Requirements to be a teacher in Brazil: effective or not?

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Abstract: The national Law of Guidelines and Standards of Education of 1996 stablished 2007 as the deadline for all Brazilian basic education teachers to have tertiary education level habilitation. This implied a significant change in the profile of teachers in basic education, the change in the provision of pre-service training, and it was expected to improve teaching quality and students' achievement in Brazil. The objective of this study is to investigate the effects of the increase in the share of public upper secondary school teachers with higher education on students' performance in math and Portuguese and analyze the role of pre-service training framework on the quality of teachers in recent years. We carried out an empirical analysis in which we estimate the Average Treatment Effect on Treated on public upper secondary students through the combination of difference-in-difference and propensity score matching method. We found no evidence of positive effects on Portuguese scores, and despite the statistically significant positive effect of the rise in teachers with higher education on math scores, we find no effect from specific math training. Finally, we discussed the possible reason for the ineffectiveness of teacher pre-service training, such as the quality of the training delivered by distance learning modalities and the low performance of secondary students that enter in the teacher schools.

Keywords: teacher quality; teacher education requirements; secondary education.

Resumo: A Lei de Diretrizes e Bases de Educação de 1996 estabeleceu que todos os professores da educação básica apresentassem habilitação de nível superior até o ano de 2007. Isso implicou numa mudança significativa no perfil dos professores na educação básica, a partir da qual se esperava uma melhoria na qualidade do ensino e, consequentemente, no desempenho dos estudantes brasileiros. O objetivo deste estudo é investigar os efeitos do aumento da proporção de professores do ensino médio com formação de nível superior sobre o desempenho dos estudantes em matemática e português e analisar o papel da formação inicial dos professores na qualidade do ensino. Estimou-se o efeito tratamento médio para os estudantes do ensino médio por meio da combinação do método de diferenças em diferenças e pareamento por escore de propensão. Não foram encontradas evidências de efeito positivo da formação de nível superior dos professores sobre o desempenho dos estudantes em língua portuguesa e, apesar do efeito positivo sobre as notas de matemática, não há indícios de que o treinamento específico nesta disciplina tenha qualquer efeito. Por fim, discutimos possíveis explicações para a ineficácia da formação inicial dos professores, como a qualidade das diferentes modalidades de cursos superiores e o desempenho dos alunos do ensino médio que ingressam nos cursos de licenciatura.

Palavras-Chave: qualidade do ensino; formação de professores; ensino médio.

JEL Codes: I26; I28; J24.

Área 12 - Economia Social e Demografia Econômica

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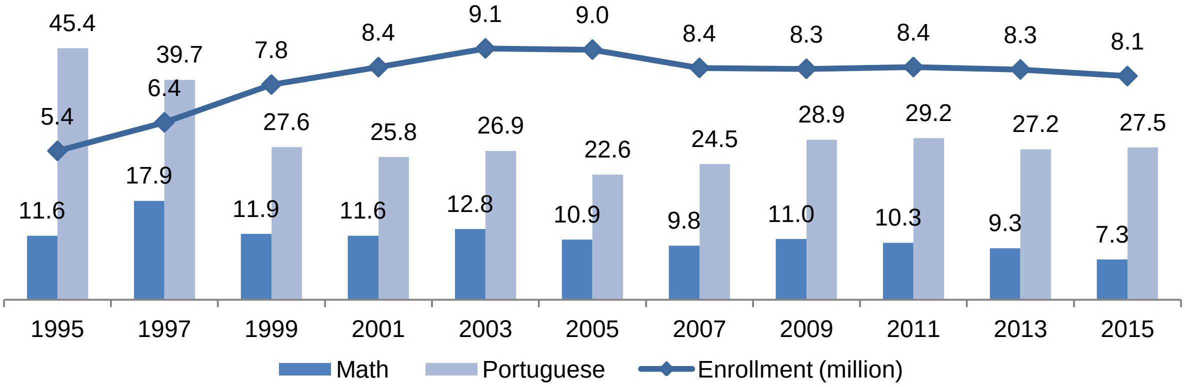
1. Introduction

In the last two decades there has been a significant change in the profile of teachers in basic education, resulted from tertiary education requirement for teaching established by the national Law of Guidelines and Standards of Education of 1996 (Law No. 9394/96, LDB). This law defined the year 2007 as deadline for all Brazilian basic education teachers to have tertiary education level habilitation.[1]

School census data of the Ministry of Education (MEC) suggest that, although this goal has not been fully achieved, this law appears to have influenced profoundly pre-service teachers' education. From 1995 to 2007, the percentage of teachers of basic education with higher education increased from 49% to 68%, then reached 83% in 2015. For upper secondary school teachers, this percentage increased from 82% to 93% in the period between 1995 and 2007, remaining stable until 2015.

At the same time, there was a significant increase in coverage of upper secondary education of 5.4 to 8.1 million students from 1995 to 2015, which was achieved in detriment of improvements in quality. National Assessment of Basic Education (SAEB) results show a drop in the percentage of graduates of basic education with adequate levels of learning in mathematics, from 11.6% to 7.3% of students, and in Portuguese, from 45.4% to 27.5% of students from 1995 to 2015. It is possible that the massive incorporation into educational system of out of school's children from lower background families have negatively influenced the quality of elementary education at first and of secondary education years later. This seems consistent with the trajectory of the Portuguese learning indicator, which fell sharply up to 2005, showed a slight improvement until 2011 and stagnation afterwards, but do not seem to have had the same influence on math learning indicator. Thus, it is not clear whether the variation in enrollments was able to counterbalance the positive effects expected from the improvement in teachers' schooling.

Figure 1 - Percentage of graduates of secondary education with adequate levels of learning in math and Portuguese and Enrollment in secondary education



Note. Minimum score on the SAEB scale that characterize adequate learning for students in 3rd grade of secondary education was 300 points for Portuguese and 350 points for math. *Source.* School Census and SAEB – INEP/MEC.

The literature has established the central role of teachers on students learning, but there is still no consensus on how teachers' pre-service training affects teacher performance. Studies that measure the value-added of teachers in a school year find that students with a good teacher can achieve an average gain of one year, and students with great teachers might gain 1.5 grade levels (Hanushek and Rivkin 2010). In addition, teachers critically impact not only children's immediate learning progress, but also their longer-term development and life choices (Bruns and Luque, 2015). However, studies based on the educational production function estimates from cross-sectional data and on regression analysis of aggregated levels of student performance fail to find statistically significant effects of teacher education measures (Hanusheck, 2003). Other series of studies developed since 2000s, based on student-level longitudinal data and involving broader sets of variables, and more recent researches that address non-observed heterogeneity and selection bias problems, find positive effects for some disciplines and grades and specific types of teacher pre-service education (Wayne and Youngs, 2003; Harris and Sass, 2011).

[1] Repealed by Law No. 12796/13, which reintroduced the secondary level Normal course as minimum level of training for teaching in early childhood education and in the first years of elementary school.

The objective of this study is to investigate the effects of the increase in the share of public upper secondary school teachers with higher education on students learning in math and Portuguese and analyze the role of pre-service training framework on the quality of teachers in recent years. To this end, we first present the recent changes on teachers' pre-service training in Brazil and an overview of the empirical literature on the subject. Subsequently we carry out an empirical analysis in which we estimate the Average Treatment Effect on public upper secondary students and conclude with a discussion on how the current policies affect the quality of teachers in Brazil.

2. Key issues on teachers pre-service training in Brazil

Since the publishing of the LDB in 1996, whose article 62 defined the minimum requirements for teaching in basic education, a new regulation on pre-service training began to be stablished. Initially, LDB determined that basic education teachers should be trained at the tertiary level, in *licenciatura* courses. The exception was a specific upper secondary level training, called *Normal* course, for teaching exclusively in early childhood and early grades of primary education. In 1999, the decree No. 3276/99 established that the training for teaching in specific fields of knowledge, such as math, biology, physics, etc., would take place in specific courses (also *licenciatura* degree) designed specifically for this purpose.

The resolution CNE No. 02 of 2015, which defines the National Curriculum Guidelines for Teacher Training, established three pre-service training options that habilitate teachers for basic education: (i) *licenciatura* degree, with a duration of four academic years and a minimum of 3200 hours of academic work; (ii) *second licenciatura* degree, for *licenciatura* degree holders that want to teach another field, with a reduced minimum workload of 1200 hours; and (iii) *pedagogical supplementation*, for bachelor degree holders, which require a minimum of 1000 for the completion depending on the equivalence between graduation already obtained and the field of the intended pedagogical training.[2]

There are many questions about the quality of teachers in Brazil related to the framework of pre-service training and the governance of the system. For example, what was the effect of the increase in teacher education requirement on basic education students' learning? Is the public education system not able to attract top performance secondary schools' graduates? Do we have a problem of quality in teacher training courses? Regarding pre-service training, there are two major vectors that may affect the quality of teachers: the first considers aspects of the educational background of those interested in teaching career; the second is regarded to the profile and structure of tertiary education (Bruns and Luque, 2015).[3]

The significant increase in coverage of primary and secondary education observed until the mid of 2000 in Brazil required hiring new teachers, which resulted in a change in the profile of the freshmen in this career (Lerch et al, 2010). In response to the rapid increase in demand for teachers with degrees, there was a boom in the provision of tertiary education programs. This led to the inclusion in the teacher career of secondary education graduates from families of lower socioeconomic background.

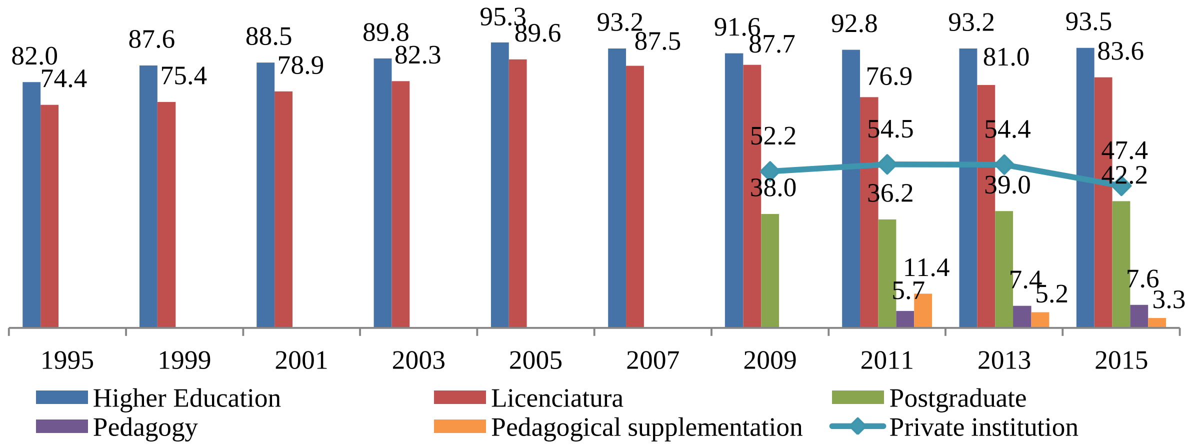
The percentage of public upper secondary education teachers with higher level increased from 82% to 93% in more than 20 years, mainly due to *licenciatura* degrees (Figure 2). However, there are still teachers without higher education or with pedagogy degree, which is not focused on secondary education, whose share corresponds to 7.6%. Also, due to a lack of minimum standards for teachers' admission, States and municipalities selected teachers with distinct profiles. All these teachers may have been trained in different types of institutions that are practically autonomous to decide about their curriculum.

Louzano et al. (2010) investigate the profile and preferences of secondary school graduates who declared themselves interested in teaching career in 2005.[4] Only 10% of this group belonged to the top performance students, and about a third were among the bottom performance students. These evidences suggest that the teaching career in Brazil is attracting a high share of less-skilled students. In fact, the cut-off ENEM score required for admission to public higher education institutions are much lower for *licenciatura* courses in these universities. In year 2014 the mean cut-off score for *licenciatura* in specific

[2] *Pedagogical supplementation* was instituted in 1997 as a provisional act and originally required a workload of 540 hours. Its provisional nature is reversed 2017, and the certification is now recognized in LDB as valid requisite for teaching.
[3] The authors find that Latin America countries are trapped in a low-level equilibrium with low standards for entry into teacher training programs, which are not prepared to produce the set of competences found in high performance educational systems.
[4] Based on socioeconomic questionnaire data of the National Examination of High School (ENEM).

disciplines and in pedagogy were, respectively, the 5th and the 2nd lowest in a classification of 75 courses.[5] In addition, *licenciatura* offered by private institutions are among courses with less competition for admission and therefore might be the choice of students with weaker educational background.[6]

Figure 2 - Percentage of Public Upper Secondary Schools Teachers with Higher Education



**Private institution* indicates percentage of higher educated teachers that attended only private higher education Institution. *Source.* School Census, microdata, INEP/MEC.

Other factors that may be affecting the quality of trained teachers are related to the nature and quality of teacher pre-service training programs. As pointed out by Bruns et al. (2012) and Carnoy et al. (2008), teachers pre-service training, in general, give low relative importance to didactics and techniques of teaching and classroom management. In order to shed light on these aspects we explore the changes in teacher pre-service training programs in the last ten years.

Table 3 – Graduates from higher education programs

Areas and Programs	**Year**			**Diference**	
	2005	**2010**	**2015**	**2005 - 2015**	**2010 - 2015**
*Training of specific subjects**	*77,795*	*95,550*	*82,158*	*6%*	*-14%*
Mathematics	10,194	11,915	10,896	7%	-9%
Portuguese	12,609	23,864	17,772	41%	-26%
*Other teacher training***	*118,570*	*108,041*	*123,867*	*4%*	*15%*
Pedagogy	74,508	107,808	122,835	65%	14%
Normal Superior	44,062	233	1,032	-98%	343%
*Bachelor in specific subjects****	*31,365*	*12,197*	*13,022*	*-58%*	*7%*
Mathematics	2,502	237	719	-71%	203%
Portuguese	7,146	1,347	1,213	-83%	-10%
All higher education programs	***730,484***	***973,839***	***1,150,067***	***57%***	***18%***

**Licenciatura* courses in typical secondary education fields, like math, Portuguese, physics, biology, etc. **Early childhood education and early grades of primary education training. ***Bachelor's degree courses in typical secondary education fields. Source. Synopsis of the Census of Higher Education - INEP / MEC.

In the aggregate, the number of graduates in pre-service training courses practically stagnated and the bachelor's degree in typical secondary education fields dropped sharply in the period (Table 3). There was a decrease in the presence of potential teachers with a bachelor degree in favor of *licenciatura* degree. Furthermore, there has been a very small growth in the number of graduates from *licenciatura* in math. All *licenciatura* in specific subjects programs has suffered decrease in the number of graduates in

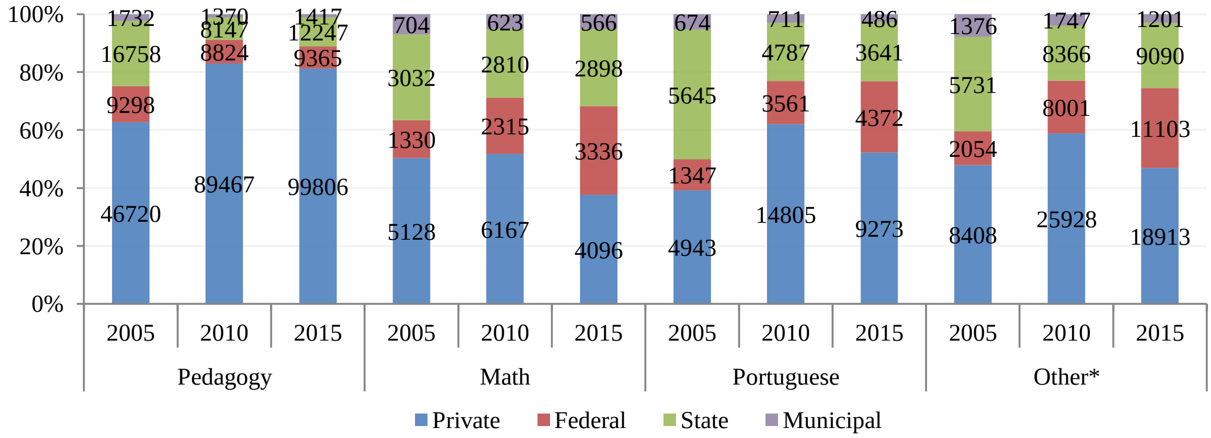
[5] Data from the Unified Selection System (SISU) of the Ministry of Education. The most recent data available in a complete and systematic way for all public higher education institutions that participated in SISU were from year 2014.

[6] Dada from Synopsis of Tertiary Education Census - INEP/MEC shows that the average number of candidates per offered place in *licenciatura* face-to-face courses is 0.68 and in bachelor degree face-to-face courses is 1.45.

the last five years, especially *licenciatura* in Portuguese.[7] The stagnation in number of graduates in math and the tendency to extinction of the Bachelor degree may be affecting the quality of math teaching. Note that the percentage of bachelor degree teachers with *pedagogical supplementation* dropped from 11.4% to 3.3% between 2009 and 2015 (Figure 2).

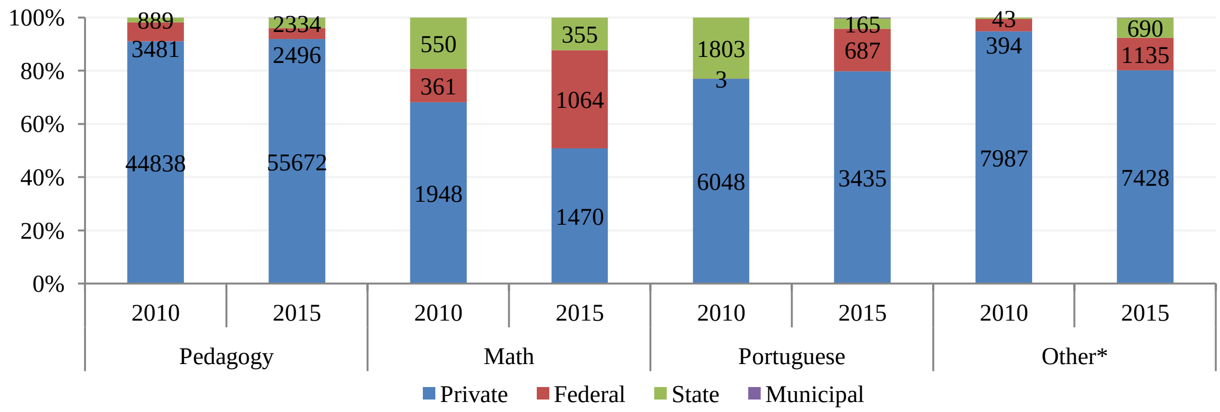
Major changes have occurred on the composition of pre-service teaching programs in recent years, which may have affected the profile of freshmen in this career. Figure 6 shows that the private institutions increased their share on the provision of graduates in pedagogy and in Portuguese, but lost participation for graduates in math and practically faced no change for other *licenciatura* in specific subjects. Federal institutions, on the other hand, more than doubled their share in total number of graduates in *licenciatura* in specific subjects, but lost participation in pedagogy. Nowadays, almost half of the graduates in Portuguese and more than half in math and in other subjects come from public institutions programs.

Figure 6 - Pre-service training graduates by the type of higher education institutions



* *Licenciatura* in Physics, Chemistry, Biology, Geography and History. Source: Statistical summaries of the Higher Education Census 2005, 2010 and 2015 - INEP / MEC.

Figure 8 - Pre-service distance training graduates by the type of higher education institutions



* *Licenciatura* in Physics, Chemistry, Biology, Geography and History. Source: Statistical summaries of the Higher Education Census 2005, 2010 and 2015 - INEP / MEC.

The most remarkable change in the period was the emergence and growth of distance learning. In the year 2015 about half of pedagogy graduates and one fourth of the graduates in specific subject *licenciatura* attended this modality. Private institutions has been responsible for the highest shares in the number of graduates from distance learning courses, remarkably in pedagogy, whose share has been kept above 90% since 2010 (Figure 8). Despite this protagonist, the share of private institutions in distance learning reduced among *licenciatura* in specific subjects, with exception to Portuguese, in which private

[7] The increase in pedagogy and decrease in *Normal* superior course graduates is related to a new regulation in 2006, which allowed pedagogy degree holders to teach in early childhood education and initial years of primary education.

institutions showed a small increase. On the other hand, federal institutions increased their share in distance learning in specific subjects programs. In particular, their participation in the total number of graduates in math rose from 12.6% to 36.8% in the period, while private institutions reduced their share. Among the graduates in Portuguese, the share of federal institutions went from none to 16% in the period.

To shed light on the potential effects of these recent changes on the quality of future teachers, Tables 4 and 5 present the mean performance of graduates in ENADE[8] exam and a measure of value-added[9] from public and private *licenciatura* programs in year 2014. In general, ENADE's results show that top performance students are enrolled in face-to-face federal university and private non-for-profit institutions programs and the bottom performance are in state and private for-profit institutions. Also, federal universities graduates performed better in both training modalities and graduates from private for-profit institution programs showed the lowest results. Finally, besides the better performance of *licenciatura* graduates in face-to-face programs as a whole, when restricting to distance learning modality this difference almost disappears for graduates in math and pedagogy. In particular, in private institutions, the performance of the distance learning programs was superior to face-to-face programs.

Table 4 – Performance in ENADE by type of higher education institution (2014)

	Pedagogy		Math		Portuguese		Other*		Total	
	Face-to-face	Distance	Face-to-face	Distance	Face-to-face	Distance	Face-to-face	Distance	Face-to-face	Distance
Private	2.42	2.00	1.96	2.07	2.20	1.90	2.29	1.88	2.30	1.94
Profit	*2.29*	*1.77*	*1.70*	*NA*	*1.92*	*1.77*	*2.09*	*1.68*	*2.13*	*1.75*
Nonprofit	*2.53*	*NA*	*2.11*	*NA*	*2.36*	*NA*	*2.36*	*1.97*	*2.41*	*2.11*
Federal	3.02	NA	2.58	2.36	2.91	NA	2.72	2.25	2.76	2.39
State	2.59	NA	1.97	NA	2.08	NA	2.24	NA	2.23	1.92
Total	**2.50**	**2.48**	**2.20**	**2.17**	**2.32**	**1.79**	**2.44**	**1.96**	**2.41**	**2.08**

* *Licenciaturas* in physics, chemistry, biology, history and geography. NA: Not available (less than five observations). *Note.* Performance in ENADE: The indicator is a result of the weighted average of the standardized scores of the graduates in the General Training test (common for all areas evaluated, weighing 25% of the grade) and in the Specific Knowledge test (75% of the grade). *Source.* ENADE/IDD microdata, INEP/MEC.

Table 5 – Value-added by type of higher education institution (2014)

	Pedagogy		Math		Portuguese		Other*		Total	
	Face-to-face	Distance	Face-to-face	Distance	Face-to-face	Distance	Face-to-face	Distance	Face-to-face	Distance
Private	2.53	2.35	2.18	2.24	2.68	2.38	2.55	2.37	2.53	2.36
Profit	*2.50*	*2.23*	*1.94*	*NA*	*2.61*	*2.08*	*2.53*	*2.49*	*2.48*	*2.21*
Nonprofit	*2.55*	*NA*	*2.32*	*NA*	*2.72*	*NA*	*2.55*	*2.32*	*2.56*	*2.48*
Federal	2.34	NA	2.58	2.40	2.59	NA	2.46	2.27	2.49	2.35
State	2.30	NA	2.27	NA	2.52	NA	2.44	NA	2.41	2.28
Total	**2.47**	**2.36**	**2.36**	**2.31**	**2.62**	**2.39**	**2.49**	**2.34**	**2.50**	**2.35**

* *Licenciaturas* in physics, chemistry, biology, history and geography. NA: Not available (less than five observations). *Note.* Value Added: Difference Between Observed and Expected Performances Indicator (Indicador da Diferença entre os Desempenhos Observado e Esperado [IDD]). *Source.* ENADE/IDD microdata, INEP/MEC.

In aggregate, private institutions tend to add as much value as federal institutions, and non-for-profit institutions are more capable of adding more value in either training modalities. This advantage is even higher for face-to-face *licenciatura* programs in pedagogy and Portuguese. On the other hand, public institutions perform better in math programs, but nonprofit private institutions add more value that state institutions. Finally, distance learning tends to add more value only for *licenciatura* in math for private institutions. Clearly, higher average scores in ENADE achieved by federal institutions programs are partly due to the better learning background of their incoming students. Therefore, the higher value-added

[8] The National Student Performance Test (ENADE) evaluates the skills and competences acquired by the graduates of all the undergraduate courses in Brazil. The first application of ENADE occurred in 2004 and each area of knowledge is evaluated triennially. The most recent edition that evaluated the *licenciatura* programs occurred in 2014.

[9] Indicator of Difference Between Observed and Expected Performances (IDD), a value-added indicator calculated by INEP/MEC used to control the performance in the ENADE by pre-university learning level of the incoming students shows the. Details on the calculation formula are available in INEP technical note Nº 33/2017/CGCQES/DAES.

of private programs may be due to decreasing returns to the educational production function, whereby it would be easier to obtain return from individuals with poor average educational background.

The above findings allow us to point out a set of factors that may explain why the raise in teacher tertiary education does not seem to have affect students learning in the last decade. Beyond the low educational background of incoming students and the raise in distance learning modality, the present analysis raises other key aspects. First, the preponderance of teachers with *licenciatura* and the sharp fall in bachelor degree in specific areas of knowledge may not have been benefic to teachers quality. It is well documented that the majority of *licenciatura* programs assigns little importance in developing core teaching competencies, like teaching techniques and planning and organizing classroom activities (Bruns et al, 2011). But it is also possible that they fail in providing the necessary knowledge on the specific subjects taught too. Second, lack of effects may lie in the mismatch between the specific subject training of the teacher and the discipline he teachers (e.g.: math teachers that have not a *licenciatura* or bachelor degree in math). The data presently available allow us to test this mismatch hypothesis, as described later.

Finally, the leading role of private institutions and of distance learning modality in the provision of pedagogy courses, while not directly affecting the quality of teaching in secondary education, can have effects on the quality of elementary and early childhood schools and, therefore, compromise the learning ability of students entering high school. This hypothesis will be addressed in an upcoming study.

3. Empirical literature on teacher training and student learning

The quality of teachers and your effect on students' learning is a central theme of educational policy. The international literature indicates that a student with a low quality teacher ends the school year dominating at most half of the curriculum planned for this year, while students with an excellent teacher advance 50 percent more than expected (Farr, 2010; Hanushek and Rivkin, 2010). Thus, exposure to low-quality teachers for years running can lead to insurmountable deficits of students' learning.

Despite the recent evidences confirming the central role of teacher quality on students learning, there's still no consensus on how much schooling and teacher training contribute to a greater and lesser degree, to raise the quality of education. The first works on the productivity of teachers were developed based on the educational production function estimates from cross-sectional data, and regression analysis of aggregated levels of student performance in teacher training measures and several other controls.

In studies conducted until mid 1990s for the public schools of the United States, Hanushek (2003) identifies 170 estimates of the effect of teacher training measures on the performance of students in United States, of which only 14% reported statistically significant results, 9% of which showing positive effects. This percentage drops to zero when limited the analysis to only the studies considered by the author as high quality (with estimates based on the "value added" by a student of the same State). The author suggests that the difficulty in capturing the effect of teacher education may be in part due to low variability of the indicator between American schools. Another compilation, spanning 63 studies applied to developing countries, Hanushek (2003) reports that 56% of estimates of the effect of teacher's education school performance were positive and significant.

Wayne and Youngs (2003) conducted an extensive review of the existing empirical literature until the early 2000s, when most of the evaluation studies of the effects of the education of teacher passes using student-level longitudinal data and involve broader sets of variables. Most of the work considered indicates that secondary school students learn more math when their teachers have higher training in mathematics, and no effect in relation to the lower grades and to other areas of knowledge. Moreover, the survey indicated that the quality of teacher education (measured by the raking of the institution) has positive relationship on the performance of the students.

Based in a review of a wide range of empirical studies, Rice (2003) reports positive effects on high school mathematics and science achievement of students whose teachers have obtained advanced degrees in these subjects, and reports mixed evidence regarding the impact of advanced degrees at the elementary level. Also, there is a positive effect on high school mathematics achievement from certified teachers only when the certification is in mathematics. Finally, reports that the training institution attended by teacher positive effect on student achievement, particularly at the secondary level, but points out that this can be a reflection of the cognitive ability of the teacher.

Harris and Sass (2011) carry out a survey of the researches developed up to 2010, highlighting the fragility of previous work to control the heterogeneity among students only by their characteristics observed (covariates of students). The authors cite evidence that students who present greater learning capacity and fewer disciplinary problems tend to be allocated in classes with more experienced and qualified teachers, so that the lack of appropriate controls for the unobservable characteristics tends to generate biased estimates of the effects associated with the training of teachers.

Regarding the studies that have addressed the problem of selection bias, Harris and Sass (2011) points out eight studies that used fixed effects at the student level to control for the heterogeneity not observed, and five that explored random assignment experiments between students and teachers or that use natural experiments. None of the studies finds positive and statistically significant effect of the nature of higher education on the future teacher performance and the majority finds no relationship between the selectivity of higher education institution and teacher performance. Finally, with the exception of two studies that have identified significant and positive effects of master degree education of teachers on students math scores, all other studies either indicate absence of statistically significant effect or even negative effect of holding a postgrad degree on math and language students' performance.

Since unobservable characteristics of teachers (like their IQ) can influence your pre-service training and also affect your future performance in the classroom, Harris and Sass (2011) incorporate in their study the teachers grade in the college admission exam as a way of controlling the effect of higher education for the pre-college skills, thus avoiding a major source of bias.[10] The authors found no robust evidence that pre-service teachers training affect the productivity of the future teacher.

For Brazil, Louzano (2010) did not find a significant correlation between pre-service training of teachers and the performance of students. Menezes Filho (2007), on the other hand, reported significant impact of teacher's education only on third grade secondary education students, and for teachers with a degree in mathematics. The author also reports that teachers with 50 years or more of age positively affect students' learning. Such studies, however, do not use methods capable of dealing with various issues, in particular with the existing selection bias in the allocation between students, teachers and schools.

4. Data and Descriptive Analysis

In this study we use data from the National Examination of Secondary School (ENEM) and from the School Census for the years 2009 and 2015, which covers proficiency indicators and a broad set of covariates at student and school levels, for potentially all Brazilian schools.[11] In total, there were 20,979 public secondary schools in ENEM microdata, of which 17,214 appeared in the year 2009, 19,847 appeared in the year 2015, and 16,082 occurred in both years. Following the MEC criteria for disseminating the ENEM results, schools with less than 10 students from the 3rd grade participating in the exam were excluded, which resulted in 11,506 schools remaining in the sample. Of these, 151 schools with a participation rate above 100% were also excluded, leaving 11,355 schools at the base in both years.

Based on the School Census data, two school level variables were constructed to characterize teachers' education for each field or discipline (math and Portuguese): (i) *Percentage of classes taught by teacher with higher education*, and (ii) *Percentage of classes taught by teacher with higher education in the field*. The calculation was restricted to the schools with at least three upper secondary school classes for each discipline, so that the indicators reflect at least one class for each series of this teaching stage.[12]

Table 6 shows statistics for outcomes and teachers education variables, and relevant available covariates in this sample. The average math score dropped from 475.6 to 450.8 points in this period, a reduction of 0.31 standard deviation from the average obtained in 2009. This decrease came together with the increase of the dispersion of results among students, captured by the rise in the standard deviation.

[10] Harris and Sass (2011) investigate the effects of the specific areas of higher education of teachers (*Education Major, Math Education Major, English Education Major, Math Major* e *English Major*) so as to take advantage of the greater variability of these variables to try to capture some effect statistically significant on student performance.

[11] ENEM incorporate the Item Response Theory for scores calculation in 2009, when a proficiency scale with an average of 500 points and standard deviation of 100 points was defined, which allowed comparing results of different editions of the exam. Moreover, since this year students' performance in ENEM has become the main access route to public university, which has significantly enlarged the number participants. The year of 2015 was the last year in which microdata are available.

[12] Resulted in 11,336 and 10,857 schools with, respectively, at least three high school math and Portuguese classes in 2009, and in 11,317 and 11,323 schools with, respectively, at least three high school math and Portuguese classes in 2015.

Portuguese average score, on the other hand, rose from 477.1 to 490.2 points, an increase of 0.15 standard deviation from the average obtained in 2009, and there was a reduction in the dispersion of scores.

Table 6 – Summary Statistics for Student and School Variables, by year, 2009 and 2011.

	2009					2015				
Covariate	obs.	mean	sd.	min.	max.	obs.	mean	sd.	min.	max.
Student level variables										
Math score	523,043	475.6	79.6	345.2	939.5	793,728	450.8	85.8	285.4	999.5
Portuguese score	523,043	477.1	90.0	224.3	835.6	793,728	490.2	66.4	303.3	795.4
Female	523,043	62.5%	48.4%	0%	100%	793,728	59.3%	49.1%	0%	100%
Black	466,681	11.2%	31.5%	0%	100%	784,540	12.5%	33.1%	0%	100%
Mother secondary	456,105	38.2%	48.6%	0%	100%	755,439	46.2%	49.9%	0%	100%
Car	463,789	44.7%	49.7%	0%	100%	793,621	42.0%	49.4%	0%	100%
Computer & Internet	463,685	41.7%	49.3%	0%	100%	793,614	56.3%	49.6%	0%	100%
Work	446,886	47.3%	49.9%	0%	100%	793,614	34.7%	47.6%	0%	100%
Private primary	466,374	14.0%	34.7%	0%	100%	793,614	15.5%	36.2%	0%	100%
Evening classes	459,708	40.2%	49.0%	0%	100%	793,613	25.6%	43.7%	0%	100%
School level variables										
Infra PNE	11,355	0.193	0.395	0.000	1.000	11,355	0.305	0.460	0.000	1.000
Class hours	11,355	4.4	0.5	3.0	8.0	11,355	4.8	1.1	2.7	12.9
Class size	11,355	34	6	11	214	11,355	31	6	7	222
Participation ENEM	11,355	35.9%	17.4%	1.3%	100%	11,355	54.5%	19.4%	3.8%	100%
Math classes higher*	11,336	93.0%	18.9%	0%	100%	11,317	95.1%	13.7%	0%	100%
Math classes higher field**	11,336	71.8%	32.7%	0%	100%	11,317	76.4%	27.9%	0%	100%
Portuguese classes higher*	10,857	94.9%	15.5%	0%	100%	11,323	96.9%	10.3%	0%	100%
Portuguese classes higher field**	10,857	84.3%	26.1%	0%	100%	11,323	82.1%	25.4%	0%	100%

Note. Students in the 3rd year of public regular secondary school that participate in ENEM. *Infra PNE*: *Indicator for school infrastructure* from Observatory of theNational Education Plan (Observatório PNE). *% classes taught by teacher with higher education. **% classes taught by teacher with higher education in the field. *Source.* ENEM,and School Census microdata.

In the same period, the percentage of classes taught by teachers with higher education increased by about 2 percentage points for both math and Portuguese. This result was accompanied by the increase of 4.6 percentage points in the percentage of math classes taught by teacher with higher education in this field, and the decline of almost 2.2 percentage points in the indicator for Portuguese classes. That is, the growth of teacher-specific training for the discipline, from an aggregate point of view, does not seem to have had a positive relationship with student performance.

Some important changes occurred in the period that may be correlated with students' results. Regarding the educational offer conditions, the percentage of students attending evening classes decreased from 40.2% to 25.6%, the average duration of classes increased from 4.4 to 4.8 hours, the average number of students per class decrease from 34 to 31, and schools infrastructure indicator increased from 0.193 to 0.305. In relation to students' profile, the percentage of students who have already worked decreased from 47.3% to 34.7%, the percentage of students with mothers with complete secondary education rose from 38.2% to 46.2%, and the percentage of students with computer and Internet access at home increased from 41.7% to 56.3%. The other covariates showed minor variation.

Table 7 presents the percentiles of the *percentage of classes taught by teachers with higher education* and *with higher education in the field* in years 2009 and 2015. While more than 80% of the schools already had all math and Portuguese classes taught by higher-educated teachers in 2009, big changes occurred in the lowest percentiles. For example, 95% of the schools had more than half of its math classes taught by teachers with higher education in 2009 and six year later the same proportion of schools had more of 66.7% of its math classes taught by teachers with that degree. For *higher education in the field* indicator, more than half of schools already had all Portuguese classes with teachers trained in this discipline but the proportion of math classes with teachers trained in math is much far from being complete. In general, while the changes in the *percentage of classes taught by teachers with higher education* were concentrated to the very lower percentiles of the distribution, for *higher education in the field* indicator the changes spread also to higher order percentiles. So schools seem to be converging to universalization of teachers training at tertiary level, excepting for field training of Portuguese teachers.

Table 7 – Percentage of Classes Taught by Teachers with Higher Education

	Percentile										
	p5	p10	p15	p20	p30	p40	p50	p60	p70	p80	p90
Math classes higher											
2009	50.0%	73.3%	87.5%	100%	100%	100%	100%	100%	100%	100%	100%
2015	66.7%	81.0%	90.9%	100%	100%	100%	100%	100%	100%	100%	100%
Portuguese classes higher											
2009	63.6%	82.4%	94.0%	100%	100%	100%	100%	100%	100%	100%	100%
2015	76.9%	90.3%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Math classes higher in the field											
2009	0.0%	16.0%	31.3%	41.7%	60.0%	72.7%	83.3%	95.3%	100%	100%	100%
2015	14.3%	33.3%	45.7%	55.0%	66.7%	76.9%	85.7%	95.2%	100%	100%	100%
Portuguese classes higher in the field											
2009	20.0%	42.9%	59.4%	69.2%	83.3%	94.4%	100%	100%	100%	100%	100%
2015	25.0%	44.4%	56.3%	64.3%	76.9%	86.7%	95.7%	100%	100%	100%	100%

More interesting would be to see how many schools increased the indicator and to what degree this happened. Tables 8 and 9 show the transition of the schools between percentile strata showed in Table 7, based on 2009's percentile intervals. The blue cells show how many schools managed to raise the indicators in the period and the red cells show how many schools faced a decrease in indicators.

Table 8 – Number of schools by *Percentage of Classes Taught by Teachers with Higher Education* – Transition between percentile strata, 2009 and 2015.

Math classes		2015				
		(87.5%, 100%]	(73.3%, 87.5%]	(50.0%, 73.3%]	(0%, 50.0%]	Total
2009	(87.5%, 100%]	**8,545**	**508**	**370**	**162**	9,585
	(73.3%, 87.5%]	**454**	65	36	27	582
	(50.0%, 73.3%]	**414**	55	45	24	538
	[0%, 50.0%]	**386**	62	72	75	595
	Total	9,799	690	523	288	11,300
Portuguese classes		2015				
		(94.0%, 100%]	(82.4%, 94.0%]	(63.6%, 82.4%]	(0%, 63.6%]	Total
2009	(94.0%, 100%]	**8,265**	**400**	**350**	**185**	9,200
	(82.4%, 94.0%]	**441**	55	28	17	541
	(63.6%, 82.4%]	**424**	48	41	22	535
	[0%, 63.6%]	**397**	55	58	41	551
	Total	9,527	558	477	265	10,827

Note. Strata were constructed based on 5th, 10th, and 15th percentiles. Blue (red) color indicates schools that moved the indicator to a superior (inferior) stratus between years 2009 and 2015.

Table 9 – Number of schools by *Percentage of Classes Taught by Teachers with Higher Education in the Field* – Transition between percentile strata, 2009 and 2015.

Math classes		2015					
		(72.7%, 100%]	(60.0%, 72.7%]	(41.7%, 60.0%]	(16.0%, 41.7%]	(0%, 16.0%]	Total
2009	(72.7%, 100%]	**4,986**	**674**	**576**	**322**	**179**	6,737
	(60.0%, 72.7%]	**630**	163	155	82	40	1,070
	(41.7%, 60.0%]	**684**	185	209	105	53	1,236
	(16.0%, 41.7%]	**519**	144	196	179	95	1,133
	[0%, 16.0%]	**445**	106	171	173	229	1,124
	Total	7,264	1,272	1,307	861	596	11,300
Portuguese classes		2015					
		(94.4%,100%]	(83.3%, 94.4%]	(69.2%, 83.3%]	(42.9%, 69.2%]	(0%, 42.9%]	Total
2009	(94.4%,100%]	**3,812**	**743**	**790**	**702**	**444**	6,491
	(83.3%, 94.4%]	**474**	168	185	149	78	1,054
	(69.2%, 83.3%]	**477**	148	197	179	114	1,115
	(42.9%, 69.2%]	**374**	136	174	228	169	1,081
	[0%, 42.9%]	**304**	97	154	251	280	1,086
	Total	5,441	1,292	1,500	1,509	1,085	10,827

Note. Strata were constructed based on 10th, 20th, 30th, and 40th percentiles. Blue (red) color indicates schools that moved the indicator to a superior (inferior) stratus between years 2009 and 2015.

In Table 8, for example, note that some schools that had high *percentage of classes taught by teachers with higher education* in 2015 (above 87.5% for math classes and above 94% for Portuguese classes) was in lower strata of the distribution in 2009 (below 87.5% for math classes and below 94% for Portuguese classes): 1,254 of 9,799 schools and 1,262 of 9,527 schools, respectively, considering the indicator for math and Portuguese classes. On the other hand, other schools that had a high *percentage of classes taught by teachers with higher education* in 2009 passed to lower levels of distribution in 2015: 1,040 from 9,585 schools and 935 from 9,200 schools, respectively for math and Portuguese classes.

These transitions from lower strata to the highest stratum of the distribution can be used to characterize school treatment condition in the following sense: schools that went from a lower strata to the greater stratum of the distribution are considered to have being treated, since they showed improvement in the indicator in the period; and schools that went from the highest stratum to a lower strata of the distribution are considered to have undergone a *negative treatment*. Due to its large number, schools that remained in the highest stratum of the distribution are considered as control group.

Based on the above strategy we constructed a set of variables that characterize different degrees of exposure to treatment, here understood as the increase (or decrease, for *negative* treatment) in the *percentage of classes taught by teachers with higher education* and *by teachers with higher education in the field*. We subdivide the exposition to treatment into three degrees (and four degrees, for the *higher education in the field* indicator) according to the stratum in which the school was in year 2009: treatment group 1 (*Treated* 1) is composed of schools whose indicator was in the stratum immediately below the highest, treatment group 2 (*Treated* 2) is composed of schools whose indicator was in the next stratum, and so on; so that the greater the order of treatment, the greater its intensity is. Similarly, the degree of *negative* treatment can also be characterized in degrees, according to the stratum of the school in 2015.

We see in Table 10 that for both years and disciplines the average scores are higher among students from untreated schools, and are smaller for more intensively treated schools. This is consistent with the hypothesis of positive correlated between teachers' education and students learning. It would be also expected a higher increase in outcome among treated schools, especially among the most intensively treated ones. Data on Portuguese scores corroborate with this hypothesis, but not for math, as students from treated and untreated schools perceived similar reduction in the average scores.

Table 10 – Mean score on ENEM by condition of exposure to treatment

	Math					Portuguese				
	2009		2015		Δ Mean	2009		2015		Δ Mean
Treatment	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Teachers with higher education										
Control	479.1	(81.0)	454.4	(87.0)	-24.7	480.7	(90.2)	493.3	(66.2)	12.6
Treated 1	463.5	(72.2)	439.0	(77.5)	-24.5	463.7	(87.5)	478.6	(65.8)	14.9
Treated 2	461.1	(72.2)	437.2	(80.1)	-23.9	460.8	(88.6)	477.5	(66.8)	16.7
Treated 3	455.6	(69.9)	431.1	(74.2)	-24.5	448.5	(85.0)	469.7	(64.6)	21.2
Treated 1,2,3	461.0	(71.8)	436.7	(77.8)	-24.3	459.4	(87.5)	476.3	(66.0)	16.9
Treated 2,3	458.9	(71.4)	434.9	(78.0)	-24.0	456.0	(87.4)	474.6	(66.1)	18.6
Teachers with higher education in the field										
Control	481.8	(82.6)	457.5	(89.0)	-24.3	487.1	(90.6)	498.4	(65.8)	11.3
Treated 1	472.2	(76.8)	446.8	(83.2)	-25.4	477.8	(90.4)	491.4	(67.6)	13.6
Treated 2	470.4	(76.1)	444.6	(81.4)	-25.8	472.1	(90.2)	486.4	(67.1)	14.3
Treated 3	466.5	(73.4)	441.9	(80.0)	-24.6	465.4	(88.3)	481.2	(66.0)	15.8
Treated 4	460.8	(72.7)	437.2	(78.5)	-23.6	448.1	(85.9)	469.5	(65.9)	21.4
Treated 1,2,3,4	468.7	(75.3)	443.6	(81.3)	-25.1	469.5	(89.8)	484.5	(67.3)	15.0
Treated 2,3,4	467.0	(74.5)	442.0	(80.4)	-25.0	464.7	(89.2)	480.8	(66.8)	16.1

Note. Students in the 3rd year of public regular secondary school that participate in ENEM in the years 2009 or 2015. *Source*. *ENEM*, 2009 and 2015, microdata.

From the perspective of the *negative* treatment, it would be expected that the mean increase (decrease) in the outcome indicator would be smaller (greater) among treated schools, the most intensively treated schools performing relatively worse. However, with the exception of the exposition of the students of math classes to higher educated teachers, there is no clear pattern indicating adherence to the hypothesis (Table 11). Average scores in math decreased most for treated students, as expected. Also, average scores in Portuguese increased least for treated students, excepting for the most intensively treated school (*Treated* 3), which showed similar advance in scores. Similar results are found when analyzing the treatment in terms of *percentage of classes taught by teacher with higher education in Portuguese* (*Treated* 3 and 4), which may reflect schools strategy of exchanging higher educated but lower performance teachers by newer teachers, who perform better despite the lower schooling.

Table 11 – Mean score on ENEM by condition of exposure to *negative* treatment

	Math					Portuguese				
Treatment	2009 Mean	SD	2015 Mean	SD	Δ Mean	2009 Mean	SD	2015 Mean	SD	Δ Mean
Teachers with higher education										
Control	479.0	(81.0)	454.4	(87.0)	-24.7	480.7	(90.2)	493.3	(66.2)	12.6
Treated 1	474.6	(78.1)	448.3	(85.1)	-26.3	477.8	(88.5)	488.2	(65.1)	10.4
Treated 2	472.9	(75.0)	445.0	(81.6)	-27.9	475.8	(91.4)	486.5	(67.7)	10.7
Treated 3	466.5	(74.4)	440.1	(78.3)	-26.4	468.7	(87.3)	481.1	(64.4)	12.4
Treated 1,2,3	473.1	(76.7)	446.3	(83.2)	-26.8	475.8	(89.4)	486.6	(66.0)	10.8
Treated 2,3	471.4	(74.9)	443.9	(80.8)	-27.5	473.8	(90.4)	485.1	(66.9)	11.3
Teachers with higher education in the field										
Control	481.8	(82.6)	457.5	(89.0)	-24.3	487.1	(90.6)	498.4	(65.8)	11.3
Treated 1	479.4	(80.3)	454.9	(87.4)	-24.5	487.4	(89.3)	496.6	(65.2)	9.2
Treated 2	478.1	(79.3)	452.6	(84.8)	-25.4	486.2	(91.1)	496.6	(65.7)	10.4
Treated 3	471.1	(75.6)	446.7	(81.3)	-24.4	480.8	(89.0)	492.4	(65.7)	11.6
Treated 4	475.9	(86.8)	446.6	(81.1)	-29.3	467.5	(87.1)	487.5	(64.6)	19.9
Treated 1,2,3,4	477.4	(79.7)	452.4	(85.3)	-25.0	482.8	(89.7)	494.5	(65.5)	11.7
Treated 2,3,4	475.7	(79.2)	450.3	(83.5)	-25.4	480.5	(89.9)	493.5	(65.6)	13.0

Note. Students in the 3rd year of public regular secondary school that participate in ENEM in the years 2009 or 2015. *Source. ENEM*, 2009 and 2015, microdata.

5. Causal inference strategy

What effect did the growth in higher education schooling of upper secondary school teachers have on students learning? One way to answer this question would be to compare the performance of the students in schools with high percentage of teachers with a degree (treated group) with the performance in schools that did not raise this percentage (comparison group). The main challenge we confront by doing this, however, is to address the problem of selection bias that may affect the estimation of this effect. This bias occurs when schools with certain characteristics, like the presence of more motivated and intelligent students, which have higher chances to achieve higher performance, are the most attractive ones for teacher with higher education. This entails in an overestimation of the treatment effects due to reverse causality.[13] Be enrolled in treated schools implies better students performance? Or characteristics related to the performance of students imply more treatment schools?

In this sense, it is necessary to compare the performance of treated schools with a group of schools that have similar chances to be treated, even if they were not. We do this by applying difference-in-difference estimation on matched samples obtained by propensity score matching, which allows us to control for several observed and unobserved school characteristics that may contribute to selection bias. Adapted from Cameron and Trivedi (2005), in a model of differences-in-differences, considering a school panel of two periods, the *ATT* can be obtained from the δ parameter in equation (1):

$$Y_{ist} = \alpha_0 + \alpha_1 t + \gamma D_s + \delta(tD_s) + X_{it}'\beta + W_{st}'\lambda + \varepsilon_{ist} \tag{1}$$

where: Y_{ist} is the achievement of the student i who attended school s in period t, with $t = 0$ for the pre-treatment period and $t = 1$ for the post-treatment period; D_s indicates treatment condition of the school s,

[13] It is expected that better schools attract or select higher performance teachers. As an example, Hanushek et al (2004) find that teachers in Texas tend to move to schools with more proficient students, especially the more experienced ones, who often have the option of going through districts and choose the school within the district in which they teach. Thus, it is necessary to isolate the characteristics of students and schools in order to guarantee that the odds of attracting/retaining teachers with higher education are similar for both treatment and control schools. In this sense, the treatment status between schools with same characteristics would be random (conditional independence assumption).

with D_s = 1 if the school has been treated and D_s = 0 otherwise; X_{it} and W_{st} are vectors of covariates (students and schools observable characteristics); α_0, α_1, γ, and δ are parameters and β and λ are vectors of parameters to be estimated; and $\varepsilon_{ist} = c_s + u_{ist}$ where c_s denotes the error component related to the unobservable characteristics that are constant in time of school s; and u_{ist} is an error term.

Note that $\hat{\delta}$ is basically the dif-in-dif estimator computed in a regression of stacked students for schools and years, which implicitly assumes constant treatment effect for schools. In order to eliminate the error in the estimation of ATT from specific characteristics of schools that are constant in the time, the parameters of the equation (1) are measured by fixed effects estimators with clustered standard errors. Besides, as almost all the high public schools in the state are managed by the state government, it is added to the linear trend model dummy variables for each state to control for changes in the state education policies. Considering these policies vary widely among States, the omission of these trends could result in a substantial bias in estimating the impact of characteristics of teachers and other school variables.[14]

Dif-in-dif assumes that in the absence of treatment the original difference between treated units and comparison schools in the outcome remain constant over time. That is, consider the potential outcome of a school s in time t like Y_{st}^0 and Y_{st}^1, where the subscript 1 indicates the result under the treatment and the subscript 0 indicates the result in absence of treatment. Thus, this assumption implies that:

$$\mathbb{E}\left(Y_{s,t-1}^0 \middle| D_s = 1\right) - \mathbb{E}\left(Y_{s,t-1}^0 \middle| D_s = 0\right) = \mathbb{E}\left(Y_{s,t}^0 \middle| D_s = 1\right) - \mathbb{E}\left(Y_{s,t}^0 \middle| D_s = 0\right)$$
$$\Longrightarrow \mathbb{E}\left(Y_{s,t}^0 - Y_{s,t-1}^0 \middle| D_s = 1\right) = \mathbb{E}\left(Y_{s,t}^0 - Y_{s,t-1}^0 \middle| D_s = 0\right) \Rightarrow \mathbb{E}\left(\Delta Y_{s,t}^0\right) \perp D_s \ .$$

Therefore, under the condition that $\mathbb{E}\left(\Delta Y_{s,t}^0\right) \perp D_s$ the treatment effect could be estimated as the difference of the difference in outcome in time of treated and non-treated schools, that is:

$$ATT = \mathbb{E}\left(\Delta Y_{s,t} \middle| D_s = 1\right) - \mathbb{E}\left(\Delta Y_{s,t} \middle| D_s = 0\right) .$$

The model of equation 1 controls for several characteristics of schools and students and for non-observed differences between schools by assuming that they are fixed in time. However, as we have only one year of pre-treatment data, it is not possible to verify if the difference in outcome between treated and comparison schools followed a constant trend over pre-treatment time. Thus, given the substantial pre-existent differences between treated and non-treated schools characteristics that may affect the outcomes, instead of relying solely on this model, we used a matching strategy to non-parametrically control any remaining differences between the two groups in the pre-treatment period (see Heckman et al. 1997, 1998). Specifically, we use propensity score matching methods to attribute weights to non-treated schools in a way that they mimic the counterfactual of the treated schools.[15]

To define a subsample not treated sufficiently similar to the sample treated in terms of covariates normally the following protocol applies (Becker and Ichino, 2002). First, get the propensity scores of treatment of treated and untreated units, from estimating of $\mathbb{E}(D_i = 1 | \, X_i)$ by a *logit* or *probit* model and select observations in common support. Then determine weight for each control unit in common support based on its proximity to a treated unit, which can be done by alternative methods.[16] Then test whether the null hypothesis that the means of control and treatment groups covariates are equal (balancing property). If null hypothesis is not rejected, use the weighted sub-sample in common support to estimate the *ATT*. In the end, it is expected that the estimated propensity scores densities are overlapping, what indicates the two groups of schools in the common support present similar pre-treatment characteristics.

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[14] Another assumption required by dif-in-dif is that the group composition does not change after the intervention, which is a minor concern once we restricted the sample of schools only to those present in both “pre” and “post” treatment years.).

[15] Rosenbaum and Rubin (1983) demonstrate that the validity of the above strategy depends on two assumptions. The first, *selection on observables* assumption, states that the potential outcomes are independent of exposure to treatment when conditioning by a set of observable features, that is, $(Y_i^0, Y_i^1) \perp (D_i | X_i)$, where X_i is a vector of variables capable of explaining the exposure to treatment. The second, *common support* assumption, states that there are no observations where the researcher knows for sure if the unit has been treated or not by observing only the covariates, that is, $0 < E(\,T_i = 1 | X_i) < 1$.

[16] Nearest-neighbor method can imply that for a treated unit the propensity scores reported by its controls is too far apart, which affect the quality of the matching. Radius method circumvents this problem by imposing a condition of maximum distance between the scores of treated and control units, but if the distance chosen is too small, it is possible that some units not find control units. In Kernel method, the closer the score of the control unit is from a treated one, the larger weight is given to it. The choice of the matching method implies a trade-off between size and quality of the matching sample, so the joint application of the methods is recommended in order to assess the robustness of ATT estimates.

In summary, to measure the effects of teacher education on the performance of schools, we first match the schools based on propensity scores, obtained by estimating a *logit* model of *ex ante* probability to be treated. Then, we apply, as a benchmark, the method of Radius matching, with maximum distance (*radius*) of 0.01. Then, the parameters of the equation (1) are measured by fixed effects estimators on school level. To evaluate the sensitivity of the results to the matching method, the *ATT* is also estimated on the matched sample by Kernel method (bandwidth calculated by Silverman rule). The procedures discussed here will apply to public upper secondary schools, observed at years 2009 and 2015.

The implementation of this strategy requires that exposure to treatment be characterized by binary variables. We have already defined them as the three (or *four*) dummy variables constructed from the percentiles of the teachers' education indicators in the previous section. Such characterization allows the estimation of effects for different degrees of exposure to the treatment, with a sufficiently large number of schools in each of the *n* treated groups and a higher number of schools in the control group.

6. Results

In order to provide a basis of comparison for the causal inference strategy, Table A1 in the Appendix shows the results of the fixed effects regressions of the students scores on the *percentage of classes taught by teachers with higher education* and *by teachers with higher education in the field*, controlling by a set of students and schools characteristics. The coefficients related to these two explanatory variables were statistically significant only for Students Portuguese scores.

Although statistically significant, the magnitude of the coefficients our two explanatory variables imply in very low effects, when compared to the magnitude of other variables that may affect Students scores. For example, if the schools in 5th percentile (as presented in Table 8 of the *Descriptive Analysis* section) increased the Percentages of Classes Taught by Teachers with Higher Education and by Teachers with Higher Education in Portuguese to 100% we would expect an increase of only 1.5 and 2.4 points in Portuguese scores, respectively, less than 0.03 standard deviations from the year 2009's mean.

The estimated coefficients suggest strong positive effects on students' scores from the following attributes: mother's education, presence of computer and Internet access at home, and having attended private primary education. Having a car at home (*proxy* for income) is positively correlated to math scores but negatively correlated to Portuguese scores. Having worked or being working is negatively correlated and having attended evening classes during secondary school is highly negatively correlated to students' math and Portuguese scores. Students' access to the Internet at home is positively correlated with performance in the exam. Also, a higher proportion of female students in school positively affects Portuguese scores and negatively affects math scores, the duration of classes is positively correlated with students' math scores and the class size is negatively correlated with Portuguese scores, and the school infrastructure indicator did not capture any effect. Finally, the addition the *participation rate in* ENEM and the *number of secondary school classes* does not affect the results for the explanatory variables. In fact, the participation rate in the ENEM is negatively correlated to the Portuguese scores, which may indicate the presence of self-selection in the exam, as explained below.

The use of ENEM scores as output indicator may present a selection bias problem, since student enrollment is voluntary and the worst students have less incentive to participate in the exam. Thus, worst schools are expected to have lower participation rates in the exam. On the other hand, a low participation rate may result from a deliberate action by the school administration to encourage only best students (or discourage worst) from attending the exam, which may artificially raise the school's average grade. To verify the sensitivity of the results in relation to this potential selection bias problem, we re-estimate the fixed effects regressions for a restricted sample, which excludes schools whose participation rates in 2009 were below the median of the distribution.[17] After carrying out the estimation, the coefficients for our two explanatory variables related to teachers education become statistically non-significant also for Portuguese scores, and do not change significantly the estimated coefficients of the other covariates.[18]

[17] MEC established a minimum participation rate in ENEM of 50% of the students for a school to have its results reported. As this filter would restrict the sample size to only 1,907 schools, we chose to restrict the sample of schools based on the median of the 2009's participation rate distribution, which was 33.3%, which resulted in 5,349 schools remained in the base.

[18] Output for restricted sample estimation provided upon request.

As we have seen in last section the validity of such estimates can be compromised by the presence of teachers selection bias, since chances to be employed in better schools are higher for those teachers with higher education. To deal with this problem, following the strategy of propensity score matching, we first estimate *logit* models of probability of treatment on a set of pre-treatment schools characteristics for each of the binary treatment variables defined in Section 4. The set of covariates used in this model and the criteria for their inclusion can be seen in Table 13.

Table 13 – Covariates of the *logit* model of *ex ante* probability to be treated

Variable	**Description**	**Justification**
Metropolitan Area	Dummy for school located in metropolitan area	Controls for the effects of the attractiveness of the municipality.
Population	Natural logarithm of the population of schools municipality.	
Per capita income	Per capita income of schools municipality population.	
University campus	Dummy for university campus in the municipality.	Controls for the effects of the offer of higher education in municipality.
University centre campus	Dummy for university centre campus in the municipality.	
College campus	Dummy for college campus in the municipality.	
Federal School	Dummy for Federal Secondary School.	Control for schools infrastructure that may affect the admission of teachers with better education.
Public water network	Dummy for school connected to public water network.	
Public sewerage system	Dummy for school connected to public sewerage system.	
Science lab	Dummy for school that has science lab.	
Computer lab	Dummy for school that has computer lab.	
Library	Dummy for school that has library.	
Internet connection	Dummy for school that has internet connection.	
Sports court	Dummy for school that has sports court.	
High School students	Natural logarithm of the number of students in high school.	
High School classes	Number of high school classes.	
Age-grade distortion	Age-grade distortion of 1st grade high schools students.	Control for the influence of the teaching effort on the school's chances of attracting teachers.
Class size	Average number of students per class.	
Class hours	Average number of hours of tuition.	
Evening classes	% of students studying at evening classes .	
Female	% female students.	Control for students and families socioeconomic status, which may influence teachers' decisions.
Black	% black students.	
Mother low schooling	% students whose mother schooling is bellow the elementary.	
Car	% students whose family own a car (proxy for family income).	

We then apply the Radius matching method to generate weights for the schools, in order to guarantee that an appropriate (that attend to both *selection on observables* and *common support* assumptions) matching between treated and control schools. Once paired the samples for all treatment conditions, differences in means between control and treatment groups of all covariates become statistically non significant, which support the validity of *selection on observables* assumption. Also, for all paired samples the estimated propensity scores densities are overlapping, which indicates that the schools in the common support present similar pre-treatment characteristics (*balancing property*).[19]

Table 14 presents a summary of the Treatment Effect on Treated Schools, estimated from Equation (1) controlling by the same set of student and school characteristics considered in previous regressions, for both no-matched and matched samples.[20] The coefficients for the no-matched sample [column (1)] are positive and statistically significant only for the schools that experienced the greatest increase in percentage of Portuguese classes taught by teachers with higher education (*Treated* 3) and with Higher Education in Portuguese (*Treated* 4). However, for matched samples [Columns (2) and (3)], the first coefficient becomes statistically non-significant and the coefficient of *Treated* 3 related to Higher Education in Portuguese becomes statistically significant at 10% of significance.

Thus, the initial results indicate that the only change in teachers' education indicators capable of affecting students' scores was that related to the increase in Percentage of Portuguese Classes Taught by Teachers with Higher Education in Portuguese, especially among the schools that had the highest increases (*Treaded* 4). For these schools, whose indicator was below 43% [or 20.1%, on average] in the

[19] Full *logit* regressions outputs, tables containing mean comparisons between groups for all covariates, and graphics of the densities are provided upon request.
[20] Full regression outputs provided upon request.

year 2009 and has risen above 94% [or 99.9%, on average] in the year 2015, the estimated *ATT* is between 6.9 and 7.5 points in Portuguese exam, what implies in an mean increase between 0.086 and 0.094 points for every 1 percentage point increase in teachers education indicator. This estimated effect is about 3 times the one previously estimated in the regressions without characterizing the treatment from binary variables, which considers all schools [see Table 13, Columns (10) to (12)].

Table 14 – Estimates of Treatment Effects on Mathematics and Portuguese Scores

Teachers education	Treatment group	All schools			Participation restriction on schools		
		No matching (1)	Radius matching (2)	Kernel matching (3)	No matching (4)	Radius matching (5)	Kernel matching (6)
Math scores							
Higher education	Treated1	1.496	2.386	2.454	-1.082	-0.568	-0.620
	Treated 2	1.116	1.684	1.672	1.215	0.057	0.684
	Treated 3	0.731	0.838	1.692	3.716	4.148	5.185*
	Treated 2,3	0.368	1.146	1.395	3.653*	4.533**	4.191*
	Treated 1,2,3	0.602	0.970	1.141	1.780	2.371	2.336
Higher education in Math	Treated 1	0.033	-0.442	-0.349	-0.352	-0.217	-0.251
	Treated 2	-0.048	0.289	0.390	-0.283	0.101	0.236
	Treated 3	0.277	-0.177	-0.106	-2.688	-1.682	-1.285
	Treated 4	-0.302	1.398	1.375	2.065	2.658	3.088
	Treated 2,3,4	-0.471	0.710	0.640	0.0639	0.426	0.146
	Treated 1,2,3,4	0.0670	0.628	0.614	0.648	0.886	0.793
Portuguese scores							
Higher education	Treated 1	0.808	-0.403	-0.385	1.358	1.005	0.932
	Treated 2	1.633	0.359	0.385	1.725	1.652	1.666
	Treated 3	5.017**	2.066	2.114	4.365	4.044	4.185
	Treated 2,3	2.533	0.707	0.672	1.391	1.099	0.967
	Treated 1,2,3	1.831	0.307	0.545	2.321	1.324	1.212
Higher education in Portuguese	Treated 1	2.909	2.972	2.357	1.917	1.651	1.745
	Treated 2	-1.189	-0.882	-1.433	0.211	-0.601	-0.836
	Treated 3	3.544	4.543*	4.367*	2.483	2.335	1.805
	Treated 4	7.598***	7.529***	6.908**	7.221**	3.980	4.275
	Treated 2,3,4	1.778	2.643	2.595	2.302	1.189	1.442
	Treated 1,2,3,4	1.724	2.736*	2.506	2.583	1.947	2.047

Note. School level Fixed Effects Model with linear trends by UF (omitted). Covariates were omitted. Cluster-robust standard errors in parentheses. *Statistically significant at 10% significance level. **Statistically significant at 5% significance level. ***Statistically significant at 1% significance level.

Again, in order to verify the robustness of the results in relation to the presence in the sample of schools with low student participation rates in ENEM, we re-estimate the model for the restricted sample, which excludes schools whose participation rate in 2009 was below the median of the distribution. As we can see, the estimated coefficients for non-matched sample are all statistically non-significant, with the exception of the coefficients for *Treated* 2,3 related to the effect of the increase in the Teachers Higher Education on math scores and for *Treated* 4 related to the effect of the increase in the Teachers Higher Education in Portuguese on Portuguese scores.

In regressions on paired samples [Columns (5) and (6)], however, the only coefficients that remains statistically significant are those for *Treated* 2,3 related to the effect of the increase in the Teachers Higher Education on math scores, and the coefficient of *Treated* 3 related to the effect of the increase in the Teacher Higher Education on math scores becomes statistically significant at 10% significance for the sample matched by the Kernel method. In special, the coefficients related to Higher Education in Portuguese on Portuguese scores become all statistically non-significant.

In summary, the results indicate that the increase in Teacher Higher Education in Portuguese that occurred in *Treated* 3 and *Treated* 4 schools (most intensively treated schools) may have positively affected students' Portuguese scores, but that this result is not robust to schools participation restriction on ENEM. Also, the increase in Teacher Higher Education seems to have positively affected students' math scores of *Treated* 2,3 schools (those whose indicator was below 73.3% in 2009 and raised above

87.5% in 2015). For these schools, whose indicator was below 73.3% [or 45.8%, on average] in the year 2009 and has risen above 87.5% [or 99.2%, on average] in the year 2015, the estimated *ATT* is between 4.2 and 4.5 points in math exam, what implies in an mean increase between 0.079 and 0.084 points for every 1 percentage point in Percentage of Math Classes Taught by Teachers with Higher Education.

Table 15 presents a summary of the so called *negative* Treatment Effect, also estimated from Equation (1) controlling by the same set of characteristic for both whole sample and matched samples. Again, the estimated results on the paired samples are statistically non-significant, except for the effect on Portuguese scores of school in Treatment group 2 in relation to the Percentage of Portuguese Classes Taught by Teachers with Higher Education in Portuguese, whose coefficient is positive and significant at 10% significance only when considering the sample matched by Radius method.

Table 15 – Estimates of *Negative* Treatment Effects on Mathematics and Portuguese Scores

Teachers education	Treatment group	All schools: No matching (1)	All schools: Radius matching (2)	All schools: Kernel matching (3)	Participation restriction on schools: No matching (4)	Participation restriction on schools: Radius matching (5)	Participation restriction on schools: Kernel matching (6)
Math scores							
Higher education	Treated 1	-2.025	-1.400	-1.427	1.740	1.719	1.943
	Treated 2	-1.078	-0.539	-0.713	-0.625	-0.436	-0.397
	Treated 3	2.305	2.539	2.211	3.053	4.491	4.342
	Treated 2,3	0.770	0.566	0.609	1.026	0.634	0.660
	Treated 1,2,3	-0.835	-0.163	-0.102	0.492	1.026	0.891
Higher education in Math	Treated 1	-1.135	-1.635	-1.557	0.495	0.213	0.219
	Treated 2	-0.732	-0.439	-0.508	0.371	0.628	0.663
	Treated 3	0.594	1.891	1.786	0.465	1.798	1.899
	Treated 4	-2.893	-2.424	-2.254	1.251	1.074	0.690
	Treated 2,3,4	0.121	0.786	0.791	1.276	1.760	1.712
	Treated 1,2,3,4	-0.483	-0.487	-0.533	1.211	1.148	1.225
Portuguese scores							
Higher education	Treated 1	-0.0589	0.295	0.0774	0.894	1.324	1.181
	Treated 2	1.019	0.129	-0.0246	2.362	2.961	2.773
	Treated 3	0.732	0.166	0.563	3.774	1.229	1.254
	Treated 2,3	0.128	-1.100	-1.049	4.026	2.037	2.016
	Treated 1,2,3	0.378	-0.650	-0.605	4.244**	3.630*	3.523*
Higher education in Portuguese	Treated 1	-2.463*	-1.198	-1.251	-2.070	-2.225	-1.714
	Treated 2	1.661	2.398*	2.079	0.359	0.686	0.763
	Treated 3	0.0466	-0.303	-0.387	1.544	1.498	1.840
	Treated 4	4.105**	1.246	2.310	3.090	2.542	2.011
	Treated 2,3,4	1.008	0.292	0.274	0.233	-0.227	-0.375
	Treated 1,2,3,4	-0.136	-0.0840	-0.355	-0.123	-0.595	-0.537

Note. School level Fixed Effects Model with linear trends by UF (omitted). Covariates were omitted. Cluster-robust standard errors in parentheses. *Statistically significant at 10% significance level. **Statistically significant at 5% significance level. ***Statistically significant at 1% significance level.

After restricting the sample by participation in ENEM exam, the only statistically significant coefficients are those related to the effect of the decrease in Teacher Higher Education on *Treated* 1,2,3 schools scores in Portuguese (schools whose indicator was above 72.7% in 2009 and dropped to below 72.7% in 2015). These schools seem to have benefited from the reduction in the percentage of higher educated teachers in the period, which may reflect a strategy of exchanging higher educated but lower performance teachers by newer teachers, who perform better despite the lower schooling.

The results do not allow us to reject the null hypothesis of no effect on Portuguese scores, and despite the statistically significant positive effects on math scores from the increase in *percentage of math classes taught by teachers with higher education*, we find no statistically significant effect from *teachers with higher education in math*. The lack of effect on Portuguese scores is consistent with the several studies that find no correlation between teachers education and student learning (Hanushek and Rivkin (2006), Harris and Sass (2011)), and the positive effect on math scores partly contradicts the findings of

Wayne and Youngs (2003), that reports that upper secondary school students learn more math only when their teachers have higher training in mathematics, and no effect in relation to other areas of knowledge.

7. Conclusions

There are only few rigorous studies that relates teachers educational background and training to the students' performance. Given the total amount of public and private investments to provide higher education training and the central role of teachers in student learning, understanding the relations between pre-service training and teachers' quality is essential to shed light on the changes capable of reversing the learning crisis in Brazil. The present study aimed at contributing to fill this gap in applied research.

We estimated the *ATT* effect of the change in the *percentage of secondary school classes taught by teachers with higher education* and *with higher education degree in the field* on the achievement in math and Portuguese of 12 graders students of public schools at ENEM, through a combination of differences-in-differences and propensity score matching methodologies. In summary, we find no evidence of positive effects on Portuguese scores, and despite the statistically significant positive effect of the rise in teachers with higher education on math scores, we find no effect from specific math training.

The incapacity of teacher education to influence students learning can have diverse origins. First, the quality of the teacher may be mostly determined by characteristics other than pre-service training, such as school performance records and innate skills. In this sense, the admission of weak educational background individuals in pre-service training could explain the absence of impact on the quality of the teaching. This seems consistent with the fact that tertiary teacher training courses are among the easiest ones to access in Brazil. Low competition to enroll in these courses reflects the low attractiveness to higher performance graduates of basic education.

A second explanation is based on the idea that lack of effect may be due to the inadequacy and/or poor quality of teacher training programs themselves, assuming that teacher quality is a function of pre-service training.[21] In this regard, Wayne and Youngs (2003) and Rice (2003) find positive effects of the quality of teachers' pre-service education on students learning. Section 2 shed some light on the issue for Brazilian case, where there was a significant change in the profile of teacher training courses, with the rapid expansion of distance learning and other recent changes in the higher education provision structure.

Our results point to a fragility in the training of teachers in the field of both math and Portuguese. It is likely that *licenciatura* courses are failing to compensate for the learning deficits accumulated by their graduates during basic education. It is also possible that the incorporation of bachelor degree holders with stronger knowledge in these fields may contribute to raise the quality of upper secondary education. In this regard, the *pedagogical supplementation* certification may contribute to raise quality of teaching. However, the percentage of these certified teachers from 11.4% to 3.3% between 2011 and 2015 and only 1.2% of math classes and 0.6% of Portuguese classes in public upper secondary education were taught by those teachers in 2015. This low share may be due to a lack of supply in *pedagogical supplementation* certification courses, the excessive increase of required duration for certification, selection barriers in the official exams, or simply the absence of interest of bachelor degree holders in joining teaching career.

The convergence of teacher wages of public upper secondary school towards the average wages received by other professionals with higher education degree and the reform of the national basic education core curriculum may influence professionals with non-education degree to join teaching career and the universities to change their pre-service curriculums. Incentives could be created to promote both changes through: (i) a reduction of the duration of *pedagogical supplementation* for a specialization of 360h to allow join the public system top performance professionals with higher education (it requires a change in the resolution of the CNE); (ii) promoting colleges or universities to restructure their curriculum of *licenciatura* degrees in accordance with the new national core curriculum through requirements in students loans in private institutions and scholarship programs in public universities.

It is still necessary, however, to deepen the analysis in search of understanding the reasons of low effectiveness of training teachers in leveraging learning of students from public schools.

[21] An extensive analysis on the key issues involving Teachers quality in Latin American and Caribbean countries can be seen in Bruns and Luque (2015).

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APPENDIX

Table A1 – Regressions of the Students Scores on the Percentage of Classes Taught by Teachers with Higher Education

Variables	Math scores						Portuguese scores					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
% Higher Education	0.00256	0.00222	0.00222				0.0427*	0.0421*	0.0412*			
	(0.0169)	(0.0168)	(0.0168)				(0.0225)	(0.0224)	(0.0224)			
% Higher Education Field				0.0146	0.0118	0.0118				0.0304**	0.0294**	0.0309**
				(0.00998)	(0.00996)	(0.00996)				(0.0124)	(0.0124)	(0.0124)
Female	-20.86***	-20.86***	-20.86***	-20.86***	-20.86***	-20.86***	7.071***	7.076***	7.077***	7.069***	7.078***	7.076***
	(0.354)	(0.354)	(0.354)	(0.354)	(0.354)	(0.354)	(0.315)	(0.315)	(0.315)	(0.315)	(0.315)	(0.315)
Black	-7.610***	-7.617***	-7.617***	-7.610***	-7.617***	-7.617***	-2.815***	-2.816***	-2.824***	-2.812***	-2.813***	-2.821***
	(0.504)	(0.504)	(0.504)	(0.504)	(0.504)	(0.504)	(0.471)	(0.471)	(0.471)	(0.471)	(0.471)	(0.471)
Mother secondary	8.575***	8.574***	8.574***	8.574***	8.573***	8.573***	9.769***	9.775***	9.775***	9.768***	9.775***	9.774***
	(0.357)	(0.357)	(0.357)	(0.357)	(0.357)	(0.357)	(0.321)	(0.321)	(0.322)	(0.321)	(0.321)	(0.322)
Car	3.880***	3.877***	3.876***	3.880***	3.876***	3.876***	-1.227***	-1.225***	-1.224***	-1.228***	-1.222***	-1.225***
	(0.380)	(0.380)	(0.380)	(0.380)	(0.380)	(0.380)	(0.339)	(0.339)	(0.339)	(0.339)	(0.339)	(0.339)
Computer & Internet	8.155***	8.145***	8.144***	8.155***	8.144***	8.143***	10.45***	10.45***	10.43***	10.46***	10.45***	10.43***
	(0.375)	(0.375)	(0.375)	(0.375)	(0.375)	(0.375)	(0.351)	(0.350)	(0.351)	(0.351)	(0.350)	(0.351)
Work	-3.981***	-3.939***	-3.938***	-3.979***	-3.937***	-3.937***	-4.373***	-4.360***	-4.358***	-4.372***	-4.361***	-4.357***
	(0.371)	(0.371)	(0.371)	(0.371)	(0.371)	(0.371)	(0.340)	(0.340)	(0.340)	(0.340)	(0.340)	(0.340)
Private primary education	12.79***	12.74***	12.74***	12.79***	12.74***	12.74***	13.17***	13.17***	13.19***	13.17***	13.17***	13.19***
	(0.587)	(0.587)	(0.587)	(0.587)	(0.587)	(0.587)	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)	(0.496)
Evening classes	-10.27***	-10.15***	-10.15***	-10.26***	-10.15***	-10.15***	-14.45***	-14.42***	-14.44***	-14.45***	-14.41***	-14.44***
	(0.417)	(0.417)	(0.417)	(0.417)	(0.417)	(0.417)	(0.396)	(0.396)	(0.396)	(0.396)	(0.396)	(0.396)
Infra PNE		0.398	0.396		0.392	0.394		0.369	0.459		0.408	0.469
		(0.796)	(0.796)		(0.796)	(0.797)		(0.851)	(0.851)		(0.850)	(0.851)
Class hours		2.424***	2.450***		2.423***	2.436***		0.562	0.911**		0.415	0.902**
		(0.416)	(0.432)		(0.419)	(0.432)		(0.428)	(0.451)		(0.433)	(0.450)
Class size		0.0348	0.0359		0.0330	0.0330		-0.277***	-0.288***		-0.290***	-0.291***
		(0.0709)	(0.0711)		(0.0712)	(0.0712)		(0.0764)	(0.0764)		(0.0764)	(0.0763)
Number of classes			0.0119		0.0137	0.0135			-0.123***		-0.110**	-0.121***
			(0.0356)		(0.0357)	(0.0358)			(0.0428)		(0.0428)	(0.0429)
Participation ENEM			-0.00224			-0.00266			-0.0982***			-0.0995***
			(0.0221)			(0.0221)			(0.0224)			(0.0224)
Dummy 2015	-27.42***	-29.55***	-29.55***	-27.55***	-29.68***	-29.65***	13.89***	12.62***	14.06***	13.99***	12.87***	14.17***
	(3.315)	(3.327)	(3.340)	(3.316)	(3.328)	(3.341)	(3.402)	(3.416)	(3.436)	(3.402)	(3.402)	(3.436)
Constant	477.2***	465.3***	465.1***	476.4***	464.5***	464.6***	455.5***	462.5***	467.3***	457.0***	467.0***	468.7***
	(1.673)	(3.431)	(3.607)	(0.891)	(3.281)	(3.308)	(2.210)	(3.900)	(4.087)	(1.170)	(3.616)	(3.632)
Observations	255,018	255,018	255,018	255,018	255,018	255,018	250,841	250,841	250,841	250,841	250,841	250,841
Schools	11,355	11,355	11,355	11,355	11,355	11,355	11,355	11,355	11,355	11,355	11,355	11,355
R2 adjusted	0.161	0.161	0.161	0.161	0.161	0.161	0.158	0.158	0.158	0.158	0.158	0.158

Note. School Fixed Effects Estimator, with linear trends by UF. Cluster-robust standard errors in parentheses. *Statistically significant at 10% significance level. **Statistically significant at 5% significance level. ***Statistically significant at 1% significance level.