# THE IMPACT OF EARLY CHILDHOOD EDUCATION ON MATHEMATICS PERFORMANCE: EVIDENCE FOR PUBLIC ELEMENTARY SCHOOL STUDENTS IN THE CITY OF RECIFE[1]

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This article sought to measure the effect of early childhood education on the future academic performance of elementary school students, based on a survey carried out by Fundação Joaquim Nabuco in 2013. The methodology used was the propensity score matching with the purpose of comparing students who claim to have attended pre-primary school with a control group, composed of students who started school from the 1st year of elementary school. Specifically, a stratification analysis was done through the quantile treatment effects. The results reveal that attending preschool has a positive impact on performance, being even more effective for children with lower performance. Several econometric techniques were used to circumvent endogeneity problems. Oster's sensitivity analysis (2019) indicated that there were no problems of omitted variables.

**Keywords**: early childhood education; impact assessment; propensity score matching.

## O IMPACTO DA EDUCAÇÃO INFANTIL NO DESEMPENHO EM MATEMÁTICA: EVIDÊNCIAS PARA ALUNOS DE ESCOLAS PÚBLICAS DE ENSINO FUNDAMENTAL NA CIDADE DO RECIFE

Este artigo buscou mensurar o efeito da educação infantil no desempenho acadêmico futuro de estudantes do ensino fundamental, a partir de uma pesquisa realizada pela Fundação Joaquim Nabuco em 2013. A metodologia empregada foi o propensity score matching, com o propósito de comparar os alunos que declaram ter frequentado a pré-escola com um grupo de controle, composto por alunos que iniciaram a escola a partir do 1º ano do ensino fundamental. Especificamente, foi feita uma análise estratificada por meio do quantile treatment effects. Os resultados revelam que frequentar pré-escola tem impacto positivo no desempenho, sendo ainda mais efetivo para as crianças de menor performance. Diversas técnicas econométricas foram utilizadas para contornar problemas de endogeneidade. A análise de sensibilidade de Oster (2019) indicou não haver problemas de variáveis omitidas.

**Palavras-chave**: educação infantil; avaliação de impacto; propensity score matching.

1. DOI: https://dx.doi.org/10.38116/ppp67art3

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## EL IMPACTO DE LA EDUCACIÓN INFANTIL EN EL DESEMPEÑO EN MATEMÁTICAS: EVIDENCIA PARA ESTUDIANTES DE ESCUELAS PÚBLICAS DE EDUCACIÓN PRIMARIA EN LA CIUDAD DE RECIFE

Este artículo buscó medir el efecto de la educación en la primera infancia en el futuro rendimiento académico de los alumnos de la enseñanza básica, a partir de una encuesta realizada por la Fundação Joaquim Nabuco en 2013. La metodología utilizada fue el propensity score matching con el objetivo de comparar alumnos que afirman haber asistido a la escuela preprimaria con un grupo de control, compuesto por estudiantes que ingresaron a la escuela desde el 1er año de la escuela primaria. Específicamente, se realizó un análisis de estratificación a través de quantile treatment effects. Los resultados revelan que asistir a preescolar tiene un impacto positivo en el rendimiento, siendo aún más efectivo para los niños con menor rendimiento. Se utilizaron varias técnicas econométricas para sortear los problemas de endogeneidad. El análisis de sensibilidad de Oster (2019) indicó que no hubo problemas de variables omitidas.

**Palabras clave**: educación de la primera infancia; evaluación de impacto; coincidencia de puntuación de propensión.

**JEL**: I21; I28; J24; C14.

## 1 INTRODUCTION

Education, from the basic to the most specialized, is an essential investment for the human capital formation which, in turn, promotes economic growth and the production of a more egalitarian society (Cunha et al., 2006; Cunha and Heckman, 2007). Educational investment in the first years of life has been widely studied, as research has shown the long-term effects on the individual's formation (Belsky et al., 2007; Phillips et al., 1987; Greenspan, 2003). It is at this stage of life that cognitive and socio-emotional skills are formed and absorbed most intensely, being the most critical period for learning (Comitê Científico do Núcleo Ciência pela Infância, 2014; Knudsen, 2004).

The identification of how educational interventions in the early cycles affect the lives of individuals was carried out for several segments, from socioeconomic, academic and financial issues (Heckman and Masterov, 2007; Heckman et al., 2010; Currie, 2001). For these investigations counterfactual methods, with randomized or quasi-experimental experiments, have become widely used. Such methods consist of dividing two groups, where one group that attends early childhood education, receives the treatment, and is then the treatment group, and the other group does not receive the treatment, and is the control group.

In the United States, the Perry Preschool Program randomly assigned children to the program and found improved school performance and lower rates of incarceration as adults, among program participants (Currie, 2001). In the same country, another early childhood education program, the Carolina Abecedarian Project (ABC), also showed positive results in future educational events. Programs in

Latin America such as the *Proyecto Integral de Desarrollo Infantil* (Pidi) in Bolivia and *Oportunidades* in Mexico have also shown favorable results for preschools (Schady, 2006). All these studies use counterfactual methods to investigate the effects.

In Brazil, most of the work developed was based, at first, on a rich qualitative analysis of the quality of early childhood education (Campos, 1997; 2013; Kagan, 2011). Among the incipient impact studies on this theme, positive results were found for children who attended pre-school when compared to those who did not (Felício and Vasconcellos, 2007; Curi and Menezes-Filho, 2009), however, these articles do not use causal analysis along with model sensitivity analysis, as we will conduct in this paper. That said, it becomes relevant to ascertain whether positive results can also be found in Brazil, since the simple generalization of international studies may not be adequate to demonstrate the Brazilian reality.

Therefore, the aim of this article is to estimate the impact of early childhood education on students' academic performance in mathematics, to generate further evidence on the subject. To this end, we used data from a survey conducted by Fundação Joaquim Nabuco (Fundaj) in 2013, which gathers information from students in the 6$^{th}$ grade of elementary school in public schools in Recife. This database highlights the fact that the students surveyed were submitted to two math tests applied at the beginning and end of the school year. This longitudinal aspect of school performance allows controlling for pre-existing heterogeneities among students, a type of control capable of minimizing the bias of omitted variables.

Entitled *A longitudinal study on the academic performance of students within the public elementary school system in Recife*, the research sample comprises 4,191 students, 3,670 parents or guardians, 120 school principals, and 131 teachers, all drawn from a total of 120 schools distributed geographically across the 18 micro-regions of the city of Recife (Fundaj, 2013). Following the elimination of observations with insufficient or absent data, the ultimate sample used in the statistical analyses for this study is composed of 3,616 students.

The method used to analyze the impact of preschool was propensity score matching (PSM), in which students in the treatment group started their school life in kindergarten, while those in the control group started their studies in the 1$^{st}$ year of elementary School. And, for stratified analysis of the sample quantiles, the quantile treatment effects (QTE), proposed by Firpo (2007), was used.

PSM, however, has strong hypotheses that must be tested, so that there is greater evidence that the results are consistent. The works carried out in Brazil, mentioned above, did not apply a robustness test to validate the method. In order to validate the method, we resorted to the application of several econometric specifications, along with other robustness analyzes such as the test of unobservables proposed by Oster (2019), a placebo test and the quality test of the matching (Dehejia and Wahba, 2002).

In addition to this introduction, the article has five other sections. The second section presents a review and discussion of the literature on the subject, with an exposition of the international and national programs evaluated. The third section introduces the database used and presents some descriptive statistics of the variables used in the estimations. The fourth section discusses the methodology used. The results and data analysis are presented in the fifth section and, finally, the final considerations.

## 2 THEORETICAL REFERENCE

There is growing consensus that early childhood learning experiences significantly influence individual short-term and long-term outcomes (Heckman and Masterov, 2007; Schady, 2006). This is underscored by evidence showing that attending preschool results in better academic performance, greater chance of completing high school, less likely to be involved in crime, and reduced teen pregnancy (Cunha et al., 2006; Curi and Menezes-Filho, 2009; Temple and Reynolds, 2007).

Such gains can be explained, firstly, by the fact that it is in the first years of life, from 0 to 6 years old,[6] that the cognitive and socio-emotional skills of individuals are formed (Knudsen, 2004).[7] Such abilities, in turn, can be acquired and not just inherited, that is, they can be influenced by a genetic component and by the environment itself. (Cunha and Heckman, 2007; Carneiro and Heckman, 2003). Thus, the family and the school have a very powerful role in the formation of these skills (Cunha and Heckman, 2007; Carneiro and Heckman, 2003). Pre-primary education works towards the intellectual, physical, social and emotional development of the child, with the school being the place where many will receive stimuli to develop these skills.

However, when the opportunities to train these skills in the early cycles are missed, the development of these skills may become irreversible, with costly delayed rehabilitation (Knudsen, 2004; Fox, Levitt and Nelson III, 2010). Cunha et al. (2006) developed a theoretical model of human skill formation, considering a scenario of educational neglect in the first years of life. The later the remediation is

6. From 0 to 6 years of age, children go through a sensitive period, in which brain structures and circuits develop and fundamental capacities are acquired, which will allow for the improvement of their abilities in the future. The lived experiences interact and modify the structures and functions of the developing brain, in such a way that the better the quality of socio-affective relationships, the better the development (Fox, Levitt and Nelson III, 2010).

7. The cognitive skills include skills such as memory, attention, language, creativity, and planning, while the socio-emotional skills, also known as socioemotional or soft skills, do not have an exclusive definition, but in general, they are the skills used daily in the way the individual relates with himself/herself and with others (Goleman, 1998). So that, they involve characteristics of self-knowledge, resilience, autonomy, empathy, collaboration, persistence, among others (Borghans et al., 2008).

given, the less effective the development of such skills will be, as they are produced more efficiently in each period of life and if training does not occur at the correct period, cognitive deficits set in and, in many cases, become impossible to recover. In the same study, the authors also conclude that the economic returns to investing at early ages are high, and these returns diminish with advancing age.

Temple and Reynolds (2007) did a cost-benefit analysis of several preschool programs, including the Chicago Parent Child Center (CPC), the High/Scope Perry Preschool Program (PPP), and the ABC. All the programs evaluated had an economic return far greater than the initial investment, according to data obtained as participants grew older, the social benefit ranged from $ 4 to $ 10.15 for every dollar invested.

The ABC program in the United States was developed between 1972 and 1977 for low-income children. A group of 111 socially disadvantaged children was randomly selected to receive the treatment, which consisted of strong language stimulation from the first months of their lives until they were five years old. Upon entering school, these children were again randomized and divided into a group that received homeschooling parallel to the school and the other group that did not receive treatment. Over time, results began to emerge, and it was possible to observe that at 15 years of age, children who received preschool intervention had higher grades (especially in reading) and lower failures. Six years later, these same children had a higher level of education, with greater potential to continue with their studies. On the other hand, the effect of additional stimulation at home was small or negligible. As for the economic benefit, there was a decrease in smoking-related costs and in elementary and high school costs (Currie, 2001; Schady, 2006).

Another well-known program, Perry Preschool also showed positive results, such as: high performance, higher rates of high school completion, high incomes, and low incarceration rates for those who attended pre-school (Currie, 2001; Cunha et al., 2006). The program consisted of a preschool intervention in low-income African American children, aged 3 or 4 years, who were randomly chosen and compared with another selected group that did not receive the treatment (Carneiro and Heckman, 2003). More recent estimates of the Perry Preschool program were made by Heckman et al. (2010) more robustly, they estimated rates of return below the previous ones reported in the literature, however it was still superior to the historical return to equity, and with the other benefits such as a reduction in the crime rate and performance, remaining.

Both programs analyzed above resemble each other in being model interventions, small-scale and implemented by better-trained staff than large-scale programs. Schady (2006) pointed out the importance of analyzing results in large-scale programs. An example of this is Head Start, an American program created in 1965 to provide preschool for children from poor families, which reached 800,000 children in 1999. Garces, Thomas and Currie (2002) found positive long-term results for the program, among whites there was a greater propensity to complete high school and attend college, while for blacks the program incurred a lower crime rate.

Investing in early childhood has also shown positive results in Latin American programs, such as the Pidi in Bolivia, *Oportunidades* in Mexico (Schady, 2006). Behrman, Cheng and Todd (2004) identified that the outcome for children participating in the program varied according to age and time of exposure to the program, positive results were observed in children who participated for at least 7 months in the Pidi, showing improvement in aspects cognitive and psychosocial when compared to the control group.

In Brazil, Curi and Menezes-Filho (2009), analyzed the role of preschool in students' school performance, completion of school cycles and future salaries of individuals, the results obtained indicated a positive relationship with the three points of analysis. First, early childhood education improved academic performance between 1% and 7.5%, children who attended day care had greater chances of completing high school and college, and finally, individuals who started their studies earlier had higher salaries in average. The authors used data from the Sistema de Avaliação da Educação Básica (Basic Education Assessment System – Saeb) for the performance of students in the 5$^{th}$ and 9$^{th}$ grades of elementary school and 3$^{rd}$ grade of high school, as well as from the Survey on Living Standards (PPV). The methodology applied was the ordinary least squares (OLS) and the logit, also considering in the regressions a set of variables with individual characteristics, family background and family environment (Curi and Menezes-Filho, 2009).

Reinforcing the debate in the national literature, the studies by Felício and Vasconcellos (2007) and Silva Junior and Gonçalves (2016) also analyzed the effect of preschool on school performance, finding positive and statistically significant results. Both papers applied methods that address the problem of selection bias, such as PSM. Felício and Vasconcellos (2007) used data from Saeb 2003 and Prova Brasil 2005 and, in addition to the PSM method, utilized the fixed effects method. The analyses conducted by the authors reveal a statistically significant effect on the improvement of students' math performance who participated in early childhood education. Silva Junior and Gonçalves (2016), using more recent data from the Prova Brasil in 2011, employed a doubly robust linear estimator known as Weighted OLS alongside PSM. The estimated results demonstrate positive and statistically significant effects on the Portuguese and mathematics scores for 5$^{th}$ and 9$^{th}$-grade students who attended preschool and daycare compared to those who began their studies directly in elementary school.

## 3 DATABASE AND THE MUNICIPALITY STUDIED

Considering that the impact assessment with quasi-experimental methods is still not widespread in Brazil, this article aims to strengthen the evidence for the country by analyzing the performance in Recife, the capital of the state of Pernambuco. Since the data pertain to public school students, this section seeks to delineate a profile of this municipality and the students' reality based a survey conducted by Fundaj in 2013.

### 3.1 Characterization of the city of Recife

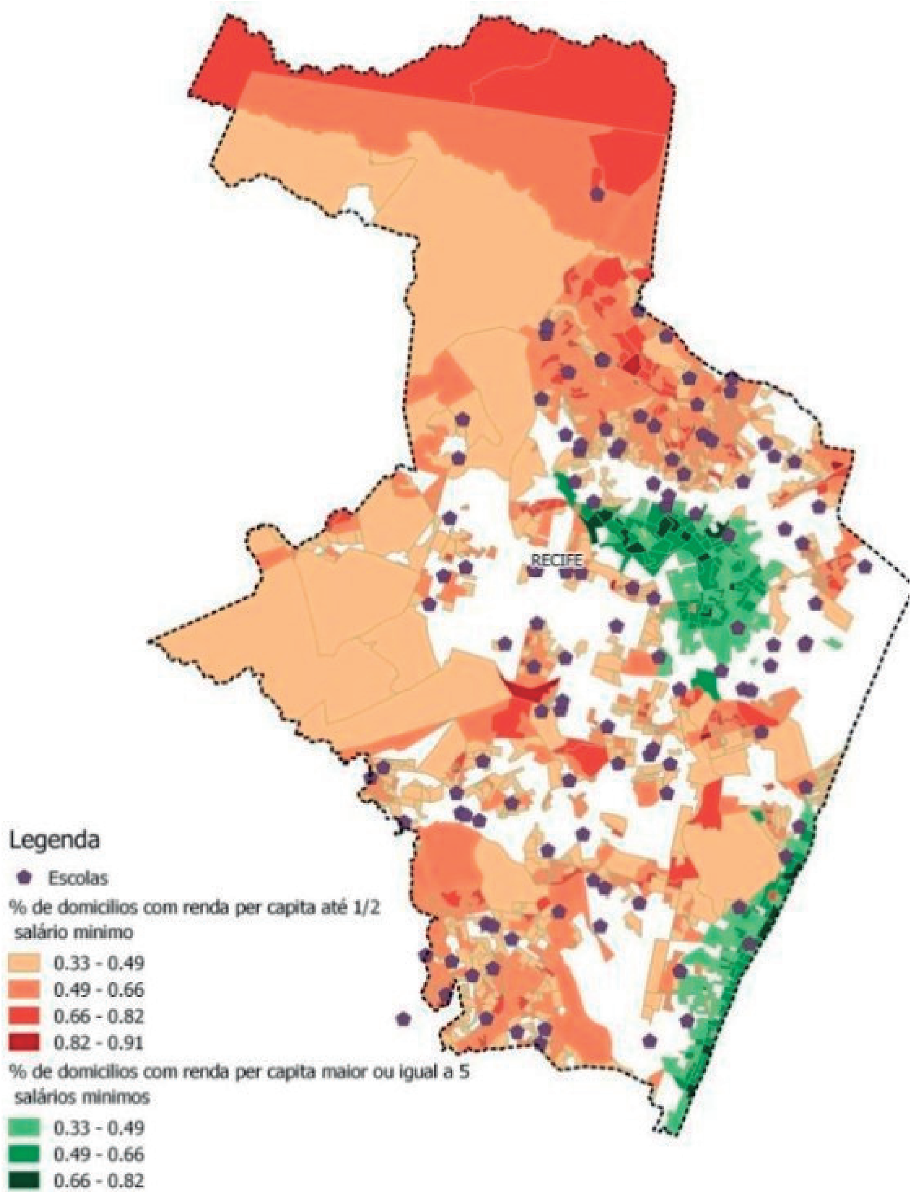
According to the 2010 Demographic Census, among the Brazilian capitals, Recife is the fourth with the highest participation of the urban population residing in subnormal agglomerations,[8] representing 23% of the local population. When analyzing the median nominal monthly income of the Recife population, it appears that residents of subnormal agglomerations receive on average 35% less than residents of the urban region outside the subnormal agglomerates, with an income of R$ 180 per month.[9]

It is also noted that the less favored areas are the ones that house the largest number of public schools in Recife. Although there are public schools located in regions that concentrate families with per capita income above 5 minimum wages, few students live in these areas. According to figure 1, most of the students in the survey live in census tracts that have a high proportion of households with an income of up to half the minimum wage, with 35% of students living in slums, a proportion greater than that observed among Recife residents, of 23% (Araujo and Silveira Neto, 2016).

8. It usually refers to subnormal agglomerations such as favelas, lowlands, communities, villages, mocambo, among others, and are characterized by urbanization outside current standards or precariousness in the provision of essential public services – water supply, sanitation, garbage collection and of electrical energy. Available at: https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2010/inicial. Accessed on: Dec. 21, 2019.

9. Available at: https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2010/inicial. Accessed on: Dec. 21, 2019.

FIGURE 1
**Mapping of schools in Recife**




Source: Araujo (2017).
Obs.: Figure whose layout and texts could not be formatted due to the technical characteristics of the original files (Publisher's note).

According to the Índice de Desenvolvimento da Educação Básica (Basic Education Development Index – Ideb), used to measure the quality of basic education, Recife had the eighth worst result in 2013 (year of application of the Fundaj survey), among the 27 Brazilian capitals. The richest are those who have the highest proportion of literate[10] and the city has low intergenerational mobility in education, that is, if the child's parents have low schooling, there is a high chance of this condition being repeated in their child (Gonçalves and Silveira Neto, 2013).

### 3.2 Data base

This article uses data from a survey carried out by Fundaj with a sample of 6th grade students from public elementary schools in the city of Recife/Pernambuco. Entitled *Longitudinal monitoring of school performance of students in the Recife public elementary school system*, the sample[11] of this research is composed of 4,191 students, 3,670 parents or guardians, 120 principals and 131 teachers from 120 schools spatially distributed throughout the 18 micro-regions of the city of Recife (Fundaj, 2013).[12] After excluding observations with inadequate or missing information, the final sample used in the estimations of this study consists of 3,616 students.

The research evaluated student performance based on two math tests, prepared by Fundaj and applied in March and November, which correspond approximately to the beginning and end of the 2013 school year, respectively. Through the administration of questionnaires to students, their parents or guardians, teachers and principals, a series of information was collected about the schools and the way they interact in the community, family and individual habits of the students, and elements of the educational behavior of each student.

Among the information measured, the main variable of interest in the model is when the child began his or her studies, whether it was in preschool (treated) or in other grades, information available among the questions in the questionnaire applied to parents or guardians. To analyze the effect of preschool only, we included

10. Available at: https://sidra.ibge.gov.br/pesquisa/censo-demografico/demografico-2010/inicial. Accessed on: Dec. 21, 2019.

11. The design of this research is a sample stratified into three strata: number of school enrollments in the 6th year of elementary school, average school grade in Prova Brasil and Political-Administrative Regions of the city of Recife. To construct the sample strata, iterative algorithms proposed by Lavallée and Hidiroglou (1988) were used. The universe of reference for the construction of the sample comes from the databases of the School Census of 2006 (Inep, 2008), together with the math scores from the Prova Brasil of 2005 (Inep, 2005). The target population of the research comprised 28,983 6th grade students enrolled in 148 public schools located in six political-administrative regions of the city of Recife. From the universe of schools evaluated, schools with less than ten participants in the 6th year, rural schools and schools intended for the exclusive service of students from indigenous communities were excluded. In addition, schools with incomplete information necessary for the construction of sample strata were excluded. For more information, access: https://www.gov.br/fundaj/pt-br/destaques/observa-fundaj-itens/publicacoes-e-notas-tecnicas/banco-de-dados-da-dipes-1/acompanhamento-longitudinal-do-desempenho-escolar-de-alunos-da-rede-publica-de-ensino-fundamental-do-recife-2013.

12. Each Political-Administrative Region of the city of Recife is divided into three micro-regions aimed at defining municipal interventions at the local level and articulation with the population, being composed of one or more of the 94 neighborhoods established by Municipal Decree No. 14,452, of October 26, 1988, to collect information for the Brazilian Institute of Geography and Statistics (IBGE) and for the Information and Planning System of Recife. The 18 microregions correspond to the division of Political-Administrative Regions, which was conceived in 1995 by the Secretariat of Social Policies, to organize Participatory Budget meetings initially limited to associations and their representatives (PNUD, 2005).

in the estimated models four groups of control variables that may influence the school performance of students. First, there are the individual characteristics of the students, such as sociodemographic information, school practices, behavior, self-esteem, and practices outside of school. The second group is the family background, through questions asked to parents about their schooling, their relationship with the student and participation in their school life. The third has characteristics of the teachers, such as gender and experience, and the last group has the characteristics of the school.

Table 1 presents the definition and descriptive statistics of the variables used for estimations. The average age of students is 11.4 years, which is expected for students in the 6$^{th}$ year of elementary school, girls, who represent 50.57% of the sample, performed better in mathematics tests, most students declare themselves as black or brown, with only 19% declaring themselves white. Nearly 17% of students are obese, model specifications use other weight categories.

As for dedication to studies, more than half of the students say they do their homework (71.5%), practice reading (86.7%), study regardless of having a test or not (65.9%) and at least three days a week (72%). Regarding self-esteem and behavior, a third say they are bullied, most say they lie to their parents often and that they would change families if they could (53%), and a minority say they are popular. As for activities outside of school, 56% practice sports and the vast majority say they do not work outside the home or do housework (78.8%).

Regarding the caregivers, 86.4% of them are female, 18.2% identified as white, and 37.3% have completed high school. The variable *presence of a guardian* was subjected to a factor analysis based on four questionnaire items. A minority of respondents reported assisting with homework (15.8%) or instructing the student to do it (24.2%), not even reaching a quarter of the total. On the other hand, only 5% resort to physical punishment when the child makes a mistake. As for the perception of safety, it is positive, with 68.4% stating that they live in a peaceful, violence-free neighborhood.

Finally, most teachers are women, accounting for 68.4% of the total. Additionally, 9.3% of teachers are aged over 55, while 14.9% of them fall under the category of *teachers working in four or more schools*, indicating that they teach in multiple educational institutions. Regarding school indicators, approximately half of schools face a shortage of teachers, the size of the classroom refers to the classrooms with more than 30 students and less than 40, not even half of the schools have sufficient supplies of satisfactory quality, except for the library, which 67.8% have, and the high dropout variable are students from schools with a percentage greater than 26% and less than 50%.

TABLE 1
**Descriptive statistics of variables**

| | Average | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| | | Dependent variables ~ | | |
| Grade 1 | 42.66 | 16.68 | 0 | 100 |
| Pre school | 0.736 | 0.441 | 0 | 1 |
| | | Individual characteristics | | |
| Grade 1 | 42.66 | 16.68 | 0 | 100 |
| Male | 0.481 | 0.499 | 0 | 1 |
| White | 0.186 | 0.389 | 0 | 1 |
| Black | 0.122 | 0.327 | 0 | 1 |
| Age | 11.63 | 0.964 | 9.25 | 22.75 |
| Bullying1 | 0.375 | 0.484 | 0 | 1 |
| Disability | 0.034 | 0.181 | 0 | 1 |
| Obesity | 0.169 | 0.129 | 0 | 1 |
| Practices sports | 0.564 | 0.496 | 0 | 1 |
| Housework | 0.212 | 0.145 | 0 | 1 |
| Works awau | 1.080 | 0.368 | 1 | 4 |
| Hates school | 0.002 | 0.034 | 0 | 1 |
| Hates teacher | 0.005 | 0.074 | 0 | 1 |
| Gun | 0.114 | 0.106 | 0 | 1 |
| Lies | 0.573 | 0.495 | 0 | 1 |
| Would change school | 0.300 | 0.458 | 0 | 1 |
| Would change family | 0.538 | 0.226 | 0 | 1 |
| Popular | 0.222 | 0.416 | 0 | 1 |
| Reproved | 0.194 | 0.396 | 0 | 1 |
| Studies before the test | 0.341 | 0.472 | 0 | 1 |
| Reading | 0.867 | 0.339 | 0 | 1 |
| Does homework | 0.715 | 0.451 | 0 | 1 |
| Study frequency | 2.593 | 1.523 | 1 | 6 |
| | | Family background | | |
| Female | 0.864 | 0.343 | 0 | 1 |
| Race | 0.182 | 0.386 | 0 | 1 |
| Complete high school | 0.373 | 0.189 | 0 | 1 |
| Presence of guardian | -0.124 | 0.986 | -1.031 | 4.911 |
| Depression | 0.006 | 0.766 | 0 | 1 |
| Psychiatric illness | 0.003 | 0.056 | 0 | 1 |
| Beats | 0.050 | 0.219 | 0 | 1 |
| Meeting | 1.443 | 0.619 | 1 | 3 |
| Charges homework | 0.242 | 0.428 | 0 | 1 |
| Helps homework | 0.158 | 0.364 | 0 | 1 |
| Talks friends | 1.797 | 0.739 | 1 | 3 |
| Talks about school | 0.946 | 0.226 | 0 | 1 |
| Without violence | 0.684 | 0.465 | 0 | 1 |

(Continues)

(Continued)

| | Average | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| | | Teachers' indicators | | |
| Female teacher | 0.684 | 0.465 | 0 | 1 |
| Teacher over 55 years old | 0.093 | 0.290 | 0 | 1 |
| Teacher in 4 or more schools | 0.149 | 0.121 | 0 | 1 |
| Teacher's experience | 0.107 | 0.309 | 0 | 1 |
| Teacher praise | 0.989 | 0.105 | 0 | 1 |
| Teacher doesn't help | 0.051 | 0.220 | 0 | 1 |
| | | School indicators | | |
| No lack of teacher | 0.471 | 0.499 | 0 | 1 |
| Size of the classroom | 0.488 | 0.499 | 0 | 1 |
| Sports Court | 0.409 | 0.492 | 0 | 1 |
| Internet | 0.427 | 0.495 | 0 | 1 |
| Laboratory | 0.389 | 0.487 | 0 | 1 |
| Library | 0.678 | 0.467 | 0 | 1 |
| Computer | 0.256 | 0.436 | 0 | 1 |
| High dropout | 0.018 | 0.135 | 0 | 1 |
| Safe School | 0.928 | 0.258 | 0 | 1 |
| Female proportion | 0.488 | 0.110 | 0.083 | 0.882 |

Source: Fundaj (2013).
Authors' elaboration.

## 4 EMPIRICAL STRATEGY

The ideal context to identify the effect of preschool on students' school performance would be comparing the performance of the same student in two situations, attending preschool (treatment) and not attending (control). However, it is not possible for the same individual to be observed for both situations simultaneously, and it is necessary to resort to econometric tools to perform this analysis.

Therefore, it is necessary to make the two distinct groups of students, sufficiently similar and comparable. For this, we will use the PSM methodology, proposed by Rosenbaum and Rubin (1983), which is widely used to verify the causal relationship between objects, and not just the correlation between data. Such a method allows the elimination (or reduction) of selection bias based on the student's observable variables.

### 4.1 The PSM method

Consider that the treatment of an individual is characterized by the variable $T$, assuming the value 1 if the individual has attended kindergarten and 0 otherwise. And, let $Yi$ (1) be the potential outcomes of student $i$ (school performance), if he/she has attended preschool, and $Yi(0)$ be the potential outcome for those who do not receive this treatment. Also consider $X$ as the vector of the control variables, composed of the observed characteristics of the individuals.

The interest of the analysis is the estimation of the causal effect on the performance of having attended kindergarten. This value is obtained by calculating the mean effect of the treatment on the treated – average treatment effect on the treated (ATT) –, which consists of a mean difference between the treated and the control, defined as:

$$ATT(x) = E[Y_i(1)|T_i = 1, X_i = x] - E[Y_i(0)|T_i = 1, X_i = x] \tag{1}$$

The unobservable term E[Yi (0) Ti = 1, X = x] of equation (1) represents the average that the treated would have had if they had not received the treatment, given their individual characteristics *Xi*. To estimate an adequate substitute for the unobservable term, the PSM is based on the Conditional Independence Assumption (CIA), which admits that the vector of observable variables *Xi* must contain all information about the potential outcome in the absence of the $Y(0)$ treatment that the individual has when making the decision to participate or not in the treatment. Thus, when controlling for the vector *Xi* (vector observable variables), the variables $Y(0)$ and $Y(1)$ become independent of the binary treatment variable *Ti*:

$$Y_i(1), Y_i(0) \perp T_i | X_i \tag{2}$$

This implies that, conditioned to the individual characteristics, *Xi*, the potential results do not depend on the participation of having attended pre-primary. In such a way that the outcome of an individual in the control group is a good predictor of the potential outcome of an individual in the treated group, in the absence of treatment, when having the same vector of observable variables. Under this hypothesis, we can rewrite the second term of equation (1), so that the ATT is only a function of observable variables, making its calculation possible. So, we have:

$$ATT(x) = E[Y_i(1)|T_i = 1, X_i = x] - E[Y_i(0)|T_i = 0, X = x] \tag{3}$$

A second hypothesis is needed for the model, the hypothesis of overlap or common support. With it, there is a guarantee that every individual in the treatment group has a close pair of comparison in the control group, and in which the outcome variable would correspond to the situation of this individual in the absence of treatment and vice versa. The hypothesis can be defined as:

$$0 < Pr[T_i = 1|X_i] < 1 \tag{4}$$

To apply the PSM, the propensity score must be estimated, since the probability of an individual receiving the treatment, given their observable characteristics Xi, is not known, for which the logit[13] parametric model is used. Following the approach of Rosenbaum and Rubin (1983), the propensity score is defined as:

$$P(X) = Probability\ [T = 1|X] \tag{5}$$

13. It is assumed that the probability of participating or not follows the following model: $Pr\ [T_i = 1 \mid x_i = x] \frac{exp(x\beta)}{1+exp(x\beta)}$.

And finally, taking the assumptions of common support, conditional independence and propensity scores, the average treatment effect on treaties (ATT) can be obtained by:

$$ATT(x) = E[Y_i(1)|T_i = 1, P(X)] - E[Y_i(0)|T_i = 0, P(X)] \quad (6)$$

With the propensity scores obtained, it is necessary to define the proximity of these scores of individuals who attended Early Childhood Education in relation to those who did not, that is, the child in the treatment group must have a pair in the control group found. To perform the matching, there are several comparison algorithms, among which we will use: i) nearest neighbor without replacement, in which each individual in the treated group has a corresponding partner in the control group, considering the closest in terms of score of propensity; ii) two nearest neighbors with replacement, for each element of the treated group, 2 individuals of the control group are selected, with the closest possible propensity score, each observation of the control group can be used more than once for comparison; iii) radius, there is a tolerance level imposed on the maximum distance between the propensity scores, in this case a 0.1% caliper; and iv) kernel, in which each treaty observation is combined with several observations from the group control, through the non-parametric correspondence estimator that uses the weighted averages between the weights, which in turn is given by the distance of these two groups.

It is important to emphasize that there are limitations regarding the model adopted, this because, according to the conditional independence hypothesis, all variables that affect the treatment and/or the results would have to be controlled in the model (Rosenbaum and Rubin, 1983), which is quite debatable. Furthermore, individual unobservable characteristics (confounders) can influence the treatment the individual receives, which could alter the effect of having attended day care. To this end, robustness analyzes are applied in the work and discussed later.

### 4.2 QTE on the treated

Most public policy evaluation studies analyze the impact of the program on average, around 95%, but the quantiles are no less important (Firpo, 2007). Quantile models can capture these characteristics of the distribution, as they estimate effects along its various quantiles. The quantile treatment effect on the treated (QTT) present more robust results to possible outliers by working with median.

$T$ is defined as a real number between [0,1], the quantile treatment effect, $\Delta\tau$, is the horizontal distance between the cumulative distribution functions of the response variable referring to the treatment and control groups, for a given quantile (Firpo, 2007):

$$\Delta\tau = q_{1\tau,} - q_{0,\tau} \quad (7)$$

In which

$$q_{j,\tau} \equiv inf_q Pr[Y(j) \leq q] \geq \tau \tag{8}$$

There are identification conditions posed by Firpo (2007), which are the two hypotheses already presented in the PSM methodology and the one that at least some quantiles are well defined and unique. The method is composed of two steps, first, as in the PSM, the propensity scores are estimated, then the scores must be used to construct weights that incorporated a modified version of the quantile regression estimator proposed by Koenker and Bassett Jr. (1978).

The estimator for the QTT parameter is $\hat{\Delta}_\tau \equiv \hat{q}_{1,\tau} - \hat{q}_{0,\tau}$ for $j = 0{,}1$ and it is necessary to obtain the estimators for the quantiles of the distribution of treated and untreated, which can be found by minimizing a sum of the check functions, where $\rho\ (\cdot)$ is a check function.

$$\hat{q}_{j,\tau} \equiv \arg\min_q \sum_{i=1}^{N} \widehat{\omega}_{j,\tau} \cdot \rho_T(Y_i - q) \tag{9}$$

This estimator differs from the estimator by Koenker and Bassett Jr. (1978) in that there is a weighting in the functions for the treated and control groups, in which the weights of each unit are given by:

$$\widehat{\omega}_{1,i} = \frac{T_i}{N \cdot \hat{p}(X_i)} \text{ and } \widehat{\omega}_{1,i} = \frac{T_i}{N \cdot \hat{p}(X_i)} \tag{10}$$

The weights are assigned in such a way that, in order to obtain the quantiles of the treated, only data from the treated are used, with a weight inversely proportional to the propensity to treat and similarly for the untreated. Therefore, children with a high propensity to attend pre-primary have a lower weight in the estimation of the quantiles of the treaty distribution.

In summary, QTT is an exogenous and non-conditional positive estimator that calculates the differential between treated and untreated for each quantile of the distribution. Such an estimator is obtained through a first step, in which the propensity score is estimated by a logit regression and, in a second step, where the differential between treated and untreated is calculated for each well-defined quantile for a single value of $T$.

### 4.3 Robustness and sensitivity analysis

PSM manages to resolve the source of bias arising from observable characteristics, which still depends on the quality of the control variables used in the model and on the quality of the matching. However, the CIA is a very difficult requirement to be empirically guaranteed, as there may be omitted unobserved factors that simultaneously affect the decision to place the child in preschool and the outcome variable. In this case, a bias is generated in the estimation of the program's impact. However, there are ways to verify the robustness of the results and analyze the potential influence of omitting variables on the estimated ATT. We used the sensitivity analysis suggested by Oster (2019).

The test developed by Oster (2019) considers that there is a set $U$ of unobservable variables not included in the model. Consider the following regression model: $Y = \beta\ T + \gamma X + U + \varepsilon$; one of the central hypotheses is the proportional selection assumption:

$$\delta \frac{\sigma_{XT}}{\sigma_X} = \frac{\sigma_{UT}}{\sigma_U} \tag{11}$$

In which $\sigma_{XT} = Cov\ (X, T)$; $\sigma_{UT} = Cov\ (U, T)$; $\sigma_X = Var(X)$; $\sigma_U = Var(U)$ and δ is the proportionality coefficient that indicates how much the observable variables affect the treatment. Also consider three regressions: the complete regression model that includes all independent variables, treatment ($T$), observed ($X$) and unobserved ($U$). The parameters $\beta$ and $R_{max}$[14] represent, respectively, the estimated coefficient of the treatment and the $R^2$ of the hypothetical regression; the intermediate equation that includes all observable variables ($X$ and $T$) and has the regression coefficient $\tilde{\beta}$ and $R^2$ as $\tilde{R}$; finally, a model that only has treatment (attending day care) as an independent variable, with $\dot{\beta}$ and $\dot{R}$ representing their statistics.

Under these constraints and when δ is close to 1, the selection bias is given by:

$$\beta^* = \tilde{\beta} - \frac{\delta(\beta - \tilde{\beta})(R_{max} - \tilde{R})}{\tilde{R} - \dot{R}} \tag{12}$$

In which $\beta *_\rho \rightarrow \beta > \rho$. Thus, it is possible to estimate an approximate value for $\delta$:

$$\delta = \frac{(\tilde{\beta} - \beta^*)(\tilde{R} - \dot{R})}{(\dot{\beta} - \tilde{\beta})(R_{max} - \tilde{R})} \tag{13}$$

With the value of δ we seek to know how big the bias should be for the treatment effect β to be considered 0. If δ =1 we have that the unobservables are at least as important as the observables, but what is sought is a value greater than unity, since δ =3, for example, indicates that unobservable variables would need to be 3 times more important than observable ones to produce an effect on the treatment (Oster, 2019).

Another test is the placebo test, in which a new dependent variable is arbitrarily chosen to test the impact of preschool, keeping all other variables used in the estimation of the prospensity score matching. The expected is not to find statistical significance in the analyses, and thus, the CIA hypothesis is assured.

In addition to these tests, it was verified whether the estimated treatment effect is sensitive to two different reweighting methods based on the propensity score.

14. $R_{max}$ is a theoretical population value.

The inverse probability weighting (IPW) and the inverse probability weighting regression adjustment (IPWRA), the combination of weighting with regression seeks to circumvent the problem of poor specification.

As for the QTT, as it is a recent methodology, there are no formal statistical tests to verify its robustness. What is done, for now, is to verify if the estimated coefficients of each quantile have statistical significance.

## 5 RESULTS

Table 2 presents the results of the average effect of having attended preschool on school performance in mathematics for students in the 6th year of elementary school, considering the different methods and specifications. Column (1) only includes variables with individual characteristics, model (2) also includes family background variables, and the specification in column (3) being the most complete, adding the characteristics of the teacher and the school.

In model (1), with a smaller set of control variables, there was no statistical significance when using nearest neighbor matching without replacement *NN* (1), however, for the other methods presented there was significance at the level of 1%. The grade of the math test applied at the end of the school year (grade 2) was used in a logarithmic way in the application of the PSM, so the interpretation of the coefficients must be done as a percentage. Having attended preschool is associated with a 10.80% improvement (by the IPW method and paired by radius) in performance.

TABLE 2
**Mean effect of treatment on student performance – PSM**

| Method | 1 | 2 | 3 |
|---|---|---|---|
| Kernel | 0.106*** | 0.117*** | 0.141*** |
| | (0.023) | (0.024) | (0.025) |
| NN (1) nr | 0.031 | 0.044 | 0.07** |
| | (0.027) | (0.027) | (0.027) |
| NN (2) | 0.123*** | 0.121*** | 0.132*** |
| | (0.028) | (0.027) | (0.030) |
| Radius | 0.108*** | 0.112*** | 0.136*** |
| | (0.023) | (0.025) | (0.26) |
| IPW | 0.108*** | 0.118*** | 0.148*** |
| | (0.020) | (0.021) | (0.026) |
| IPWRA | 0.101*** | 0.112*** | 0.137*** |
| | (0.020) | (0.020) | (0.022) |
| Individual characteristics | Yes | Yes | Yes |

(Continues)

(Continued)

| Method | 1 | 2 | 3 |
|---|---|---|---|
| Family background | | Yes | Yes |
| Teacher characteristics | | | Yes |
| Schook characteristics | | | Yes |
| Comments | 2.509 | 2.487 | 2.421 |

Source: Fundaj (2013).
Authors' elaboration.
Obs.: 1. NN (1) nr – nearest neighbor method without replacement; NN (2) – method with two nearest neighbors with replacement; Radius – 0.1% caliper using common support; IPW– weighted by the inverse of the PSM; IPWRA – adjusted regression, weighted by the inverse of probability.
2. Robust standard error in parentheses.
3. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

By including a larger set of control variables (model 3), so that the students compared have a greater number of similar characteristics, all the estimated ATTs were significant. And students who attended preschool had an average performance superior by 13% to 14% when compared to those who did not, the lowest average effect recorded, 7%, was for the nearest neighbor method without replacement.

It is also observed, in table 2, that the intensity of the effect increases as we insert controls in the model, when inserting the family background control, model 2, there is a small increase in the coefficient, and with the insertion of the characteristics of the school and teacher, model 3, there is a new increase in the coefficient. This suggests that attending preschool is effectively influencing the student's grade, and no other factors such as, for example, the teacher's effort or the quality of the school. By the doubly robust method, IPWRA, the average treatment effect went from 10.63% in model 1 to 14.68% in model 3.

Another relevant analysis is the heterogeneous responses to the models. Table 3 shows the differences in performance regarding the student's gender, black or white color and the fact that those responsible have schooling up to the 5$^{th}$ year of elementary school or complete high school. The effect of having attended preschool is higher for boys than for girls and is statistically significant in both genders.

Higher effects were also found for students self-declared black, 21%, compared to 10% for self-declared white, and for those responsible for having completed the 5$^{th}$ year of elementary school, 20%, compared to 15% for those who have completed high school. This is an indication that the benefits generated can be even more intense, given the characteristics of the students or their guardians.

TABLE 3
**Heterogeneous response to the effect of attending preschool**

| | Coefficient | Standard deviation |
|---|---|---|
| Male | 0.223*** | (0.047) |
| Female | 0.088*** | (0.031) |
| White | 0.100* | (0.077) |
| Black | 0.213** | (0.102) |
| 5th year of Elementary School | 0.204*** | (0.069) |
| High School | 0.145*** | (0.039) |
| The whole sample | 0.141*** | (0.025) |

Source: Fundaj (2013).
Authors' elaboration.
Obs.: 1. Generated based on full model and kernel pairing.
2. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

To make sure that the observed variables sufficiently explain the model ensuring the consistency of their estimators, Oster's (2019) approach for omitted variable bias was performed and is reported in table 4. The proportionality coefficient (δ) represents the value that would be necessary for the estimation of the treatment effect to be null (β =0). Five Rmax values are considered, since R2 is not known for the model with all variables (observed and unobserved).

Oster (2019) defines (δ = 1) as the cut-off point in the test, in which the observable variables are at least as important as the unobservable ones. The test value must be equal to or greater than 1 so that there is no impact of unobservable effects on the treatment. By considering only the characteristics of the students (model 1), there is a positive result only for Rmax 0.6 and 0.7, while model 2 also has a good result for Rmax 0.6, with δ =1.14. For the lower limit the value is 5 percentage points – p.p. (Rmax 0.6) and goes to 1 p.p. (Rmax 0.6).

TABLE 4
**Oster test for treatment effect**

| R max | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|
| | | | Model 1 | | |
| δto β= 0 | 1.31 | 1.05 | 0.88 | 0.76 | 0.66 |
| Set Id. (δ=1) | [0.02; 0.10] | [0.01; 0.10] | [-0.01; 0.10] | [ -0.03; 0.10] | [-0.05; 0.10] |
| | | | Model 2 | | |
| δto β= 0 | 1.71 | 1.37 | 1.14 | 0.97 | 0.85 |
| Set Id. (δ=1) | [0.05; 0.10] | [0.03; 0.10] | [0.01; 0.10] | [-0.02; 0.10] | [-0.02; 0.10] |
| | | | Model 3 | | |
| δto β= 0 | 2.12 | 1.68 | 1.39 | 1.19 | 1.04 |
| Set. Id. (δ=1) | [0.07; 0.11] | [0.05; 0.11] | [0.04; 0.11] | [0.02; 0.11] | [0.01; 0.11] |

Source: Fundaj (2013).
Authors' elaboration.
Obs.: Estimates using the PSM method with kernel pairing. Model 1 only considers student control. Model 2 also includes the family background. Model 3 considers all controls.

It is observed that the test criterion is only fulfilled, for all Rmax, in model 3, in which all controls are included. This demonstrates that the complete model is the most suitable for the analyses, because it does not incur omitted variable bias. More specifically, when considering an Rmax of 0.6, the proportionality coefficient was 2.12. This implies that unobservable factors would need to be 2.12 times more potent than the observable factors to fully account for the positive effect of preschool attendance on school performance. When increasing Rmax to 1, value quite unlikely, the coefficient δ is still 1.04.

One of the essential prerequisites for the PSM to be effective is that the set of observable variables includes all the information concerning the potential outcome in the absence of treatment, following the Counterfactual Independence Assumption (CIA). To assess the statistical significance of this assumption, a placebo test was conducted, substituting the math test score with four distinct dependent variables that are assumed to be unrelated to the treatment for model estimation. The outcomes of this test are outlined in table 5.

TABLE 5
**Estimates of placebo outcomes by PSM**

| | Bullying | University education | Female teacher | No lack of teacher |
|---|---|---|---|---|
| Pre school | 0.0011<br>(0.024) | 0.006<br>(0.008) | 0.0001<br>(0.024) | -0.009<br>(0.024) |
| Comments | 2.412 | 2.412 | 2.412 | 2.412 |
| R square | 0.050 | 0.050 | 0.050 | 0.050 |

Source: Fundaj (2013).
Authors' elaboration.
Obs.: 1. Generated based on full model and kernel pairing.
2. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

It is expected that the estimated preschool coefficients are not different from zero, that is, there is no significance in the model when using the placebo variables. For none of the models tested there was statistical significance: whether to be bullied, the person responsible has completed higher education, the teacher is a woman or there are no problems with a lack of teachers in the school. This suggests that there are no omitted variables related to treatment.

TABLE 6
**Pairing quality test**

| Sample | Pseudo $R^2$ | LR chi2 | P > chi2 | Average Bias | Median Bias |
|---|---|---|---|---|---|
| Unpaired | 0.050 | 139.75 | 0 | 6.5 | 5.5 |
| | | 1 nearest neighbor (no replacement) | | | |
| Paired | 0.07 | 124.19 | 0 | 5.4 | 4 |

(Continues)

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| Sample | Pseudo $R^2$ | LR chi2 | P > chi2 | Average Bias | Median Bias |
|---|---|---|---|---|---|
| | | | 2 nearest neighbor | | |
| Paired | 0.012 | 59.82 | 0.409 | 2.6 | 2.3 |
| | | | Kernel | | |
| Paired | 0.005 | 23.85 | 1,000 | 1.6 | 1.4 |
| | | | Radius | | |
| Paired | 0.005 | 25.11 | 1,000 | 1.8 | 1.4 |

Source: Fundaj (2013).
Authors' elaboration.

Still with the purpose of checking the robustness of the model, table 6 reports the pairing quality tests, in which a comparison of the characteristics of treated and untreated individuals is made before and after matching to make sure there are no differences between the groups. There is a drop in the pseudo R2 for all adopted algorithms, as well as the likelihood ratio (LR) test points to joint non-significance of the matched sample regressors, except when using the nearest neighbor without replacement. Furthermore, there is a reduction in the mean and median bias, given by the difference between the treated and control groups, indicating that a good fit has been made.

Finally, an investigation was carried out on the quantiles to observe the stratified effect. Table 7 presents the results of students who attended kindergarten. The estimates point to a positive and statistically significant effect in most of the quantiles. Nevertheless, this effect decreases as we approach the higher quantiles of the distribution.

TABLE 7
**QTE on school performance**

| Quantiles | QTE | Standard error |
|---|---|---|
| 0.1 | -7.65E-16 | 1.000 |
| 0.2 | 0.214*** | 0.000 |
| 0.3 | 0.176*** | 0.000 |
| 0.4 | 0.15*** | 0.000 |
| 0.5 | 0.13*** | 0.000 |
| 0.6 | 0 | 1.000 |
| 0.7 | 0.115*** | 0.000 |
| 0.8 | 0.103*** | 0.000 |
| 0.9 | 0.086*** | 0.000 |

Source: Fundaj (2013).
Authors' elaboration.
Obs.: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Students who benefit most from preschool are those who perform below the median, excluding the first quantile that was not significant. The average treatment effect measured in table 2 is a 14.10 p.p improvement (by kernel pairing), while the average performance of students below the median is 19.76 p.p. When the student is at the bottom of the tail (with lower grades), she or he scores 21.40% higher on the math test compared to a student who did not attend preschool. But when the student is in the highest quantile (with the highest scores) the preschool effect is reduced to 8.60%.

## 6 FINAL CONSIDERATIONS

Evidence in the literature indicates that attending school from the early years implies an improvement in the child's development, whether in their cognitive or socio-emotional skills and for different time horizons. However, the studies carried out in Brazil, in general, do not investigate whether this is a causal relationship, since the available data generally do not allow for this analysis.

Using longitudinal data from an educational assessment conducted by Fundaj together with the PSM technique and the QTE, we investigated the effect of attending preschool on a child's future school performance when he/she is in the $6^{th}$ grade of elementary school. We found positive results for those who attended preschool with the effect ranging from 10% to 15%. Estimates were sensitive to different matching algorithms, as well as to two reweighting methods, the IPW and the IPWRA. Robustness for omitted variable bias was assessed by the Oster test (2019) and the validation of the CIA through the placebo test. The results were significant, passing the bothe Oster and placebo tests.

Assessments for heterogeneous populations were also conducted. Findings revealed that the effect of early childhood education was even greater for male students, who declared themselves to be black or who had parents or guardians with less education. Furthermore, the effect was stronger for students whose performance was in the lower tail of the grade distribution. According to Cunha et al. (2006), when the child lives in a vulnerable family environment, without housing conditions, poor nutrition and health, the benefit of attending preschool is more evident. This is because, it is in the school environment that children can have access to good nutrition and stimulation to develop their skills that they would ideally have at home.

The sample used in this work consists of 35% of students living in slums, 95% of them live in families with an average per capita income of less than one minimum wage (as of 2013, year of research) and 63% of them receive some form of government assistance. This may be an indication that the positive effect found is due to children living in an unfavorable environment, and it is not possible to distinguish the effect between children with a favorable environment from those who do not. In that regard, further research should be done so that the family environment can be better evaluated.

The investigation in this current study underscores the necessity of considering policies designed to expand access to preschool, particularly given that, within the utilized sample, 26% of children did not have this opportunity. Creating a safe learning environment is a responsibility of the state, and investing in early childhood education can be a means of breaking the cycle of poverty, enabling intergenerational income mobility. It is important to note that this study focused on the analysis of the impact of early childhood education on the field of mathematics. However, it is crucial to understand this effect in relation to other areas of knowledge. Was this response better or worse? Better Worse Same

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Data da submissão em: 1º fev. 2023.

Primeira decisão editorial em: 10 out. 2023.

Última versão recebida em: 17 out. 2023.

Aprovação final em: 20 nov. 2023.