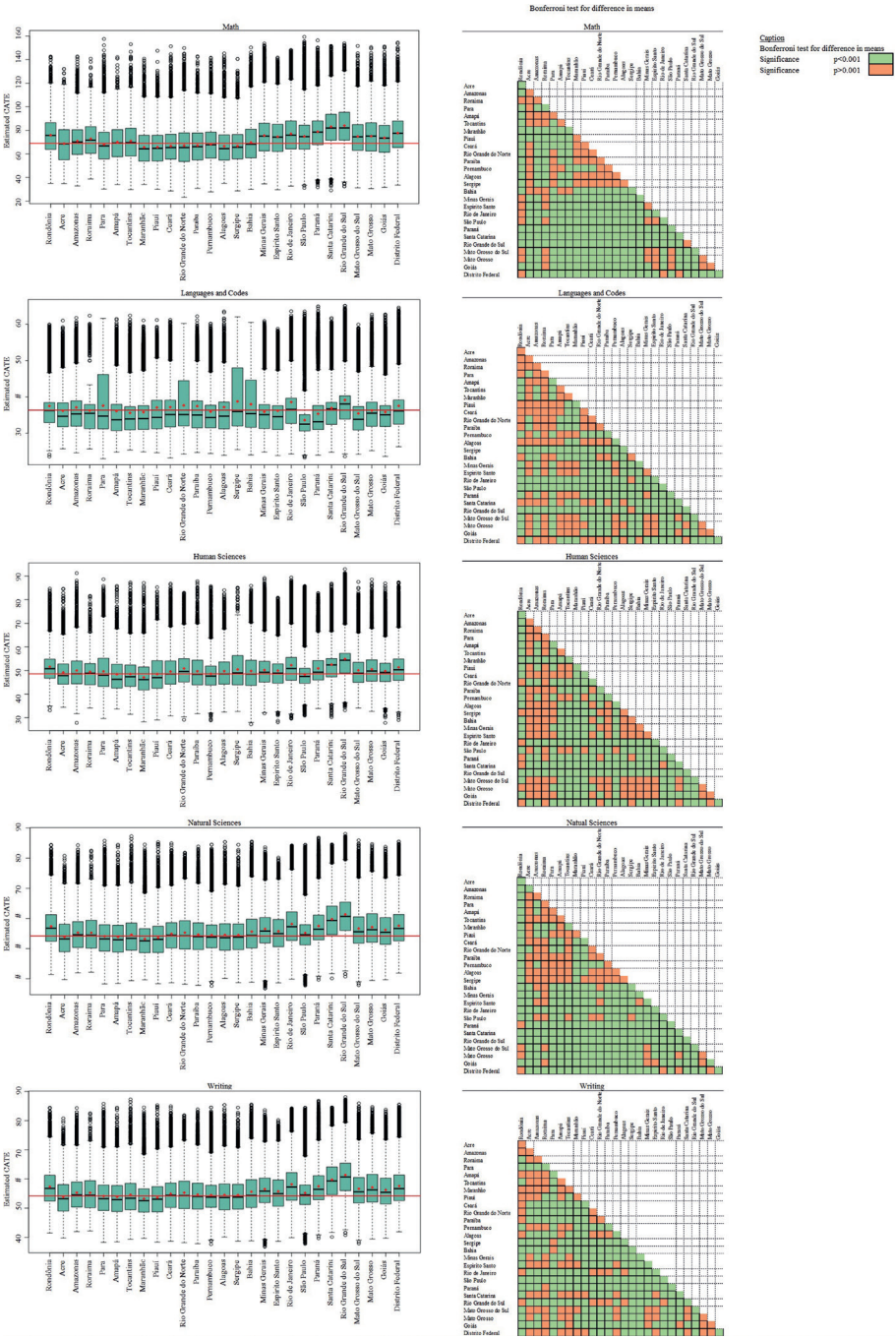
In languages and codes, and in the human sciences, the frequency of significant differences between means is lower, but still important. In language and codes, the effect is greater and statistically significant, in the states of Rio de Janeiro, Sergipe and Rio Grande do Sul, for example, and a smaller statistically significant effect in São Paulo (red dot below and further from the red line in the boxplot graph). In the human sciences, the largest effect is most visible (boxplot graph)

in the states of Rio Grande do Sul, Santa Catarina, Rio de Janeiro and Rondônia, and a smaller effect in the state of Maranhão. In languages and codes, and in the human sciences, the frequency of significant differences between means is lower, as can be seen in the significance matrix for the Bonferroni test for difference in means, which shows that there is a smaller predominance of green squares than in mathematics, but still important.

The matrix of significance for Bonferroni test for difference in means to the natural sciences, as in math, seems to show more heterogeneous treatment between states (predominance of green squares). This figure, along with the boxplot graph, shows greater effect in Rio Grande do Sul, Santa Catarina, Rondônia and Rio de Janeiro states. For the state of Rondônia, for example, when compared with the other 26 federative entities, there was only no significant difference in four situations (orange square). This situation refers to the comparison of the effect with the state of Paraná, Mato Grosso do Sul, Mato Grosso e Distrito Federal. Thus, in the other 22 comparisons, the difference is significant.

In writing, significance for the Bonferroni test is less frequent, but it is still possible to detect the presence of heterogeneous treatment. In the boxplot graph, it is possible to visualize the greatest effect in the states of Rio Grande do Sul, Santa Catarina, Rio de Janeiro, Rondônia and Distrito Federal (distance from the red dots to the red line). The smallest effect is also seen in the state of Maranhão.

FIGURE 4
Estimated Cates and difference in means by States



Author's elaboration.
Obs.: Figure whose layout and texts could not be formatted due to the technical characteristics of the original files (Publisher's note).

5 DISCUSSION

Causal forest method was employed to study treatment heterogeneity effect in Enem scores in Brazil, especially to estimate the effect of studying in federal schools. Returning to the core questions of this study, first it can be conjectured that, controlling for the variables considered in the econometric model, there is a statistically significant positive effect of studying in federal schools compared to state schools, in all subjects that make up the Enem, and the biggest effects are observed in math and writing. Compared to private schools, the positive effect is substantially smaller, and negative in writing. In this sense, it can be conjectured that the educational production of federal public schools is very close to the educational production of private schools.

On this finding, it is possible to speculate that differences in the structure and institutional organization of federal public schools might bring benefits in terms of educational production, as stated by Weller and Horta Neto (2020), Deitos and Lara (2016) and Pacheco (2010). Obviously, this hypothesis should be tested in other researches, that is, which factors that differ between federal and state public schools could be causing positive effects in favor of federal schools, such as more funding, offer of education at all levels, research, extension and innovation projects, vocational education integrated with high school, among others.

Also, regarding the superiority of federal public schools, which prioritize vocational education, as suggested by Albuquerque et al. (2020) and Silva Filho and Moraes (2017) may be the result of the pedagogical organization, in the sense that the contents are contextualized, require practice, specific knowledge and skills, which enriches the knowledge construction process. Thus, vocational education can be considered as a way to improve the quality of education.

Concerning the second question, also controlling for the variables considered, it is possible to deduce that there are heterogeneous effects across states and students' household income levels in all school subjects of Enem, but with different strengths.

As for the heterogeneous effects over the family income, the estimates are consistent with the work of Araújo et al. (2020), Tran and Nathan (2010), Sirin (2005) and Woessmann (2004), for example. Mainly in mathematics and natural sciences, it is possible to verify that students from families with higher incomes are able to absorb educational production more effectively, demonstrating higher academic performance. In the other subjects from Enem, this verification is not conclusive.

It is possible to accept the hypothesis that students from families with higher income have access to resources that enhance their learning during high school. But this enhancement does not occur equally between subjects, as can be seen in this research, which showed that students with higher family income are better

able to absorb the positive effects of studying in federal schools in the subjects of mathematics and natural sciences. Just conjecture, a possible (but not definitive) explanation for this fact is the curricular design of professional and technological education that characterizes the Federal Institutes of Education, Science and Technology in Brazil, which are the federal institutions that offer, in addition to other levels, basic education mainly high school courses integrated with technical professional education.

As described by the Ministry of Education (MEC), one of the basic premises of the curriculum design of Federal Institutes is verticalization, with degrees from basic education to postgraduate studies, with high school professional education as the core paradigm (Brasil, 2010) – 50% of opportunities.

In teacher training, there is a requirement for at least 20% of opportunities, with emphasis on natural sciences (chemistry, physics, and biology) and mathematics, given the lack of teachers in these areas. As professors who work at different levels are, in general, the same, it is easier to create high school courses integrated with technical education in areas related to these. The same can be said about the structure, such as laboratories. In this way it is possible to consider the hypothesis that families' greater financial resources find greater resources from federal institutions in these areas, and thus, students from families with higher income also appear to be more impacted in these areas.

This finding calls for a reflection on the impact that the covid-19 pandemic can cause and on the importance of thinking about the institutional duty of education to provide each generation with a common formative experience, despite the family disadvantages that each citizen may face. Thus, heterogeneous learning will be confirmed, even more, as the general rule, and not only in special cases, which demands from educational agents an understanding of the process, as well as results of this new scenario (Bellei et al., 2021).

On the heterogeneity between states, also in mathematics and natural sciences, the differences are more significant. Some states stand out for having greater estimated effects in all subjects in the Enem, such as Paraná, Santa Catarina, Rio Grande do Sul, Rondônia, Rio de Janeiro and Distrito Federal.

Significant inequalities within a country can originate from several factors, including different income scales, dissimilarity between urban and rural populations, between females and males, or even between public and private schools. In fact, rurality, gender issues, income and school characteristics can account for more than half of the inequality in learning, requiring the correct observation and consideration of the possible consequences of these facts among different regions (Azevedo and Goldemberg, 2020; Azevedo et al., 2021). Furthermore, additional care is required when analyzing the estimates of the present work. As the discussion

approaches an effect in terms of academic performance, a smaller effect can be a result and better performance of state schools and some states, not necessarily being an adverse result. As an example, we can mention the state of Ceará, which has been showing positive results in recent years, after the implementation of programs such as full-time and vocational schools in state public schools (Martins et al., 2021).

6 FINAL CONSIDERATIONS

The objective of this research was to estimate the potential heterogeneous effects on Enem scores by studying in federal schools in Brazil, and found out that, controlling to the variables specified in the econometric model adopted, studying in federal schools improves student achievement in Enem scores in Brazil when compared to state schools. Even, it was possible to verify a heterogeneous effect of higher performance of students from federal schools across states and across different levels of household income.

These findings are useful to analyze the efficiency of potential public policies that aim to reduce learning disparities and improve the quality of education in Brazil. These policies can be directed towards improving, for example, the availability of supplies for disadvantaged families and for specific states, through social protection programs, or improving the availability of school supplies, such as computers, books, internet, school materials, training parents, or even teachers and professionals to specific qualifications, such as psychologists and pedagogues.

Furthermore, the recent past shows that inequality in learning has the potential to increase inequality between and within countries. Poor education systems do not adequately equip students to build basic reading, math, science and humanities skills. This restricts the accumulation of human capital in a country or a region, putting the long-term growth of nations at risk (Azevedo et al., 2021).

Specifically, about the federal education network, as Brazorotto and Venco (2021) point out, the entrance into federal public schools, in general, includes exams involving elementary school contents, which has increased the competition and excluded a portion of those interested in these schools, especially the less favored ones. To reduce these discrepancies, federal schools have adopted affirmative policies, such as social and racial quota systems, but still not enough to solve this obstacle.

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APPENDIX A

TABLE A.1
Average treatment effect for studying in federal schools whit a reduced sample

	Federal against state schools			
	All observations		Observations with propensity score in range 0.05 to 0.95	
	Cate	95% C. I.	Cate	95% C. I.
Math	65.68	+-8.5	71.30	+-9.1
Languages and Codes	33.79	+/- 3.8	33.84	+/- 3.9
Human Sciences	45.92	+/- 4.5	47.00	+/- 5.1
Natural Sciences	44.98	+/- 8.3	46.61	+/- 9.3
Writing	105.232	+/- 11.8	102.88	+/- 12.1

Author's elaboration.
Obs.: C. I. – Confidence interval.

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