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Bullying effect on student's performance☆

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Abstract

This article seeks to measure the effect of bullying in math scores of students in the 6th grade of public (Nansel et al., 2001). school in the city of Recife, Pernambuco, Brazil with the use of data from a survey by Joaquim Nabuco Foundation in 2013. The methodology applied is Propensity Score Matching (PSM) in order to compare students who reported having suffered bullying with a control group, consisting of students who did not suffer bullying. Specifically, we aim to understand the role of social emotional skills and their potential influence on bullying. The results suggest that bullying has a negative impact on performance in mathematics and that social emotional skills can help students deal with bullying. Several econometric techniques were used to circumvent endogeneity problems. To identify personality traits, we use a factor model that also serves to correct for prediction error bias. The sensitivity analysis indicated potential problems of omitted variables. The results indicate that anti-bullying programs should take into account social emotional skills.

JEL classification: I21; I28; J24

Keywords: Bullying; Propensity Score Matching; Impact evaluation; Personality traits; Mathematics

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1. Introduction

Bullying is a behavioral phenomenon that has attracted the attention of educators and policy makers in many parts of the world in recent years. For Fante (2005), bullying is a situation which is characterized by intentional verbal or physical abuse, made repetitively, by one or more students against one or more peers. The author states that this phenomenon is a form of violence quickly growing in the world. In Brazil, during November 2015 the Federal government established the nationwide initiative called the Systematic Program[1] to Combat Bullying.[2] This federal law aims to combat bullying throughout society, especially in schools.

Levitt and Dubner (2014) state that trillions of dollars were spent on educational reform projects around the world, usually focusing on some sort of overhaul of the system: better curriculum, smaller classes, more testing and so on. For the authors, the main raw material of the educational system – the students themselves – is often overlooked. For Kibriya et al. (2015) bullying is an important issue that could affect performance in school, which is often overlooked.

There is a consensus among economists that higher levels of education increase economic growth, the income of individuals and the quality of life (Barro, 1991; Hanushek and Kimko 2000; Doppelhofer and Miller, 2004). For Glewwe et al. (2016) a greater number of school enrollment may have little influence on economic growth and personal income if children do not learn effectively while they are in school. Bullying can affect the child's learning and trigger effects on further income throughout life, since the child's school life is compromised.

According to the data resulting from research conducted by Joaquim Nabuco Foundation in 2013 with 4191 students in 6th grade (grade 5) of the public schools of Recife it was shown that 36.41% of students said they fully agree with the fact that they suffered bullying and 40.71% when the question was stated with a "maybe". A study by Nansel et al. (2001) with a sample of 15,686 American students of the 6th year (the 1st year of middle school) showed that about 30% of students reported moderate or frequent involvement in bullying.

Mullis et al. (2012) suggest in a survey from 2011 with more than 300,000 students from 48 developed and developing countries, that more than 50% of the students reported that they experienced bullying in school and 33% of the sample reported having been bullied weekly. Note that bullying is a problem present in several countries, be they rich or poor countries (Brown and Taylor, 2008; Ammermueller, 2012; Eriksen et al., 2012; Dunne et al., 2013; Ponzo, 2013).

In this context, the objective of the current study is to investigate whether bullying has an effect on the grades of students in mathematics. Specifically, we seek to understand potential factors that may influence the effect of bullying among students as well as we seek to investigate the effect of social emotional skills and their ability to reduce the negative effect of bullying in school.

For this, data from a survey of 2013 conducted by the Joaquim Nabuco Foundation was used with students of the 6th year of different public schools in Recife. We used a quasi-experimental setting consisting of both OLS estimation and Propensity Score Matching (PSM). This approach reduces the selection bias to find a more similar control group to the treatment group, based on observable characteristics and then compares the effect of bullying on the mathematics performance of students who have experienced bullying (treated) with students who have not experienced bullying (control). Several robustness analyses were performed to ensure the validity of the results.

Further on, after this introduction, the publications proceed as follows. The next section presents a brief review of the literature. Section 3 presents the description of the database and some descriptive statistics. Section 4 presents the empirical strategy used in the estimation models. Section 5 presents the results and interpretations. The robustness and sensitivity analyses are presented and discussed in Section 6. Finally, the last section presents the final considerations.

2. Literature review

The literature is quite rich when investigations involve the effects of school, families, teacher characteristics, parental schooling, student gender, cognitive ability in various social dimensions such as Hanushek (1986), Farkas et al. (1990), Card and Krueger (1992), Farkas et al. (1997), Murnane et al. (2000), Kerckhoff et al. (2001), Riani and Rios-Neto

[1] Anti-bullying laws and campaigns have also been implemented in the US, Canada, UK, Germany, Scandinavian countries, Colombia and South Korea.

[2] For details, see Law No. 13,185, of November 6, 2015.

(2008). On the other hand, the amount of work that has addressed the effect of bullying on academic performance is limited (Ponzo, 2013).

Besides that, bullying is a widespread problem, it is also very costly, especially because not only sufferers but also those who cause bullying suffer negative consequences throughout life, Sarzosa and Urzúa (2015). By repeating this behavior several times, the oppressor can express emotional frailty and high level of psychic suffering. According to some data that was produced by a website managed by the U.S. Department of Health and Human Services called stopbullying.gov, 160,000 children miss school every day in the US due to fear of being bullied (this represents 15% of all students missing classes); Bullying sufferers are between 2 to 9 times more likely to consider suicide than non-bullying sufferers; In the UK at least 50% of the suicides among young people are related to these experiences and of every ten students, one leaves school or move to another one due to the stress and traumas that are commonly related to bullying.

Researchers as Bowles and Herbert (1976) have discussed the importance of non-cognitive skills as good indicators of success in life. They argued that non-cognitive skills can be considered even more important than cognitive abilities to determine various factors throughout people's lives. In the same sense, Almlund et al. (2011) also consider traits of more malleable personalities more important throughout the life cycle than cognitive factors, which becomes highly stable at around 10 years. The study suggests that interventions that are capable of changing personality traits are promising ways for combating poverty and social disadvantages. Gensowski (2014) points out that lifetime earnings are substantially influenced by education and personality traits.[3]

In a British study of the National Institute of Child Development, Brown and Taylor (2008) investigated the effect of school bullying. The results suggest an adverse effect on the accumulation of human capital. The impact of bullying on 16-year-old school teenagers is equivalent to the effects of class size. The effect of class size disappears for young people at more advanced ages, however, the effect of bullying remains during adult life, directly influencing the salaries received during the life cycle and indirectly through the levels of schooling reached. Harmon and Walker (2000) argued that levels of schooling at higher ages are not affected by class size, but contact with bullying has an impact on educational level throughout life.

The study by Kibriya et al. (2015) analyzed school bullying in Ghana from a survey of 7323 8th grade students in 2011. The results show a negative impact of bullying on math scores and the magnitude of the effect found was greater among girls. The effect of bullying decreases in the case of students who have a female teacher. The authors used Propensity Score Matching and a series of robustness to validate their results. For them, bullying policies must take into account the gender of students.

Sarzosa and Urzúa (2015) used a structural model through a longitudinal research with young people to estimate the effects of bullying based on the identification of latent abilities. The authors find that non-cognitive,[4] as opposed to cognitive, abilities significantly reduce the chances of bullying, or cyberbullying during high school. The structural model allowed us to estimate the mean effect of treatment (ATE) with children who practice bullying and are bullied at age 15 and various outcomes measured at age 18. The effect is damaging for both groups and the damage differences occur because of how cognitive and non-cognitive abilities attenuate or aggravate the consequences. For them, the development of non-cognitive skills is fundamental in any policy to combat bullying.

Heckman et al. (2006) used data from a representative sample of young Americans aged 14–21 from the National Longitudinal Survey of Youth in 1979 to determine that non-cognitive skills are at least as important as cognitive abilities[5] when explaining some social performances throughout life. For example, non-cognitive skills appear to have a strong influence on decision-making about school choices, work choices, and profession. In addition, such skills are important in explaining the chance of someone engaging in risky behavior.

For Brown (2004) the period of adolescence is very vulnerable to social pressure and young people seek to be part of a group and desire popularity. According to Bursztyn and Jensen (2015) adolescents may be more likely to give in to such pressure and engage in behaviors that may have long-term effects. The authors analyzed a computer

[3] As Gensowski (2014), personality traits are constructed from the Big Five taxonomy for this study. The items dedicated to each personality factor are constructed with factorial analysis. For a discussion of the Big Five model, see Mccrae and John (1992), Almlund et al. (2011) and the articles they cite. To access an online version of the Big Five instrument, visit <http://www.outofservice.com/bigfive/> the instrument is free.

[4] Non-cognitive abilities are defined as personality and motivational traits that guide the way one feels, behaves and formulates thoughts, Borghans et al. (2008).

[5] Skills normally measured by standardized tests, such as IQ tests and performance tests.

learning program, used in more than 100 predominantly American schools through natural and field experiments. For the authors, when the effort is observable to their peers, students can avoid social sanctions according to the norms in force. At the first moment of the experiment, the individual results were secret, but after a period the program started to generate public rankings and this led to the introduction of the ranking leading to a decline of 24% in performance. Classes with "honor classes" have an inverse effect, that is, when the rule is to have good grades, being in the ranking increases the popularity, encouraging the effort, since when the norm is to be a normal student and to have average grades the efforts are not to stand out.

Most of the studies claim that bullying leads to poor academic performance[6] and lower incomes after school completion (Le et al., 2005; Kosciw et al., 2013; Ponzo, 2013; Kibriya et al., 2015). According to Boulton and Underwood (1992) some aspects that may explain these results of worst outcomes in terms of academic success are the following: bullying victims have a higher tendency to report unhappiness and loneliness at school, as well as reporting having fewer close friends. In addition, another study done by Kumpulainen et al. (2001), Fekkes et al. (2006) showed that victims of bullying are more likely to develop new psychosomatic and psychosocial problems compared to children who were not bullied, therefore difficult time to deal with loneliness, anxiety and depression, which can be related to academic performance with the expected struggles students might have when facing such challenges.

The theme is very relevant for national and international literature. Quantitative evidence of this problem in the context of developing countries has been scarce and the causal direction remains unclear. Our study aims to fill this gap in the literature. We use a rich dataset from Joaquim Nabuco Foundation that allows us to identify the children who suffered bullying and be the first study that estimate the causal impact of bullying in Brazil. In this case, a randomized control trial would be ideal for the investigation, however it would be unethical to have a child being put in this situation. Therefore, it is challenging to draw causal inferences about the relationship between bullying and school performance.

Besides concerns regarding the over selection and endogeneity bias, students' performance might also get affected by peer effect environment both inside and outside school. According to Kibriya et al. (2015) it is possible that a student has a lower academic performance because of being a victim of bullying, or the likelihood of a student being bullied is higher due to worst academic performance itself. Ponzo (2013) attempted to solve the reverse causality problem by employing a non-parametric method, in the case, the author used Propensity Score Matching. Using only a linear regression analysis may underestimate or overestimate the effect of bullying. Hence, we decided to employ the Propensity Score Matching to reduce selection bias and estimate the average effect of bullying that will be described in detail in the next sections.

3. Data

The main source of information in this study is the result of the research Longitudinal Follow-up on the Student Performance of the Public-School Network of Recife, carried out in 2013 by the Joaquim Nabuco Foundation, among students of the 6th grade of public schools in the city of Recife.

The research consisted of a stratified sample[7] of the school enrollment in the 6th grade of public schools (municipal and state) of Recife's elementary school and their respective mathematics scores in Prova Brasil.[8] After applying these selection criteria, the target population of the research comprised of 28,983 6th grade students who were enrolled in 148 public schools located in the six Political-Administrative Regions (RPAs) of the city of Recife. The determination of the sample strata was based on iterative algorithms proposed by Lavalleé and Hidiroglou (1988), in which the boundaries of strata are estimated to minimize the variance of the estimator used in a stratified sampling.

From this procedure, a total of 17 strata were generated through the combination of grades and school's enrollment. The sampling plan required that students were selected with probability proportional to the enrollment strata and

[6] An exception is Woods and Wolke (2004).

[7] Of all the schools evaluated in the research, those with less than ten participants in the series evaluated were excluded, as well as rural schools and those destined to the exclusive care of students from indigenous communities were not considered. Also eliminated were schools with unavailable information or that presented values equal to zero for the school supplies needed to construct the sample strata.

[8] The 2006 School Census (Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira (INEP)/Ministry of Education (MEC), 2006), together with the Mathematics notes of Prova Brasil (2005), constituted the database for the construction of information about the Recife public schools of elementary education evaluated in this study.

Fig. 1. Spatial distribution of schools in Recife.

Source: Fundaj. Elaboration: Fundaj.

mathematical grade, by RPAs, as it appears in the target population. Therefore, a random sample of students was selected and 118 schools were then drawn for participation in research.[9]

In total, of 26 schools with 6th grade students were drawn of two classes each due to the high number of registrations, making the total number of classes selected for the study composition 146 classes. Data was collected from March to November 2013 from 4191 students, 3670 parents or guardians, 120 directors and 131 teachers of 120 schools spatially distributed among 6 (RPAs) in Recife.

The research aims at evaluating the students' proficiency in mathematics (based on the criterion of Item Response Theory[10]) and to collect information regarding the internal and external aspects of the school. The information collected comes from questionnaires undertook by the students and their parents or legal guardians, the school director and the math teacher of the class in which the student is. All schools and all classes belonging to those were selected randomly. The questionnaire for the students has an affirmation that seeks to understand the degree of agreement / disagreement with the bullying suffered by the student.

The questionnaire that students had to do was made of 96 items. Although the questionnaire does not aim at constructing non-cognitive skills, it is possible to establish through a factorial analysis some traits of students' personalities, such as conscientiousness, extraversion and emotional stability. In addition, the questionnaires address information such as; anthropometric measures, student behavior, school practices, school resources, work environment information, and other information. Fig. 1 shows the spatial distribution of the schools selected by Fundaj.

In addition to bullying, five other groups of factors captured by research can affect math performance. The first of them refers to the individual characteristics of the students, such as gender, age, race, body mass index and non-cognitive abilities. The second factor refers to the characteristics of the family, which are the level of education of the person in charge, per capita income, and the presence of those responsible in the student's school life. The third factor is the characteristics of the teacher, such as gender and age. The fourth factor is that the student participates in the family scholarship program if he/she has already been denied one or more times. The last factor that affects performance in mathematics refers to the characteristics of the school.

Table 1 presents the descriptive statistics in the 6th grade students of public schools in Recife. The average age of the students is approximately 11 years. Girls performed better than boys on the math test and this difference had a 5%

[9] In addition, two schools integrated the sample with probability equal to 1, totaling a total of 120 schools surveyed. These two schools were selected as control, since they present distinct characteristics of most public establishments education.

[10] This criterion allows the comparability of the results between the applications made in different periods with different tests. This methodology is used in the main evaluations, such as Prova Brasil and National High School Examination (ENEM).

Table 1
Descriptive statistics of the characteristics of students, teachers, schools.

	Observations	Mean	Standard deviation	Minimum	Maximum
Score	3.688	41.83	16.53	0	100
Male	1.865	41.27	16.67	0	95
Female	1.823	42.41	16.36	0	100
Bullied 1	1.330	0.37	0.48	0	1
Male	664	0.37	0.48	0	1
Female	666	0.37	0.48	0	1
Bullied 2	1.487	0.40	0.49	0	1
Male	765	0.41	0.49	0	1
Female	722	0.39	0.48	0	1
Male student	1.865	0.50	0.50	0	1
White	669	0.18	0.39	0	1
Black	456	0.12	0.32	0	1
Age	3.688	11.40	1.07	9	23
Underweight	1.933	0.52	0.49	0	1
Normal weight	1.423	0.38	0.48	0	1
Overweight	264	0.07	0.26	0	1
Presence of the person in charge	3.216	0.00	1.00	−1.05	5.01
Bachelor/undergraduate	55	0.01	0.12	0	1
High school	1.073	0.33	0.47	0	1
Elementary school	1.767	0.54	0.49	0	1
Female teacher	2.534	0.68	0.46	0	1
Teacher age	108	0.02	0.16	0	1
Disapproved 1 time	763	0.20	0.40	0	1
Disapproved 2 times	311	0.08	0.27	0	1
Program transfer	1.857	0.57	0.49	0	1
Class 1	62	0.01	0.12	0	1
Class 2	501	0.13	0.34	0	1
Class 3	1.845	0.50	0.50	0	1
Low drop out	3.163	0.85	0.34	0	1
Average drop out	457	0.12	0.32	0	1
High drop out	68	0.01	0.13	0	1

Source: Own elaboration based on data from Fundaj 2013.

significance. The likelihood of bullying between boys and girls is similar. Other variables of interest are presented in the same Table 1.

Score refers to a math test with 20 items applied in March. Bullied 1 refers to all students who have fully agreed to have already suffered bullying, and Bullied 2 is when we group students who said “maybe” into bullying. The weight measures found in the table are derived from the body mass index[11] (BMI), where Underweight are students who have a BMI of less than 18.5, Normal weight students with BMI greater than or equal to 18.5 and lower than 25 and overweight are students with BMI greater than or equal to 25 and less than 30. The variable presence of the responsible was constructed with factorial analysis from 4 items of the questionnaire of the responsible.[12]

The variable Teacher age are teachers aged up to 24 years. The model specifications use other age categories. The Class variables refers to the number of students in the classroom, where Class 1 are rooms with up to 20 students, Class 2 has more than 20 students and less than 30 and Class 3 are rooms with more than 30 students and less than 40. Finally, dropout means the average percentage of abandonment of the 6th grade of elementary school. In the case, low dropout are students in the schools with a percentage below 10%, average dropout are students in the schools with a value of 11%–25% and high dropout are students in the schools with a percentage greater than 26% and less than 50%.

[11] It is an international measure used to calculate whether a person is at ideal weight.
[12] Parent questionnaire items can be found in the Appendix in Supplementary material.

Table 2
Descriptive statistics of students non-cognitive abilities.

	Conscientiousness		Extroversion		Emotional stability	
	Mean	Stan. Desv.	Mean	Stan. Desv.	Mean	Stan. Desv.
All	−0.000	1.00	0.000	1.00	0.000	1.00
Boys	0.165	1.09	0.025	1.018	0.038	0.994
Girls	−0.157	0.89	−0.023	0.981	−0.036	1.004

Source: Own elaboration based on data from Fundaj 2013.

3.1. Construction of non-cognitive skills

To construct the empirical strategy, the estimation of the distribution parameters of non-cognitive latent variables uses scores that measure the socio-emotional competences. The questionnaires applied by Fundaj use a variety of measures related to socio-emotional skills. From the questionnaire,[13] it was possible to establish indicators related to conscientiousness, extraversion[14] and emotional stability to be used in our estimations.

The student who has conscientiousness demonstrates self-discipline, motivation, organization and is focused on performing duties and achieving the defined objectives. Their behavior follows a plan of action, which lowers their level of spontaneity. Extroversion is defined as the orientation of interests and energy toward the external world, people and things. The extroverted student is characterized by his or her ability to communicate, assertiveness, sociability and the tendency to draw attention to him- or herself within a group. Neuroticism refers to the emotional instability/stability of an individual, considering negative emotions such as anxiety, helplessness, irritability and pessimism.

Many have suggested a potential way of measuring personality traits of individuals. One way is presented by Mischel et al. (1989) through the "Marshmallow Test[15]" experiment to measure these traits. The results show that children with higher capacities to postpone the reward are on average more intelligent, more likely to have a greater social responsibility and that the postponement time is significantly related to the SAT.[16] These results suggest that children who have an ability to postpone the larger reward are better able to cope with more personal and social problems. These are problems that are not completely attributable to school. According to Michell et al., the presence of the father is fundamental in the first years of the child's life for such behavior, since his presence stimulates the development of the child's executive functions during the first 4 years of life, even subtly the child learns to inhibit and not grant his or her desires.

Therefore, it is indispensable to use variables that express students' non-cognitive abilities, since this set of variables allows better specifications for model construction. Most of the social emotional measures found in the questionnaires are recorded in categories that group student reactions, such as "fully agree or disagree strongly".[17] According to Sarzosa and Urzúa (2015) it is common practice in the literature to construct socio-emotional measures by adding categorical answers to several questions on the same topic, since this method incorporates a certain degree of continuity in the scores, something essential for the estimation process. The items used in the questionnaire to construct such measures can be found in Appendix A in Supplementary material. Table 2 shows the descriptive statistics of these skills.

According to the items identified by the questionnaire for the construction of socio-emotional measures, the lower the value of the score, the greater is their conscientiousness. The lower the score, the more extroverted the student will be in relation to the score related to emotional stability, the lower the student's more unstable value in relation to emotional stability. These results are also found by Santos and Primi (2014).

[13] It was not possible to construct the personality traits öpenness to new experiencesänd ämiability,, taxonomy of the Big Five model, since these measures were not present in the questionnaire.

[14] One of the items answered by the evaluator at the time of the questionnaire is whether the student is physically attractive. This item is used to build the Extroversion. For Lukaszewski and Roney (2011) the origins of variation of extroversion are miscreant. The authors state from two studies that attraction and physical strength account for a large portion of extroversion and this plot is independent of the variance explained by a polymorphism of the androgen receptor gene. These arguments support the use of this item for the construction of this personality trait.

[15] The test consists of offering a small reward (marshmallow, or some other candy) for 4-year-old children immediately or two small rewards if the child waits until the researcher returns (approximately 15 min).

[16] SAT (Scholastic Assessment Test) is a standardized test widely used for admission to colleges in the United States.

[17] The questionnaire applied to the students to build the socio-emotional abilities has several items with categorical answers.

The measure of cronbach's alpha has the objective of evaluating the magnitude in which the items of an instrument are correlated. The internal consistency of Cronbach's alpha is greater the closer to 1 is the value of the statistic.[18] In our study, cronbach's alpha for Conscientiousness is 0.49, Neuroticism 0.43, Extraversion 0.52 and Presence of the Responsible 0.41. For Landis and Koch (1977) the results found are considered moderate. In this way, the items that make up measure the same instrument created.

Santos and Primi (2014) investigated the socio-emotional skills of students from Rio de Janeiro and Soto et al. (2011) also sought to understand the profiles of students in various places around the world and the results were quite similar. Both studies found that girls tend to be more conscientious, outgoing, and loving, despite having less emotional stability. According to Kyllonen et al. (2014) these characteristics are components of the five major factors that are identified as relevant to measure the traits and personality in the educational context.

4. Empirical strategy

We estimate the following model for student math score using ordinary least squares (OLS):

$$Y_i = \beta_0 + \beta_1 bullied_i + \beta_2 X_i + \varepsilon_i$$

where Y_i stands for the math student grade *i*, $bullied_i$ is a binary variable that assumes the value 1 if the student claims to have suffered bullying and 0, otherwise, X_i is the vector of control variables, which refer the characteristics of students, teachers, principals and schools, as described in Table 1, and the term ε_i is related to idiosyncratic error. Our interest lies in estimating β_1, as this parameter represents the impact of bullying on the math score, that is, the expected average difference in academic performance among students who are victims and not victims of bullying.

However, the estimate made by the OLS can be skewed due to problems of endogeneity. This bias arises as a result of an inadequate group of comparison. For this analysis, students who do not suffer bullying may have different characteristics from those present in students who suffer from bullying due to the heterogeneity that may be present in the observations. Therefore, it is necessary to find a way to make these groups comparable. To overcome the problem of selection bias, a control group should be found (students who have not been bullied) to allow comparison with the treatment group (students who have already suffered from bullying). In this case, the propensity score method[19] is used to construct a control group similar to the treatment group in terms of certain observable characteristics.

The Propensity Score Matching (PSM) method seeks to find for each member of the treated group a more similar control group based on observable characteristics, which represents the result that it would have obtained had it not been treated. For this, the method uses the conditional probability of treatment through a vector of observable characteristics (Rosenbaum and Rubin, 1983).

The objective of this method is to estimate the mean effect of treatment on treated subjects. For this to be possible, the hypotheses of conditional independence assumption (CIA[20]) and common support[21] need to be met. The implementation of the face estimator can be more complex when the size of the vector X' is large. One way around this problem is to use a function of X' which summarizes all the information contained in this vector. This function represents the propensity score[22] and means the probability in this case of suffering bullying, given the set of characteristics X and has the advantage of reducing the problem of dimensionality (Angrist and Pischke, 2008; Caliendo and Kopeinig, 2008; Khandker et al., 2009).

To estimate the effect of bullying on the students' math score, we used several estimation methods with different criteria presented in the literature. We used the propensity score method with several matching algorithms criteria: nearest-neighbor, radius and kernel as described by Becker and Ichino (2002). The reweighting method[23] is also used in

[18] For Landis and Koch (1977) values greater than 0.80 have an almost perfect internal consistency, values from 0.61 to 0.80 are considered substantial, values from 0.41 to 0.60 is moderate, from 0.21 to 0.40 is reasonable and less than 0.21 is considered small.

[19] The empirical and theoretical literature on this method is quite extensive. For further details, Rosenbaum (2002), Rosebaum and Rubin (1983), Rubin (1973, 1977, 1979), Heckman et al. (1997), Abadie and Imbens (2002), Lalonde (1986) and Dehejia and Wahba (1999).

[20] $(Y_i(1), Y_\mathrm{i}(0)) \perp T_i|X_i$Also called selection in observables.

[21] $0 < Pr\,[T_i = 1|X_i] < 1$.This hypothesis ensures $X_\mathrm{i}$that for each treated individual there is another individual not treated with similar values of $X_{i.}$

[22] Formally, we have $Y_i\,(0) \perp T_i|X_i \Rightarrow Y_i\,(0) \perp T_i|\mathrm{p}X_i$.

[23] For a review of the reweighting method, see Imbens (2004) and Imbens and Wooldridge (2009).

our estimates. This estimator is based only on the estimation of the propensity score, therefore, a great deal of attention must be paid to the specification of the model chosen to determine the propensity score, Menezes-Filho et al. (2012). The method weights each unit in the control group because of the probability of not receiving the treatment, that is, the greater the probability that the student in the control group did not suffer from bullying, the lower their weight when we balance the control group. However, Firpo and Pinto (2012) do not recommend the use of traditional implementations, such as imputation or reweighting (IPW), since they do not allow immediate conclusions to the asymptotic properties requirement. Moreover, when the value of the propensity score is close to one, this estimator can assume very high values, due to its sensitivity to specification of the propensity score, Menezes-Filho et al. (2012).

Thus, the results reported in this paper refer to the estimator that combines the regression method with the reweighting method, since its estimator has the property of being double robust,[24] as the weighting of the independent variables avoids potential sources of variable bias omitted, regardless of the parametric model adopted, introducing an additional robustness both by eliminating the correlation between the omitted covariates and by reducing the correlation between the omitted and included variables (Wooldridge, 2007; Imbens and Wooldridge, 2009; Firpo and Pinto, 2012).

If the parametric model for the propensity score is correctly specified or if the parametric model for the linear regression is correctly specified, the estimator is consistent to estimate the mean treatment effect on the treated (ATT[25]) (Robins and Ritov, 1997). To compare and demonstrate the robustness of the results, the coefficients of both estimators are presented in the next section.

5. Empirical results

Although the results for the OLS estimators are reported, the emphasis is on the PSM, reweighting and double robust estimator methods. The different reported estimators present the robustness of the results, allowing the comparability between the estimates. Table 3 presents the results of bullying using Ordinary Least Squares.

Table 3 shows several specifications[26] with OLS. Column (1) is the simplest specification, it has no control variable. In column (2) are added some variables of control of the student, of the parents and the socio-emotional abilities of the student. Column (3) includes variables related to the characteristics of the teacher: gender, experience and age. In addition, it includes whether the student has already been disapproved 1 or 2 times or more and if the student's family receives family scholarship. Column (4) adds controls pertaining to school characteristics. Column (5) uses an alternative way of controlling teacher and school characteristics through the fixed effects of the school, since in this way the model proposed in column (5) is more parsimonious and captures potential unobservable effects present in the school's characteristic.

It is emphasized that in column (1) to column (5) the R-squared increases as the number of variables is included in the models. Although the coefficient[27] of bullying between -0.043 and -0.056 on all models were significant at a level of 5%. These oscillations between the magnitudes of the coefficients occur because the control variables are correlated with the bullying, making the coefficients of the bullying overestimated. Thus, a possible reason for the decay is the inclusion of more variables to the models. In all models, the student's perception of having suffered bullying is negatively related to his performance in mathematics. According to column (5), students who have already undergone bullying have a lower performance of approximately 4.34% lower than students who say they have not suffered bullying.

It is noticed that younger students perform better. Socio-emotional skills such as conscientiousness and extroversion also affect student grades, that is, the higher the student's conscientiousness[28] the worse his performance. And the more emotionally unstable the student, the lower his grade. These results are also found by Santos and Primi (2014).

[24] According to Bang and Robin (2005) this method produces more consistent estimates when at least one of the estimation stages is correctly specified.

[25] Average Treatment Effect for the Treated

[26] We also do not find evidence that the characteristics of attritors by missing observations differ between the treatment and control group. Specifically, we regress specifications 1–3 with the same number of observation on specification 4 and we got the same consistent results.

[27] The math proficiency scale used in the Joaquim Nabuco Foundation survey refers to 20 items applied where each one worth 5 points, totalizing 100 points. In this way, the results suggest that students suffering from bullying have an approximate performance of one item less than students who do not suffer from bullying.

[28] Remember that the lower the conscientiousness, the better for the student, that is, he tends to be more perseverant and responsible.

Table 3
Effect of bullying on math performance, estimated by OLS.

	(1)	(2)	(3)	(4)	(5)
Bullying	−0.056***	−0.048***	−0.051***	−0.043**	−0.044**
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)
Age		−0.066***	−0.044**	−0.035**	−0.030*
		(0.012)	(0.017)	(0.017)	(0.017)
Conscientiousness		−0.042***	−0.040***	−0.037***	−0.034***
		(0.009)	(0.010)	(0.010)	(0.009)
Extroversion		−0.008	−0.003	−0.008	−0.007
		(0.008)	(0.008)	(0.010)	(0.008)
Emotional stability		0.025***	0.022**	0.019**	0.020**
		(0.008)	(0.008)	(0.008)	(0.008)
Disap. 2 times or more			−0.078	−0.080	−0.086
			(0.049)	(0.050)	(0.046)
Disap. 1 time			−0.088***	−0.096***	−0.103***
			(0.026)	(0.027)	(0.026)
Program transfer			−0.024	−0.024	−0.013
			(0.016)	(0.015)	(0.171)
Preschool				0.096**	0.080
				(0.037)	(0.040)
Literacy				0.088**	0.072
				(0.040)	(0.042)
Schools with differentiated enrollment				0.424***	
				(0.052)	
Student control	No	Yes	Yes	Yes	Yes
Person in charge characteristic	No	Yes	Yes	Yes	Yes
Teacher Control	No	No	Yes	Yes	No
School characteristic	No	No	No	Yes	No
School Fixed Effect	No	No	No	No	Yes
Observations	3.531	3.081	3.057	2.948	2.972
R-square	0.003	0.078	0.094	0.126	0.184

Source: Own elaboration based on data from Fundaj 2013.
Notes: Standard error in parentheses. “Student control” includes the student’s gender, race, body mass index (BMI), and whether the student has any disease. “Parental Controls” include family per capita income, higher education and high school dummies and the presence of those responsible for the student. “Teacher Control” includes the gender of the teacher, experience and age. “School Characteristics” include dummies that capture the size of the class, dropout level dummies, average daily dummies of absences and proportion of girls per class. Standard error adjusted for classes with clustering and heteroscedasticity.
*** $p < 0.01$ indicates the level of statistical significance.
** $p < 0.05$ indicates the level of statistical significance.
* $p < 0.1$ indicates the level of statistical significance.

In addition, students who failed once scored significantly below 5% of significance, but students who failed twice or more did not score significantly lower than students who did not fail. Column (4) shows that students who started their pre-school or literacy school perform better when compared to students who begin their school life later at a 5% level of significance. Finally, it should be noted that schools with a differentiated[29] enrollment system perform better when compared to other schools in Recife’s public schools.

Table 4 reports the results of Propensity Score Matching. In order to estimate the average treatment effect on treated (ATT), we applied three methods: nearest neighbor matching with replacement and nearest neighbor matching without replacement, radius matching and Kernel matching. In all methods, bullying has a negative effect on students’ scores at a 5% level of significance and the estimated parameter was considered even higher.

In all of the estimated models, socio-emotional skills play an important role in reducing the student’s likelihood of being bullied. According to Table 5 it can be noted that the student’s emotional stability negatively affects the student’s

[29] These are schools in the sample that present different selection criteria from schools in the Recife public school.

Table 4
Impact of bullying on performance in mathematics with PSM.

Matching method	Math score	Std. Err.	Std. Err. *boostrap*	Statistic T	Treated	Control
Nearest neighbor with replacement	−0.074***	0.024	0.024	−3.06	1.111	1.837
Nearest neighbor without replacement	−0.055***	0.019	0.017	−2.89	1.111	1.837
Radius/caliper	−0.050***	0.018	0.019	−2.67	1.104	1.837
Epanechnikov kernel	−0.054***	0.017	0.018	−3.01	1.111	1.837

Source: Own elaboration based on data from Fundaj 2013.
Notes: Content common support. Standard error in parentheses. The default error estimated with 200 bootstrap replications is reported in brackets.

Table 5
Role of non-cognitive skills – logit 34.

Bullying	Coefficient	Std. Err.	Statistic t	P Value	Confidence interval	
					Inferior limit	Superior limit
Boy	−0.01	0.08	−0.17	0.86	−0.17	0.14
White	−0.10	0.10	−0.97	0.33	−0.31	0.10
Black	0.31	0.11	2.65	0.00	0.08	0.55
Age	−0.18	0.05	−3.42	0.01	−0.29	−0.08
Underweight	−0.71	0.27	−2.55	0.01	−1.25	−0.16
Normal weight	−0.79	0.28	−2.84	0.00	−1.34	−0.24
Overweight	−0.43	0.30	−1.42	0.15	−1.03	0.16
Conscientiousness	0.05	0.04	1.30	0.19	−0.02	0.13
Extroversion	−0.02	0.04	−0.72	0.47	−0.10	0.05
Emotional stability	−0.36	0.03	−9.18	0.00	−0.44	−0.28
Disap. 2 times or more	0.41	0.19	2.17	0.03	0.04	0.78
Disap. 1 time	0.10	0.11	0.90	0.36	−0.12	0.32
Program transfer	0.06	0.08	0.81	0.42	−0.09	0.23
Scho. with dif. enroll.	−0.80	0.30	−2.60	0.00	−1.40	−0.19
Preschool	0.09	0.20	0.49	0.63	−0.31	0.51
Literacy	−0.07	0.21	−0.33	0.74	−0.50	0.35
Constant	2.69	0.87	3.07	0.00	0.97	4.40
Student control	Yes					
Person in charge characteristic	Yes					
Teacher control	Yes					
School characteristic	Yes					
Observations	2.948					

Source: Own elaboration based on data from Fundaj 2013.
Notes: First stage of the nearest neighbor matching applied with replacement. Student control, Parental controls, Teacher control and School characteristics include the same variables cited in model 4, of the table.

chance of being bullied. This result is also found by Sarzosa and Urzúa (2015) in which they verify that non-cognitive abilities[30] reduce the chance of suffering bullying.[31]

For Carneiro et al. (2007) economists often have a simplified view on how non-cognitive skills act and can determine social and economic outcomes. This is partly because these abilities are intrinsically multidimensional. For the authors, these abilities can impact the behavior of individuals throughout life, as for example; the possibility of smoking at age 16, health status at age 42, employability at this age, among other factors. The study suggests that non-cognitive skills appear to be more malleable than cognitive abilities. An education policy aimed at such skills may be more effective in generating well-being than a policy that achieves only cognitive abilities.

Other facts also drew attention. The results suggest that black students are more likely to report being bullied and younger students are also more sensitive to bullying at a 5% level of significance. The results suggest that students

[30] The authors work with locus of control, self-esteem and irresponsibility.
[31] The same procedure was performed with OLS and reported in Table 3

Table 6
Impact of bullying on performance in mathematics, ATT estimated from the IPW and IPWRA estimators.

Variable	IPW			IPWRA		
	Coefficient	Std. Err.	z	Coefficient	Std. Err.	z
Bullying	−0.047***	0.017	−2.65	−0.045**	0.017	−2.57

Source: Own elaboration based on data from Fundaj 2013.
* p < 0.10.
** p < 0.05.
*** p < 0.01.

with a BMI below healthy level and with a healthy BMI tend to report having suffered less bullying when compared to obese students at 5% significance. Finally, it is noticed that with a differentiated enrollment systems schools are less likely to declare students bullying.

Table 6 presents the results of the reweighting method (IPW) and the double robust technique (IPWRA). The results reveal the parameters of the weights estimators by the inverse of the propensity score and the double robust estimator. In both cases, the coefficients referring to the bullying variable are negative and significant at 5%.

6. Robustness analysis

This section provides the robustness analysis of the results from the common support hypothesis and the matching quality. The first one is verified from the graphical analysis, while the quality is analyzed from the covariates distribution between the treatment and control groups. In addition to these tests, the regression method is still used to test the unconfoundedess assumption to analyze the placebo effect.

The common support hypothesis ensures that students with the same propensity score have a positive probability of being treated or untreated. One of the ways to test this assumption is through a graph. Fig. 2 compares the propensity score distribution of the two groups. The good adhesion of the pairing can be noticed when observing the distribution of the propensity score (Table 7).

Another important procedure in this type of methodology is the checking of the balancing conditions. Table 8 shows the means of the variables in the treatment and control groups. After pairing, for all covariates it was not possible to reject the null hypothesis of equality of means and, therefore, one has a pairing with a good balance.

One of the assumptions of PSM is conditional independence assumption, that is, the vector of observable variables contains all information about the potential outcome in the absence of treatment. The placebo regression is used to test this assumption. For this, we selected all the variables used in the estimation of propensity score, but with a new dependent variable that we assumed to be exogenous to the treatment. If there is any omitted variable correlated with the treatment, it is expected that the estimated coefficient of bullying is statistically different from zero, otherwise the hypothesis of CIA is assured.

We use the gender of the teacher allocated in the math classes, since this variable is independent of the student performance. Table 8 shows the results of the placebo regression. Note that it was not possible to reject the null hypothesis of the bullying variable, suggesting that omitted variables that are related to the treatment do not exist.

6.1. Sensitivity analysis

This section provides a sensitivity analysis[32] proposed by Rosenbaum (2002) that seeks to evaluate the potential impact of selection bias arising from unobserved variables. For this, we used different values of Γ that measures the difference in the chance of receiving the treatment between the observations with the same observable characteristics, to verify the changes in the inference due to the existence of unobservable confounding factors. Table 9 shows the results for Γ ranging from 1 to 1.5 and the corresponding p-value limit values.

[33] Due to the non-experimental character, the concern with the bias of omitted variables is relevant.
[32] We find the same result when we run the same number of observation in column 1.

Table 7
Difference of means, before and after matching, between treatment and control groups.

	Before matching			After matching		
	Treatment	Control	P-Value	Treatment	Control	P-Value
Student characteristics						
Boy	0.499	0.499	0.97	0.484	0.484	0.99
White	0.169	0.189	0.12	0.171	0.165	0.70
Black	0.148	0.112	0.00	0.148	0.151	0.83
Yellow	0.009	0.019	0.03	0.008	0.008	0.95
Indigenous	0.018	0.015	0.51	0.016	0.015	0.82
Age	11.707	11.743	0.32	11.657	11.646	0.78
Below ideal weight	0.518	0.523	0.77	0.512	0.511	0.95
Normal weight	0.371	0.398	0.11	0.375	0.372	0.92
Overweight	0.081	0.064	0.06	0.085	0.087	0.86
Disease	0.158	0.145	0.27	0.182	0.184	0.86
Conscientiousness	0.020	−0.033	0.15	0.012	0.011	0.97
Extroversion	−0.005	−0.000	0.88	−0.015	−0.032	0.67
Emotional stability	−0.221	0.138	0.00	−0.218	−0.211	0.87
Characteristics of those responsible						
Presence of the person in charge	0.051	−0.020	0.05	0.041	0.014	0.52
Family income per capita	207.26	218.28	0.10	208.05	210.40	0.74
Superior	0.009	0.021	0.01	0.009	0.009	0.98
High school	0.298	0.350	0.00	0.303	0.294	0.65
Elementary School	0.514	0.563	0.00	0.521	0.514	0.74
Characteristics of teachers						
Female teacher	0.696	0.677	0.25	0.694	0.691	0.86
Teacher experience 1	0.109	0.115	0.56	0.104	0.104	0.96
Teacher experience 2	0.266	0.227	0.00	0.263	0.251	0.51
Teacher experience 3	0.124	0.139	0.22	0.124	0.132	0.56
Teacher experience 4	0.095	0.123	0.01	0.101	0.099	0.85
Teacher age 1	0.036	0.026	0.10	0.034	0.031	0.65
Teacher age 2	0.145	0.148	0.80	0.141	0.135	0.69
Teacher age 3	0.263	0.269	0.69	0.263	0.268	0.78
Teacher age 4	0.328	0.315	0.41	0.331	0.329	0.93
Teacher age 5	0.142	0.143	0.95	0.144	0.146	0.93
Characteristics of the school						
Class 1	0.019	0.015	0.36	0.017	0.017	0.93
Class 2	0.143	0.127	0.17	0.143	0.141	0.91
Class 3	0.501	0.496	0.77	0.495	0.500	0.79
Low drop out	0.833	0.873	0.00	0.839	0.840	0.94
Average drop out	0.143	0.111	0.00	0.139	0.139	0.97
Proportion of girls	0.482	0.488	0.13	0.482	0.481	0.96
Schools with differentiated enrollment	0.013	0.031	0.00	0.016	0.016	0.98
Less than 30% and greater than 10%	0.159	0.166	0.56	0.156	0.157	0.94
Greater than 30%	0.010	0.016	0.15	0.011	0.011	0.91
Variables of school performance and social program						
Disapproved 1 time	0.207	0.209	0.91	0.201	0.199	0.94
Disapproved 2 times	0.087	0.080	0.43	0.079	0.081	0.85
Program transfer	0.598	0.566	0.08	0.596	0.583	0.54
Preschool	0.733	0.720	0.40	0.737	0.729	0.68
Literacy	0.212	0.233	0.16	0.221	0.223	0.92

Source: Own elaboration based on data from Fundaj 2013.
Notes: Common support satisfied. Radius caliper is applied.

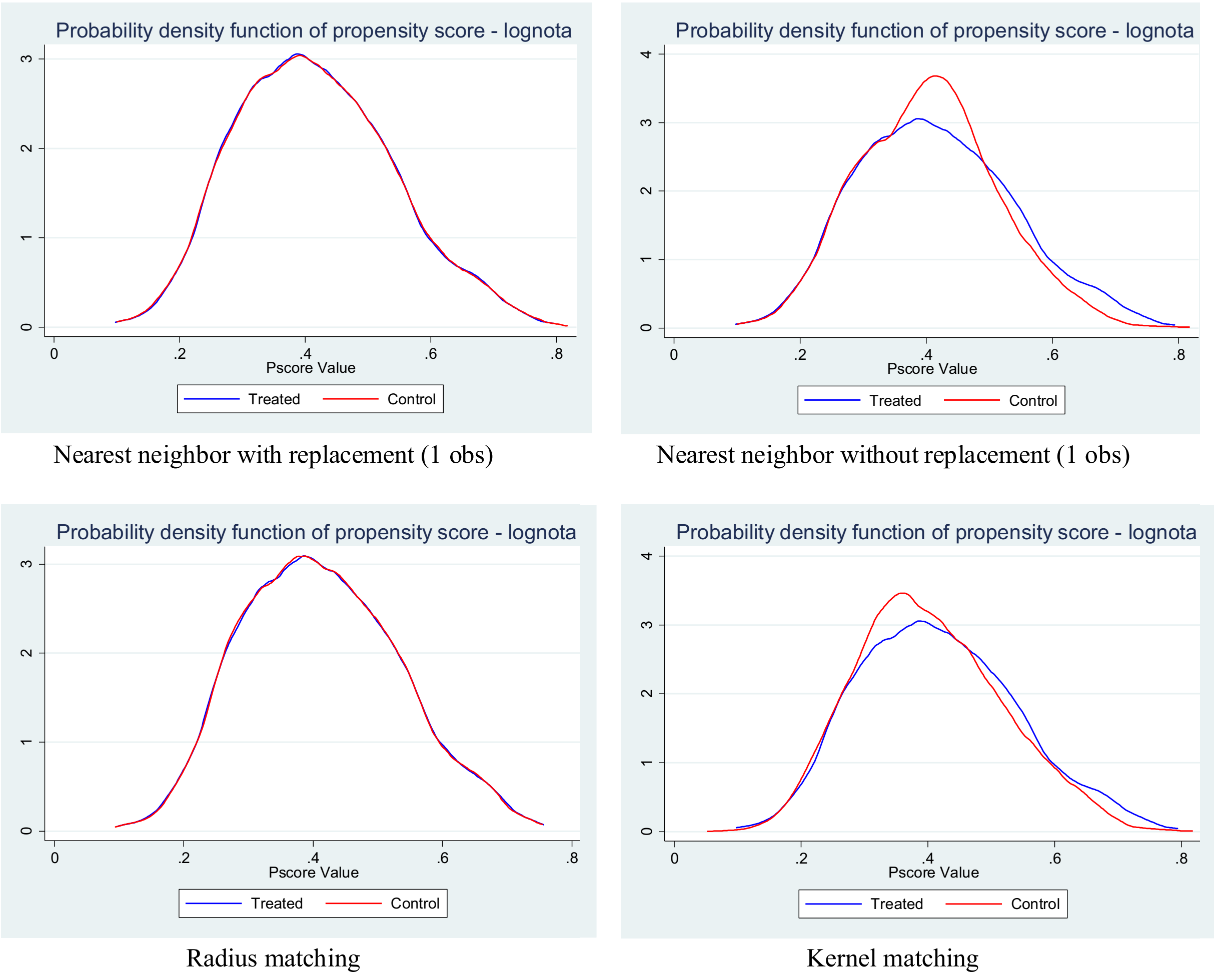

Fig. 2. Kernel density of the propensity score after pairing of 6th graders.
Source: Own elaboration based on data from Fundaj 2013.

Table 8
Estimated placebo outcomes by OLS.

	(1)	(2)
Bullying	0.018 (0.019)	0.010 (0.018)
Other Controls	No	Yes
Observations	3.531	2.948[33]
R-squared	0.000	0.403

Source: Own elaboration based on data from Fundaj 2013.
Notes: 'Other controls' refers to all controls used in model 4 of Table 4. Standard error adjusted for clusters with clustering and heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ indicates the level of statistical significance.

Table 9 reveals that the critical gamma value Γ is between 1.25 and 1.27 for the kernel method, considering the ATT for the math grade of the students. This result indicates that the paired students are apparently similar in terms of their observable characteristics and that they are part of the common support region, may differ in their probabilities of participating in the treatment (bullying) by a factor of up to 1.25 that the results of the ATT remains unchanged.

Table 9
Sensitivity analysis for the mathematics grade.

Γ	p−crit+	p−crit−
1.02	0.00	0.00
1.05	0.00	0.00
1.08	0.00	0.00
1.10	0.00	0.00
1.13	0.00	0.00
1.15	0.00	0.00
1.18	0.00	0.01
1.20	0.00	0.03
1.23	0.00	0.06
1.25	0.00	0.10
1.27	0.00	0.16
1.30	0.00	0.24

Source: Own elaboration based on data from Fundaj 2013.

7. Final considerations

This work aimed to evaluate the impact of bullying on mathematics performance of 6th grade students in the public schools of Recife city, using the Ordinary Least Squares and Propensity Score Matching methods, applying robustness tests and sensitivity analysis proposed by Rosenbaum (2002).

For Kibriya et al. (2015) quantitative analyses that seek to understand bullying in developing countries are rare. This work aimed to fill this space in the national literature through a study using the data resulting from the research conducted by the Joaquim Nabuco Foundation in the year 2013. The main analysis was based on the suffering of bullying reported by the students, and it was observed that this phenomenon has a significant and negative impact on mathematics. In addition, the findings suggest that social-emotional skills can help students cope with bullying. Thus, programs to combat the practice of bullying may have special attention with non-cognitive skills.

A limitation according to Bryson et al. (2002) in the case of random assignment, properly conducted, it is possible to be confident that the treated and non-treated populations are similar on both observable and unobservable characteristics. This is not true in the case of PSM, which takes account of selection on observables only. Omitted variable, such as peer effects, could bias ours results. Several econometric techniques have been used to overcome problems of endogeneity. In addition, robustness tests support the results found. The sensitivity test proposed by Rosenbaum (2002) indicated that the results are sensitive to the presence of omitted variables.

A similarly designed experiment used by Bursztyn and Jensen (2015) can help identify how much of a student's performance decrease is explained by the consequences of bullying and how much of that decrease is purposeful, since students can study less for the purpose of avoiding social costs.

This paper highlights the importance of new research involving the influence of the network of friendships in the classroom. An unprecedented factor in the Fundaj database for Brazil is the information regarding the student's network of friends within the classroom. This network of friendships was explored by Raposo (2015), with the aim of identifying peer influences on individual school performance. The authors identify a positive and significant effect of direct friends school performance on individual school outcomes. New studies that seek to explore the network of friendship of students involving bullying can contribute to this theme.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.econ.2017.10.001.

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