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Escolas em Foco: The Impact Assessment of the 'Evidence-Based Public Policy' Program of Rio de Janeiro's Municipal School System[1]

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Abstract: The paper assesses the impact of a data use program on student's educational achievement in language and math in public schools in Rio de Janeiro, Brazil. The idea behind this kind of program is based on the perspective that interventions aimed to encourage the use of educational data for planning and pedagogical activities would bring changes in the attitudes, knowledge, and practices of school agents and, therefore, would contribute to engage student's achievement and reduce inequalities. The impact of the program was examined using differences-in-differences statistical models (DiD). The first strategy of analysis did not include any pre-processing mechanism. In the second strategy, to reduce bias selection and increase the power of

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causal inference, the matching method was adjusted before DiD model. Although descriptive statistics suggest a constant increase in students' academic performance and schools approval rates of both groups over four years of analysis, the results using both strategies are substantively weak and not statistically significant.
Keywords: educational policy; elementary education; student's performance; data use

***Escolas em Foco*: La evaluación de impacto del programa 'políticas basadas en evidencia' del sistema escolar municipal de Río de Janeiro**

Resumen: El artículo investiga el impacto de un programa de fomento del uso de datos por parte de actores escolares sobre el desempeño de los alumnos de la red pública municipal de Río de Janeiro, Brasil. La premisa asociada a este tipo de programas parte de la perspectiva de que las intervenciones para incentivar el uso de datos educativos para la planificación generarían cambios en las actitudes, conocimientos y prácticas de los actores escolares y, por tanto, contribuirían a elevar el rendimiento de los estudiantes y reducir desigualdades El impacto del programa se verificó utilizando el modelo Diferencias en Diferencias (DiD). La primera estrategia de análisis no contó con ningún mecanismo de preprocesamiento de datos y la segunda, con el fin de reducir el sesgo de selección y aumentar la capacidad de inferencia causal, se utilizó la técnica de emparejamiento antes que el modelo DiD. A pesar de que las estadísticas descriptivas indican un crecimiento constante en el rendimiento académico de los estudiantes tanto en matemáticas como en portugués y en el flujo escolar de ambos grupos durante los cuatro años de análisis, los resultados encontrados en ambos análisis son sustancialmente débiles y no estadísticamente significativos.
Palabras clave: política educativa; enseñanza fundamental; desempeño de los estudiantes; uso de datos

***Escolas em Foco*: The impact assessment of the 'evidence-based public policies' program of the municipal school system in Rio de Janeiro**

Resumo: O artigo investiga o impacto de um programa de incentivo ao uso de dados por atores escolares no desempenho dos estudantes da rede pública municipal do Rio de Janeiro, Brasil. A premissa associada a esse tipo de programa está baseada na perspectiva de que intervenções de incentivo ao uso de dados educacionais para planejamento trariam mudanças nas atitudes, conhecimento e práticas dos atores escolares e, portanto, contribuiriam para elevar o desempenho dos estudantes e reduzir desigualdades. O impacto do programa foi verificado a partir do modelo de diferenças em diferenças (DiD). A primeira estratégia de análise não contou com qualquer mecanismo de pré-processamento dos dados e a segunda, com objetivo de reduzir o viés de seleção e aumentar a capacidade de inferência causal, foi empregada a técnica de pareamento antes do modelo de DiD. Apesar das estatísticas descritivas indicarem crescimento constante no desempenho acadêmico dos alunos tanto em matemática como em língua portuguesa e no fluxo escolar de ambos os grupos ao longo dos quatro anos de análise, os resultados encontrados nas duas análises são tênues substantivamente e pouco significantes estatisticamente.
Palavras-chave: política educacional; ensino fundamental; desempenho dos estudantes; uso de dados

***Escolas em Foco*: The Impact Assessment of the 'Evidence-Based Public Policy' Program of Rio de Janeiro's Municipal School System**

The purpose of this article is to investigate the impact of the *Escolas em Foco* (Schools in Focus) program[2] - a program to encourage the use of educational data by school actors - in the performance and grade retention of students in Rio de Janeiro's municipal public system. In this sense, it seeks to bring an original and relevant contribution to the literature on the different uses of large-scale assessment systems and, particularly, the impact of programs to encourage data use on students' academic performance.

In the last decades, we have observed the proliferation of educational reforms in several countries that, in the same direction of the standard-based reforms (SBR) carried out in the USA, included the expansion of the availability of data from large-scale assessments and educational indicators and the introduction of goals, educational standards, and accountability pressures (Brooke, 2013). The reforms brought incentives and pressures for using data, by actors at different levels of the educational hierarchy, for planning and decision-making, as strategies to improve student performance (Kerr et al., 2006). In general, educational data involves all levels in the educational hierarchy, from the education departments to intermediate levels of management and schools (Custer et al., 2018).

Nonetheless, studies indicate that educational data are still underused, especially by school actors. The context of data expansion and school accountability policy pressures is not enough to guarantee effective use of educational data to inform pedagogical practices and promote learning improvement (Marsh et al., 2015; Schildkamp et al., 2013). According to the bibliography that focuses on data-driven decision making or DDDM, such use depends on the format in which the data are made available (Gorard et al., 2020) and a large number of skills such as: a) problem formulation skills, b) ability to collect, analyze, synthesize and interpret data and c) ability to make decisions or find appropriate solutions (Mandinach & Gummer, 2016; Marsh et al., 2016, Schildkamp et al., 2013).

Programs to encourage data use or data literacy aim to develop the skills mentioned above and, consequently, encourage the effective use of data and educational indicators for planning and decision-making in the daily life of schools by principals and teachers. The premise behind these programs is based on the perspective that school agents' everyday use of educational data can lead to increased student performance. Based on the diagnosis of student learning, teachers and principals can make adjustments and adopt more effective school practices, helping students' progress and cognitive development (Marsh, 2012; Schildkamp & Pootman, 2015). The programs can have different formats, such as professional development courses and either with the direct intervention of a specialist outside the school (coaching) or encouraging collaborative professional learning communities. The focus of interventions would be to promote the skills and knowledge necessary for the effective use of data and change attitudes towards educational data and indicators (Núñez et al., 2019b).

In Brazil, the consolidation of a monitoring system for basic education over the last two decades provided the evolution of the tools and methodologies used to assess and diagnose the quality of education. States and municipalities also implemented assessment systems with different designs, focusing on different educational stages, grades, and disciplines (Ceneviva, 2011; Koslinski et al., 2015). This context allowed the elaboration of different quality indicators and, consequently, the implementation of a series of educational policies that consider the results and indicators deriving from large-scale assessment systems. However, the focus of such policies has been the implementation of school accountability policies and, less frequently, policies focused on promoting data use or encouraging data literacy and data use by school actors (Brooke & Cunha, 2011; Sousa & Koslinski, 2017).

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From 2009 to 2016, Rio de Janeiro's local educational system implemented a series of measures to assess more accurately the results of schools and improve quality indicators. At first, the municipality adopted a management model focused on planning, goals, and incentives or sanctions linked to the performance of schools in the municipal system, including wage bonuses for school actors (Andrade et al., 2018). In 2015, amid the pressure of school accountability, the Municipal Department of Education implemented the *Escolas em Foco* program, which aimed to encourage the use of data by schools and, consequently, increase the municipality's educational indicators. A portion of the schools that had the lowest performance in large-scale assessments or with high grade retention rates and high school dropout rates were the focus of the program (Núñez, 2019; Núñez et al., 2019). An external specialist accompanied the selected schools to assist in interpreting and elaborating diagnoses, and strategic action plans to raise the indicators (performance and grade retention/dropout). Only a specific set of schools selected based on agnostic and non-random criteria participated in the program. It was possible to define a control group (which did not receive the intervention) and another treatment group (which received the intervention). Thus, we have evaluated the program's impact on performance and grade retention rates between the two groups using a quasi-experimental research model called the Differences in Differences (DiD) method.

The rationale for studying the impact and effectiveness of the systematic use of data and programs to encourage the use of data on academic performance and/or grade retention rates is twofold. In Brazil, and according to the international literature, we observe the proliferation of studies that sought to estimate the impact of school accountability policies/wage bonuses of school actors on the performance of schools. However, there is still a scarcity of works that focus on the effects of programs to encourage data use or data literacy. Secondly, Brazil has consolidated large-scale educational assessment systems in the last twenty-five years but, we know little about the formative use of data produced by assessments in schools and public education systems. In this sense, the attempt to understand the possible causal mechanisms that link the use of data and the increase in student performance has theoretical and methodological justifications and political ones. It can generate evidence capable of assisting the decision-making of educational policy implementers and managers in what concerns the choice and allocation of resources in more effective programs.

In addition to this introduction, this work also brings a literature review on the use of educational data; a section that details the characteristics of the *Escolas em Foco* program; a methodological section that describes in detail the data and the empirical analysis strategies used to estimate the effect of the program on academic performance in mathematics, Portuguese and on the grade retention rates of schools; a section that discusses the results of the analyses; and, by way of conclusion, a section that makes some final considerations that try to establish hypotheses to explain the results found.

Data Use Incentive Programs

The concept that decisions should be made based on educational data (DDDM) is not recent in the educational field. However, it becomes stronger after the dissemination of the so-called standards-based reforms (SBR) in the North American context. These reforms gained prominence mainly after the implementation of the No Child Left Behind (NCLB) policy in 2002. Even without a consensual definition of SBRs, much of the debate about such reforms include the following characteristics: academic expectations about students, that is, what students should know and what they should be able to do; alignment of key elements of the education system to meet expectations; using student performance assessments to monitor learning; decentralization of responsibilities for decisions related to curriculum and training in schools; technical support and assistance to improve educational services; and accountability measures to reward or sanction schools or students based on performance measures (Hamilton et al., 2008).

Programs to encourage the use of data are closely related to school accountability policies, developed with the advance of large-scale monitoring and evaluation systems. In educational systems with accountability policies, educational data has become a key element in making diagnoses and increasing student performance (Kerr et al., 2006). The premise behind programs to encourage data use is that the use of educational data by school agents can leverage student learning by allowing a more detailed diagnosis of their learning, allowing teachers and principals to carry out pedagogical planning focused on adjusting their school practices and allocation of material and human resources (Schildkamp & Poortman, 2015).

However, the increasing availability of data and the pressures of accountability policies do not seem enough to promote the effective use of educational data and, consequently, increase academic performance. Systematic reviews and meta-analyses of studies on the effects of school accountability policies have not observed significant and/or lasting impacts on school performance, particularly in the North American and UK contexts (Hout & Elliot, 2011). Accountability pressures do not seem to be sufficient to promote changes in the attitudes, beliefs, knowledge and skills, and practices of teachers and/or principals. On the other hand, some studies have observed unexpected consequences of these policies, such as gaming the system, teaching/training for the test, or focusing on "bubble children" (with scores close to average; Diamond & Spillane, 2004; Heilig & Darling-Hammond, 2008). These unintended effects were present in the US, even in contexts characterized by high-consequence school accountability policies together with interventions to promote data literacy (Marsh, 2012).

Studies that defend the importance of data use indicate that the lack of knowledge about data and choice of adequate pedagogical practices lead to decision making that is usually based on intuition and limited to teachers' observations and experience (Ingram et al., 2004; Rosistolato et al., 2014). The DDDM literature discusses the conditions that would be most conducive to evidence-based decision-making and argues that the effective use of data requires diverse skills, knowledge, and predisposition of teachers, such as a) skills for formulating problems; b) ability to collect, analyze, synthesize and interpret data, c) ability to act and find an adequate solution (Mandinach & Gummer, 2015; Marsh et al., 2015; Schildkamp et al., 2013). The first set of skills includes identifying a problem and setting a goal. The second set includes skills to read and interpret tables and graphs and recognize data quality criteria and reach correct conclusions (Carlson, 2011; Schildkamp et al., 2013). Finally, the last set of skills requires pedagogical literacy: the ability to choose good practices and adequate resources to solve the identified problems after data analysis (Marsh et al., 2015; Schildkamp & Poortman, 2015; Schildkamp et al., 2013). Some examples of these practices include decision making related to curriculum change, reallocation of resources, targeting students who need assistance, determining learning needs, and pacing classes, among others (Marsh et al., 2015, Schildkamp et al., 2013).

Recent studies mainly carried out in the USA and the Netherlands have discussed the potential of programs and interventions that encourage the use of data by school communities for planning and decision-making. Incentives can range from more passive strategies, such as disseminating results in a more accessible way, to more active strategies, including professional development activities (Núñez et al., 2019). More active interventions generally rely on the mediation of a coach - with constant on-site visits by an external professional to schools to assist teachers and principals in the use of data for pedagogical planning - or on professional learning communities or data teams, with collaborative work among peers, with a focus on the exchange of practices, and the presence of a lead teacher or facilitator (Knight, 2006; Mandinach & Gummer, 2015; Marsh et al., 2015; Marsh et al., 2010; Schildkamp & Poortman, 2015).

Regarding the impact of such programs and interventions, some literature reviews identified that teachers lacked pedagogical literacy skills and had difficulty making instructional decisions (Marsh, 2012). In addition, Marsh (2012) points out that most research on the impact of data literacy interventions relies on data users self-reports. Few studies use observation and assessment of teachers' knowledge or student performance and robust research designs that allow causal inference.

Only recently, studies with more robust research designs (which include a pre-test, post-test, matching, and randomized controlled trials) have observed the impacts of interventions on data literacy and data use. Some studies have observed a positive impact of interventions on skills related to data literacy (ability to collect, analyze and interpret data), attitudes towards data, and/or the ability of teams to solve problems related to student performance (Ebbeler et al., 2017; Kippers et al., 2018; Poortman & Schildkamp, 2016). However, studies identified that teachers, the focus of interventions, still had difficulties defining a purpose/formulating a question. Other studies have looked at the impact of professional training and data use interventions on overall or on specific groups of students' performance (low-achieving, high/low socioeconomic status students; Poortamn & Schildkamp, 2016; Visscher, 2020; Waymar et al., 2017; Staman et al., 2017).

It is worth mentioning that most of the interventions involved long periods of professional development of teachers at the workplace. Still, impact studies recognize that there are restrictions on the ability of interventions to modify teachers' knowledge, skills, and attitudes and argue that these skills should also be a focus of initial teacher education (Schildkamp et al., 2017).

In Brazil, the consolidation of the national assessment system provided the expansion and improvement of the tools and methodologies used to assess and diagnose the quality of education. Numerous states and municipalities have also adopted their assessment systems to expand the information available about the education system. Many of these assessment systems have characteristics and designs different from the Prova Brasil, the national system, focusing on other school grades, subjects and frequency of application (Koslinski et al., 2015). If the uses to reward teachers and schools were widely disseminated, even without robust evidence of the impact on student performance and other school indicators, the same is not true for disseminating initiatives to encourage data use (Brooke & Cunha, 2011; Souza & Koslinski, 2017).

Some current diffuse actions in Brazil aim to help schools interpret their educational data/results. Those arise from both governmental and non-governmental actions. Such initiatives include more passive strategies for disseminating the results of external assessments in formats that facilitate reading and, consequently, interpretation and use by school actors, up to more active strategies that include workshops and teacher training in the use of data. As an example of more passive strategies, we cite the *Prova Brasil* pedagogical school reports and the platform '*Devolutivas Pedagógicas*'[3] (Pedagogical Feedback) of INEP[4] and tools that provide more detailed information to schools, such as the DESESQ[5]. More active strategies include the *Programa de Intervenção Pedagógica-PIP* (Pedagogical Intervention Program) and the *Gestão Integrada da Escola-GIDE*[6] (Integrated School Management) implemented by the State Education Departments of Minas Gerais and Rio de Janeiro, respectively. Both programs relied on visits by agents from the local department of education or pedagogical teams external to schools whose objective was to assist teachers or principals in understanding and using data from the information and assessment systems of the respective State Departments of Education (Bengio, 2015; Brooke & Cunha, 2011).

In the city of Rio de Janeiro, the agents of the *Coordenadorias Regionais de Educação-CRE*s (Regional Education Coordination), intermediary instances of the Department of Education

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[3] Source: http://devolutivas.inep.gov.br, accessed in Nov. 2016.

[4] The main objectives of the platform are to improve students' performance, show principals and teachers the skills assessed by the *SAEB*, enable teachers and the management team to understand the assessment results, and collaborate with teachers in their teaching activities.

[5] Source: http://sdm2.rio.rj.gov.br/je-desesc/login.seam, accessed in Nov. 2016.

[6] Source: http://www.rj.gov.br/web/seeduc/exibeconteudo?article-id=451562, accessed in Nov. 2016.

management, and the school principals showed a lack of knowledge of numerous technical aspects of educational assessments and indicators and a superficial appropriation of data. Consequently, the studies observed, in general, limited and instrumental use of the data, with the interest of artificially raising the quality indicators (Cerdeira, 2015; Cerdeira et al., 2017; Rosistolato et al., 2014).

The *Escolas em Foco* Program

Starting in 2009, the *Secretaria Municipal de Educação -SME* (Municipal Secretary of Education) implemented many educational policies to measure school results more accurately and improve educational indicators. The Department adopted a management model focused on planning and clear goals[7] and introduced several incentives for schools to achieve targets and greater efficiency. To this end, it adopted its student performance evaluation system (Prova Rio) and accountability devices for school agents. Following a similar model to the *Índice de Desenvolvimento da Educação Básica-IDEB* (Basic Education Development Index), an *SME* prepared the *Índice de Desenvolvimento da Educação do Município do Rio de Janeiro-IDE-Rio* (Education Development Index for the Municipality of Rio de Janeiro), which combined the results of the students in the local external assessment (Prova Rio) and the school flow. The Department established school performance goals using the IDE-Rio on even-numbered years since the goals for the odd-numbered years used the IDEB.

Another provision of the accountability policy was the *Prêmio Anual de Desempenho-PAD* (Annual Performance Award). This program rewarded all school employees who achieved performance targets with a wage bonus. These targets were established annually for schools according to measures based on rates of performance increase calculated from assessment results from previous periods. In this way, schools with lower performances had more audacious goals than schools with higher starting indicators (Koslinski et al., 2014).

The following year, the Department extended the school accountability system, including goal setting to central management (SME) and intermediate management instances such as Regional Education Coordinators. Another policy implemented at the SME was the Fenix Project (*Projeto Fênix*), aimed at schools with the lowest performance in the education network. The schools included in this program received priority in allocating resources, employees, and projects of the local education system (Lopes et al., 2015). Despite the large amount of information about the education network, there was still no specific program to encourage the use of this data. Therefore, in 2015, the municipality implemented the program 'Escolas em Foco'[8], aimed at around 400 schools that offered 3rd and 5th grades of elementary school with the lowest performances or high rates of school grade failure/dropout (Núñez, 2019).

The program design approached an intervention to promote data use with the mediation of a coach. The participating schools received frequent visits from agents selected and trained by the SME, the *Professores de Acompanhamento Escolar-PAE*s (School Monitoring Teachers). The agents helped principals and teachers elaborate their diagnoses and strategic action plans, leading to increased student learning and a reduction in school dropout and failure rates in their schools. The functions of *PAE*s included: accompanying schools with on-site visits; articulating, together with the school principal, the pedagogical follow-up/mediation actions of the classes; carrying

[7] Much of the educational programs and policies are closely linked to the period of management of Eduardo Paes as mayor of Rio de Janeiro (2009-2016) and Cláudia Costin as secretary of education (2009-2014). With the election of Marcelo Crivella (2017-2020), most educational policies and programs were gradually revoked.

[8] We did not have access to detailed information about the characteristics, objectives and the program design, methodology and protocol of action of the PAEs at the schools. We obtained the information included in this work from the official gazette *Diário Oficial* do Rio de Janeiro: Nº 205, Year XXVIII. Accessed in Nov. 2016.

out analysis and diagnosis of the school scenario to outline goals and strategies for improving performance, reducing school dropout and failure, in partnership with the Pedagogical Coordinator and the Principal; to collect and study data from the monitored schools and generate weekly information for the definition of protocols aiming at the development of teaching actions; ensure the organization and filing of documents and follow-up terms; promote, together with the teacher-supervisor, the necessary referrals to solve pedagogical demands; participate in continuing education actions, be proactive and have knowledge and mastery of regulations, assessments, indicators, school and central level goals, through the systems and tools available to support their action[9].

Data and Methods

This section brings the descriptive characteristics of the sample and the methodological strategy adopted to analyze the program's impact on mathematics, Portuguese language performance, and school approval rates performance. We have carried out the program impact analysis process in two parts. The first did not have any pre-processing of the data. Therefore, the analysis included all schools in Rio de Janeiro with third-year elementary school classes during the four years of analysis (2013 to 2016). The quasi-experimental model of differences in differences allows us to divide our sample into four distinct groups, the control group before and after the intervention and the treatment group before and after the intervention. The assumption is that the control group has not suffered any impact from the program. Therefore, significant changes in outcome variables (performance and school flow) would be associated with other characteristics, which may also influence the treatment group.

Although this model does not allow establishing a causal relationship, it makes it possible to examine the exogenous impact of the program on the treatment group. However, as it is a database with data grouped at the school level, it is not possible to explore the performance variation within the control and treatment groups.

However, the choice of schools was not random, and there was a selection criterion that defined the schools that would participate in the program from those that would not. Therefore, in the second part of the impact assessment, we adopted a preliminary data analysis strategy, with the propensity score matching pairing technique[10], with replacement of cases, to find for each school in our treatment group, another school in the municipal network with the same characteristics. After the matching process, we adjusted the differences-in-differences model again to compare the control and treatment groups.

Table 1
Number of Schools that Offered Third Grade of Elementary School over the Four Years of the Analysis

Year	2013	2014	2015	2016
Escolas Foco [Schools in focus]	384	376	374	373
Escolas Não Foco [Non-focus schools]	343	328	309	301

Source: Prepared by the authors.

[9] Published in *Diário Oficial* do Rio de Janeiro: Nº 205, Year XXVIII., Thursday, January 15, 2015 on p. 42 and No. 199, Year XXIX, Thursday, January 7, 2016, p. 91. Accessed in Nov. 2016. http://doweb.rio.rj.gov.br/visualizar_pdf.php?reload=ok&edi_id=00002652&page=42&search=paulofreire.

[10] We performed the analyzes using R software and the package 'Matching' for pairing the cases.

Table 1 shows the number of schools with third-grade elementary school classes over the four years analyzed. The numbers indicate a reduction in the number of schools with these classes over the years in both groups. It is relevant to point out that the municipal education network in Rio de Janeiro does not have a homogeneous characteristic of offering elementary education. Some schools offer classes from first-third grade, while others offer the entire first stage of elementary education. Therefore, reducing the number of schools, but not necessarily the number of classes, may suggest some ongoing restructuring in the municipal education system.

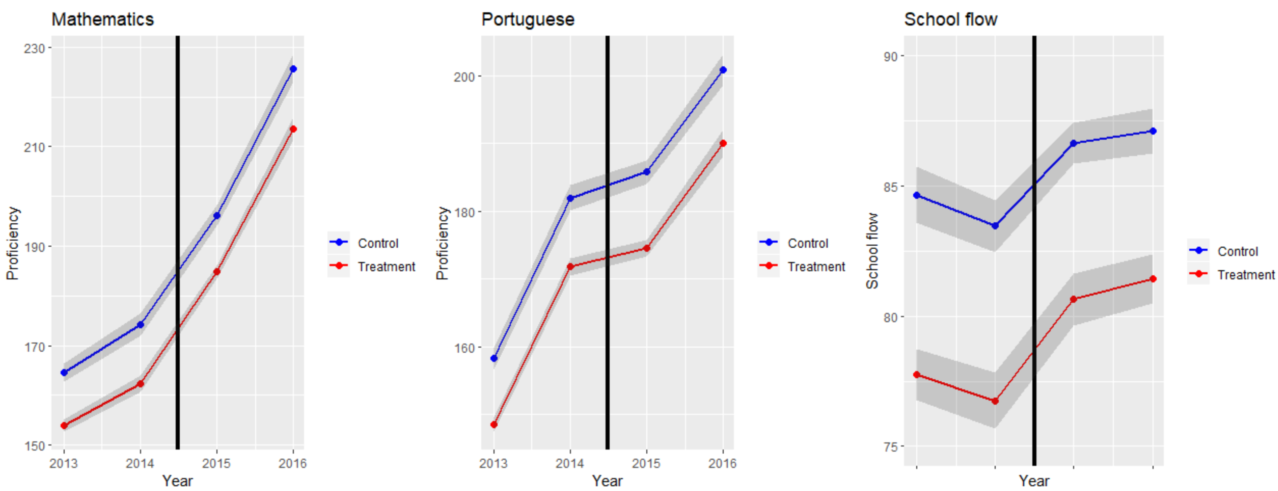
First Empirical Analysis Strategy: No Data Pre-Processing

As the first analysis strategy did not rely on any pre-processing of the data, we fitted the differences-in-differences model inserting a series of observable contextual variables. We estimated the program's impacts on performance variables in mathematics, Portuguese language and school approval rates for the year 2016.

Table A1, inserted in the statistical attachment[11] displays the variables used in the models, including type, description, and origin. The explanatory variables correspond to the characteristics of the schools in the sample. In addition to a variable that specifies the schools that received/did not receive the intervention, we included variables associated with time, which indicates the period before and after the implementation of the policy, and an interactive term that marks the differences of the differences. This last variable indicates the difference of the difference between the groups in the period before and after the implementation of the program. In line with the literature, this analysis assumes that the explanatory variables can impact the dependent variables, justifying their inclusion in this study. They are also controls to verify the magnitude of the relationship between the intervention and school approval rates and math and Portuguese language performance.

Graph 1

Comparison of Groups Year by Year



Source: Prepared by the authors.

[11]We chose to display Tables A1 and A2 in the statistical attachments due to their respective sizes.

The analysis of the graphs above indicates that, despite the performances in mathematics and the Portuguese language increasing over the years, the differences between the control and treatment groups, in the three variables of interest, remained constant in the observed historical line. This strategy seeks to monitor, through visual inspection, the behavior of the control and treatment schools' straight lines before implementing the program in 2015. The results suggest that there was minimal impact on the school quality indicators analyzed.

Table A2, in the statistical annex, displays descriptive statistics of the variables inserted in the models and a test of the difference of means between the groups. It is possible to notice that the schools of both groups are different in almost all variables, but mainly, performance, and approval rate. These differences were also present in the demographic characteristics of schools, such as management complexity[12], maximum parental education[13], poverty index[14]and percentage of non-white students. These differences indicate that there was, in fact, a selection bias in schools that received the Escolas em Foco program. Despite the program's focus on schools with lower performance or flow, they also have a distinct student composition profile and a more complex school structure for principals.

Although this preliminary analysis suggests a very slight effect of the program, we adjusted linear regression models with the dependent variables of proficiency in mathematics, Portuguese language, and approval rates, controlled (explanatory variables) only by the year and a dummy that indicated whether the school participated in the program or not.

Table 2
Comparing Treatment and Control Groups Year by Year

	Mathematics	Portuguese language	Approval rates
Year 2014	9.703***	23.740***	-1.197
	(1.451)	(1.211)	(1.048)
Year 2015	31.580***	27.573***	1.983*
	(1.474)	(1.230)	(1.073)
Year 2016	61.120***	42.610***	-4.966***
	(1.484)	(1.239)	(1.047)
Foco school	-10.576***	-9.659***	-6.916***
	(1.396)	(1.165)	(1.009)
Year 2014 * Foco	-1341	-0.530	0.204
	(1.991)	(1.662)	(1.438)
Year 2015 * Foco	-0.760	-1556	0.910
	(2.009)	(1.677)	(1.458)
Year 2016 * Foco	-1516	-1136	6.309***
	(2.017)	(1.684)	(1.434)

[12] Inep provides numerous educational indicators calculated based on data from the School Census. One of them is Management Complexity, a variable with six categories that aims to distinguish schools with more complex and less complex management. The variable includes the following dimensions: the number of students enrolled in the school, the number of stages, the complexity of the stage, and the number of working shifts. We have transformed it into a dummy variable to make it more accessible. Schools with complexity up to level 3 received the value 0 and schools with complexity from level 4 to 6 received the value 1.

[13] Based on the education level statement indicated by the students' parents, we constructed the maximum education per school indicator as to the percentage of at least one parent having completed high school or other higher education.

[14] This variable indicates the percentage of students per school included in income transfer programs, such as *Bolsa Família* and *Cartão Família Carioca*.

	Mathematics	Portuguese language	Approval rates
Constant	164.544***	158.232***	84.660***
	(1.015)	(0.847)	(0.733)
Observations	2,788	2,788	2,811
R^2	0.616	0.508	0.053
Adjusted R^2	0.615	0.506	0.051
Residual Std. Error	18.793 (df = 2780)	15.684 (df = 2780)	13.555 (df = 2803)
F Statistic	637.825 (df = 7; 2780)	409.398 (df = 7; 2780)	22.462 (df = 7; 2803)

Source: Prepared by the authors. *p<0.1; **p<0.05; ***p<0.01

The first column of Table 2 corresponds to the math proficiency results. The results indicate that schools that did not receive the intervention showed significant growth in proficiency concerning the reference category, in this case, proficiency in 2013. As for schools that received the intervention (Year * *Foco*[15]), the results indicate that the difference in performance between control and treatment groups decreases, but with a small and not statistically significant effect. In the indicator 'Year 2016 * *Foco*', the year after the program's implementation, the difference between schools in the treatment and control groups decreases. The '*Foco*' variable, on the other hand, indicates the average effect on mathematics proficiency over the four years of analysis for the schools that received the intervention.

The second column corresponds to the comparative effects of treatment and control groups on Portuguese language proficiency from 2013 to 2016. Similar to the first column, schools that did not participate significantly increased their performance over the next three years. The *Foco* variable suggests an average negative effect on the focus schools during the four years. The third column is equivalent to the results on the flow of schools. The effects are different from those associated with proficiency. Over the years, there seems to be no pattern for schools that did not receive the intervention, increasing and decreasing. For schools that received the intervention, approval rates are increasing compared to 2013, although only 2016 is statistically significant. The *Foco* variable has an effect in the same direction as proficiency in mathematics and Portuguese. The schools in the treatment group face two distinct problems: low student learning and lower school approval rates. On the other hand the school approval rates may be an aspect that is more easily modified by the school compared to the increases in mathematics and Portuguese language performance.

This exploratory investigation intends to compare the performance and approval rates of school groups (treatment and control) over the years, before and after program implementation. On the other hand, such analyzes do not yet have any variables of endogenous characteristics of schools, which can lead to differences in the results found. Table 3 presents the analyzes with such controls.

The next step in this analysis relied on a differences-in-differences model to investigate the program's effect on participating schools compared to non-participating schools. In addition, the models also included school demographic variables, such as the proportion of black students per school, male students, highly educated parents, students with families enrolled in cash transfer programs, and a dummy that differentiates schools with more complex and less complex management.

Table 3

Regression Models (Differences in Differences)

[15]This variable was constructed from a multiplicative interaction indicating the year and the dummy variable corresponding to the schools selected for the program.

	Mathematics	Portuguese	Approval Rates
Pre/Post	40.940***	22.979***	-1.117
	(1.167)	(0.985)	(0.727)
Schools in focus	-6.208***	-4.834***	-3.509***
	(1.156)	(0.976)	(0.725)
DiD	-0.0003	-0.839	3.764***
	(1.581)	(1.335)	(0.987)
% of non-white students	-0.241***	-0.287***	-0.016
	(0.053)	(0.044)	(0.023)
Gender	-0.570***	-0.476***	-0.412***
	(0.128)	(0.108)	(0.080)
Maximum Education	0.300***	0.288***	0.225**
	(0.030)	(0.026)	(0.019)
Poverty index	-0.081**	-0.094***	-0.016
	(0.033)	(0.028)	(0.020)
Management Complexity	-3.847***	-2.796***	-4.353***
	(0.918)	(0.775)	(0.570)
Constant	200.996***	200.245***	95.941***
	(7.416)	(6.261)	(4.636)
Observations	2,76	2,76	2,785
R^2	0.536	0.391	0.126
Adjusted R^2	0.535	0.389	0.124
Residual Std. Error	20.676 (df = 2751)	17.454 (df = 2751)	12.976 (df = 2776)
F Statistic	397.499 (df = 8; 2751)	220.525 (df = 8; 2751)	50.248 (df = 8; 2776)

Source: Prepared by the authors. *p<0.1; **p<0.05; ***p<0.01

The first column corresponds to the analysis results on the dependent variable of proficiency in mathematics. The first variable (Pre-Post) refers to a dummy indicating the difference in the effect in 2015 and 2016 compared to 2013 and 2014. It reveals that the schools of both groups (treatment and control) grew on average by 40 points in mathematics proficiency between the years 2013 and 2014. The variables that indicate color and sex suggest that the more significant the proportion of black and male students per school, the lower their respective performance. As expected, the poverty indicator and management complexity variables exhibit significant effects in the same direction as the previous variables. Schools with a higher proportion of students with more educated parents, with complete high school and/or higher education degree, tend to have higher average proficiencies. The estimator that indicates differences in differences (DiD), the focus of this analysis, suggests that the differences between schools in the control and treatment groups, controlled by the other variables included in the model, decreased after implementing the program. Still, the results show that the impact is of low magnitude and not significant.

The second column presents the effects of variables on Portuguese language proficiency. As expected, the results of the contextual variables are similar, in terms of effects and statistical significance, to those verified for mathematics proficiency. The differences in differences estimator in this column verifies the same trend: a reduction in Portuguese proficiency inequality, but with little relevance and significance. The third column, which refers to the school approval rates, does not follow the same pattern as the previous columns. For example, the variable 'Pre

Post' indicates that the average flow rate of schools in 2015 and 2016 is lower compared to previous years, despite the non-statistical significance. The contextual variables exhibited effects similar to those seen for math and Portuguese language proficiencies and followed the results already documented in the literature. However, our estimator of interest (DiD) points out that the differences in the approval rates of the treatment and control schools increased after the start of the intervention.

In short, this first analysis strategy points out that, although the differences in mathematics and Portuguese language performance decreased between the two groups of schools, they were of small magnitude and not very significant from a statistical point of view. On the other hand, the difference in school flow between the groups increased. It is possible to infer, from the results above, that the program to encourage the use of data had modest or minor substantive effects in the first two years of analysis on the performance variables in mathematics, Portuguese and school approval rates.

Second Empirical Analysis Strategy: With Data Pre-Processing

To increase the power of causal inference of the analyses, since the treatment and control groups have a series of distinct observable characteristics, we performed the pre-processing of the data from the pairing of the schools of both groups.[16] In addition, these analyses also allow a robustness test to the investigations carried out in the previous section.

The pairing technique via propensity score used the logistic model to estimate the probability of a school in the control group being a school included in the program[17]. As the objective is to monitor schools throughout the four years of analysis, the pairing technique used data from schools in 2013, two years before program's implementation. However, no case in the sample (schools) can present any missing value to perform the matching. Therefore, we removed all cases that did not have complete information on the variables used during this process.[18]. To verify the hypothesis of bias in excluding cases with missing data, we calculated the means and standard deviations of the missing cases to dismiss the hypothesis of bias in excluding cases with missing data.[19] The procedure allowed comparison of this group with the previous sample. We calculated the means of the variables inserted in the model before and after the pre-processing of the data to verify the matching quality. In addition, graphs were also adjusted for mathematics, Portuguese language, and school approval rates, comparing the control and treatment groups before and after matching[20]. Based on the results, which indicate good pairing quality[21], again, we fit the differences-in-differences model comparing these groups before and after the program implementation.

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[16] The variables used in the model to perform the matching are in table A3 of the statistical attachment.

[17] To increase the number of matched schools, we opted for the case replacement model, that is, any school in the treatment group could be matched with more than one school in the treatment group. After this process, we removed duplicate cases from both groups. For example, if school X in the treatment group was matched with school W in the control group, and if the same school X in the treatment group was matched again with school Z in the control group, it (school X) appeared in our new sample only once. This procedure was used both in the control group and in the treatment group.

[18] The total number of cases excluded from this analysis due to lack of information on one of the variables used in the model was equal to 54.

[19] The characteristics of the schools that were excluded from the analysis during the pre-processing of the data seem different from those with complete information on the variables analyzed. Therefore, as these schools could not be paired with others in the sample, the results cannot be generalized to these cases.

[20] The table and graphs that indicate the quality of matching are in the statistical attachment of this work.

[21] Table A4 of the statistical attachment compares schools in the control and treatment groups before and after matching.

Table 4
Comparing Treatment and Control Groups After Matching

	Mathematics	Portuguese language	Shcool approval rates
Year 2014	11.310***	25.549***	−0.127
	(1.923)	(1.594)	(1.072)
Year 2015	32.930***	28.622***	3.416***
	(1.923)	(1.594)	(1.084)
Year 2016	59.803***	41.905***	3.479***
	(1.920)	(1.592)	(1.070)
Schools in focus	-3.252**	-3.370**	-4.132***
	(1.631)	(1.353)	(0.909)
Year 2014 * Foco	-2.960	-2.327	-0.956
	(2.311)	(1.916)	(1.288)
Year 2015 * Foco	-2.423	-2.795	-0.594
	(2.309)	(1.915)	(1.298)
Year 2016 * Foco	-0.472	-0.616	0.126
	(2.306)	(1.913)	(1.286)
Constant	157.465***	152.096***	81.960***
	(1.357)	(1.126)	(0.757)
Observations	2,141	2,141	2,131
R^2	0.637	0.522	0.076
Adjusted R^2	0.636	0.520	0.073
Residual Std. Error	17.436 (df = 2133)	14.460 (df = 2133)	9.719 (df = 2123)
F Statistic	534.422*** (df = 7; 2133)	332.240*** (df = 7; 2133)	25.068*** (df = 7; 2123)

Source: Prepared by the authors. *p<0.1; **p<0.05; ***p<0.01

The results in Table 4 compare the performance of schools in the treatment and control groups on the three variables of interest in our study. The first column indicates mathematics performance, establishing the performance in the subject in 2013 as a reference category. As the results suggest, the schools in the control group showed growth in all subsequent years. For schools in the treatment group (Year * *Foco*), the effects for each year of analysis is low from an educational point of view and not statistically significant.

The picture is very similar when we analyze the results for the Portuguese language, as the schools in the control group showed increasing and significant developments over the years, while the schools in the treatment group showed more modest effects. The results for the school approval rates are also quite similar to the previous ones, increasing each year. As the schools of both groups already have high school approval rates, a significant increase in this variable is less likely.

However, is worth mentioning that the schools in the treatment group started with a lower level of academic performance, both in Portuguese and in mathematics, so we expected this result. More importantly, as the results indicate, after the program's implementation, the difference in academic performance between the schools that received the treatment (that is, that underwent the data use program) and the schools not included in the program decreased from magnitude year by year. This result indicates that students from schools in the treatment group had better academic performance in Portuguese and mathematics than their peers from schools did not participate in the *Escolas em Foco* program. However, as these results are of low magnitude and not statistically significant, the substantive impact of the program must be interpreted and analyzed with caution.

Table 5

Regression Models (Differences in Differences) After Matching

	Mathematics	Portuguese language	School approval rates
Pre/Post	40.770***	22.548***	3.512***
	(1.587)	(1.369)	(0.762)
Shcools in focus	−4.737***	−4.557***	−4.607***
	(1.349)	(1.163)	(0.644)
DiD	0.017	−0.528	0.241
	(1.907)	(1.644)	(0.914)
Constant	163.103***	164.832***	81.897***
	(1.122)	(0.968)	(0.536)
Observations	2,141	2,141	2,131
R^2	0.504	0.294	0.075
Adjusted R^2	0.503	0.293	0.074
Residual Std. Error	20.357 (df = 2137)	17.552 (df = 2137)	9.718 (df = 2127)
F Statistic	724.051*** (df = 3; 2137)	296.352*** (df = 3; 2137)	57.333*** (df = 3; 2127)

Source: Prepared by the authors. *p<0.1; **p<0.05; ***p<0.01

Table 5 displays the results of the difference-in-difference models for the three outcome variables after matching the schools in the control and treatment groups. The Pre-Post variable only compares schools, without distinction in control and treatment, in the period before (2013-2014) and after (2015-2016) the program's implementation. The effect indicates that schools grew in mathematics, Portuguese, and school approval rate. The second variable (*Foco*) considers the average effect of schools that received the intervention over the four years, even before the program's implementation. Therefore, these schools have a lower performance in the three variables analyzed, which indicates, as previously mentioned, that the schools selected to receive the *Escolas em Foco* program present, on average, when compared to the schools in the control group, worse academic performance, even after pairing. The last estimator (DiD) suggests that for mathematics, the difference between the two groups increases after the program's implementation. Still, the effect of this variable is small and not statistically significant. For Portuguese, the scenario is different, as the performance difference between the two groups decreased in 2016, but as for mathematics, the effect is also low and not significant. There is an increase in the difference between treatment and control for school approval rate, but with a modest estimator and without statistical significance.

It is interesting to note that in this second part, the possible impacts of the program were estimated only for schools in the control and treatment groups with similar characteristics. The results, therefore, corroborate those already described and commented on in the first part of this work, which indicates that the program had very tenuous effects on math performance, Portuguese language, and school approval rates. However, the results suggest that school performance in Portuguese and Mathematics of the students in the schools that received the *Escolas em Foco* program was, on average, slightly higher than their peers in the control group schools. Although starting from a lower level, the differences in the school performance of the two groups decrease year by year.

Final Considerations

The objective of this work was to investigate the impact of a program to encourage the use of data for school planning at the *SME* in Rio de Janeiro on a specific, non-random group of schools selected based on performance in Portuguese, mathematics, and school approval rate.

Verifying the results presented makes it is possible to establish some hypotheses for the tenuous or little substantive effect on the performance and approval rate of the schools that received the intervention. The first one refers to the short historical series analyzed in this work. The short period of analysis may not be enough to explain part of the low impact of the program. In addition, this program intended to change the behavior of these schools. This objective may only be achieved with a more extended intervention/training of school agents, as indicated by the DDDM literature.

Another hypothesis is related to the practices and actions of *PAE*s with schools. Although these agents have received similar training from the *SME*, they may have adopted different strategies according to the profile of the schools and management. The varying actions of the PAEs can also be due to the relationship they established with the management of schools. Some administrations may have been more 'receptive' to the actions of these agents and the implementation of new teaching and learning practices and methodologies. Such receptivity could ultimately mean performance gains in mathematics, Portuguese and approval rates. In addition, we also do not have information on how the program was implemented and how they were interpreted and appropriated by the actors at the end.

Another hypothesis to explain part of the effects may be related to the concurrence of programs and projects implemented in schools. Schools receive numerous programs and projects, coming from different instances and levels of government, with diverse and often similar and complementary objectives. The interaction of actions in schools makes it difficult to estimate the effects associated with each program. It is not possible to know with certainty whether the effects verified in the analyzes correspond only to the *Escolas em Foco* program.

Finally, this work focused only on the impact on the indicators of schools with 3rd grade classes of elementary school. However, this program, in the first year of implementation, also privileged a group of schools that had third and fifth grade classes. Therefore, we do not know whether the program affected the performance and school approval rates of fifth-grade schools.

Appendix

Table A1
Description of the Variables Used

Name	Type	Description	Source
		Dependent Variables	
PL and MT proficiency	continuous	Average proficiency per school in Mathematics and Portuguese Language in the 3rd year	[22]Prova Rio (2013, 2014, 2015, 2016)
School Approval rates	continuous	School approval rates of the 3rd year of elementary school	Censo Escolar (2013, 2014, 2014, 2016)
Explanatory Variables			

Name	Type	Description	Source
		Dependent Variables	
Foco School	dummy	0- Indicates schools that did not receive the program; 1- Indicates schools that received the program	[23]Dados SME (SCA 2014)
Gender	continuous	Percentage of male students by school	[24]Dados SME (SCA 2014)
Management Complexity	dummy	0 - Indicates less complex schools; 1- Indicates more complex schools.	Indicadores Educacionais INEP (2014)
Maximum Parent Education	continuous	Percentage of students whose parents completed high school or higher education.	Dados SME (SCA 2014)
Poverty Indicator	continuous	Percentage of students enrolled in income transfer programs.	Dados SME (SCA 2014)
% of Non-White Students	continuous	Percentage of non-white students by school.	Dados SME (SCA 2014)
Pre/Post	dummy	0- Indicates the year 2013 and 2014; 1- Indicates the year 2015 and 2016	
DiD	dummy	Interactive term (PRE/POST **Escola Foco*)	

Note: Prova Rio is an external assessment applied only to schools in the city of Rio de Janeiro. Initially applied in 2009 and with the same reference matrix as the *Prova Brasil*, the *Prova Rio* is a census assessment that evaluates, in even years, students from the 3rd, 4th, 7th, and 8th grades of elementary school in Portuguese language and mathematics. More information on the characteristics of this assessment can be found in Koslinski et al., 2015. This analysis is using data from *Prova Rio*, not *Prova Brasil*, because the focus of the *Escolas em Foco* project is on the 3rd year of elementary school, grade not covered by *Prova Brasil* and because this evaluation is a census, that is, all schools with this grade are participating. The *SME* Data used in this work corresponds to the *Sistema de Controle Academico-SCA* (Academic Control System) databases, which are generated annually with information about the school, classes, enrollment, students and their families, and student performance and annual income. These databases are updated annually, allowing students to be monitored over the years. The 2014 *SCA* bases were used because we did not have access to the 2013 bases.

Table A2

Descriptive Statistic of the Variables Used

	Schools in Focus		Non-focus schools		Difference	
Name	Mean	*SD*	Mean	*SD*	*T*-test	*P*-value
Math proficiency 2013	153,9	11,9	164,5	17,4	9,415	0,000***
Math proficiency 2014	162,3	15,7	174,2	21,6	8,262	0,000***
Math proficiency 2015	184,7	13,5	196,1	18,8	8,874	0,000***
Math proficiency 2016	213,5	23	225,6	26	6,310	0,000***
Portuguese proficiency 2013	148,5	10,5	158,2	14,5	10,166	0,000***
Portuguese proficiency 2014	171,7	12,5	181,9	17,5	8,720	0,000***
Portuguese proficiency 2015	174,5	11,7	185,8	16,5	10,020	0,000***

	Schools in Focus		Non-focus schools		Difference	
Name	Mean	*SD*	Mean	*SD*	*T*-test	*P*-value
Portuguese proficiency 2016	190	19,1	200,8	21,3	6,835	0,000***
School approval rates 2013	77.7	9,6	84,6	10,1	9,338	0,000***
School approval rates 2014	76,7	10,7	83,4	9,4	8,836	0,000***
School approval rates 2015	80,6	10	86,6	7,4	8,858	0,000***
School approval rates 2016	81,4	8,17	87.1	9,31	8,399	0,000***
Gender 2014	51,7	2,8	51,5	3,4	-0,224	0.8224
Management Complexity 2014	0,37	-	0,17	-	-	-
Maximum Education 2014	41,6	13	51	15,2	8,286	0,000***
Poverty index 2014	31,8	12,2	28,3	14,2	-1,569	0.117
% of Non-White students 2014	64,9	7,4	60,4	9,5	-7,056	0,000***
Number of schools	384		343			

Source: Prepared by the authors. *p<0.1; **p<0.05; ***p<0.01

Table A3
Variables Used in Matching

Variable	Type	Description
PL and MT proficiency	continuous	Average proficiency per school in Mathematics and Portuguese Language in the 3rd year
School Approval rates	continuous	School approval rates of the 3rd year of elementary school
Schools in focus	dichotomous	0- Indicates schools that did not receive the program; 1- Indicates schools that received the program
Gender	continuous	Percentage of male students by school
Maximum education	continuous	Percentage whose parents completed high shcools or higher education
Poverty index	continuous	Percentage of students enrolled in income transfer programs
% of non-whyte students	continuous	Percentage of non-white students by school
Management education	dichotomous	0 -Indicate less complex schools; 1- Indicate more complex schools

Source: Prepared by the authors.

Table A4
Comparing Means Before and After the Matching

Variable		Matching	
		Before	After
% of non-white students	Treatment mean	65.04	65.04
	Control mean	60.07	66.06
Gender	Treatment mean	51.71	51.71
	Control mean	51.55	52.15
Maximum Education	Treatment mean	41.85	41.85
	Control mean	51.65	41.12

Variable		Matching	
		Before	After
Poverty index	Treatment mean	31.56	31.56
	Control mean	27.94	32.88
Management Complexity	Treatment mean	0.37	0.37
	Control mean	0.15	0.31
Portuguese proficiency 2013	Treatment mean	148.73	148.73
	Control mean	159.14	147.65
Math proficiency 2013	Treatment mean	154.21	154.21
	Control mean	165.51	152.18
School approval rates 2013	Treatment mean	77.82	77.82
	Control mean	85.24	78.57

Source: Prepared by the authors.

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