Measuring the Effect of Competitive Teacher Recruitment on Student Achievement: Evidence from Ecuador

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Measuring the Effect of Competitive Teacher Recruitment on Student Achievement: Evidence from Ecuador

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Abstract

In the last decade, several Latin American governments have implemented new teacher recruitment policies based on evaluations of candidates' competency and knowledge so as to raise the quality of their teachers and schools. Since 2007, the Ecuadorian government has required teacher candidates to pass national standardized tests before they can participate in merit-based selection competitions for tenure at public schools. Has this new recruitment system served as an effective screening device? Has it ultimately helped to raise student learning? To answer these questions, I analyze data from a unique Ecuadorian survey of schools in the academic year 2011-2012. I first estimate the value-added to student achievement using OLS and hierarchical linear regressions to evaluate the effect of Ecuador's new competitive recruitment policy. I then use propensity score matching to simulate a random assignment of students to teachers and estimate causal treatment effects. The evidence suggests that teachers who were granted tenure through the new competitive recruitment policy were no more effective, overall, in raising students' learning in reading or math than their peers at schools. Nonetheless, poorer children who were assigned to these teachers had significantly better scores in reading. Furthermore, test-screened teachers, regardless of their tenure status, seem to have had positive significant effects in reading, particularly for students living in poverty. This finding suggests that Ecuador's teacher recruitment policy had a positive impact on the nation's most vulnerable students.

Keywords: teacher quality, education policy, education reform, Latin America.

JEL Classification: I20, I21, I28, J45

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1. INTRODUCTION

Latin American countries have significantly increased primary and secondary enrolment in the last decades, but learning outcomes are still substantially lower than in high-income and other middle-income economies (OECD PISA, 2014, 2016). Research also suggests that the low level of educational achievement in the region has accounted for its slow growth relative to the other regions (Hanushek & Woessmann, 2012). In this context, some Latin American governments have implemented systems for recruiting and promoting teachers based on tests of candidates' knowledge and competences in order to raise teacher and school quality. For instance, Colombia (since 2002), Ecuador (2007), México (2008) and Peru (2012) now all require teacher candidates to pass mandatory tests before they can opt for long-term careers at public schools (Bruns & Luque, 2015; Elacqua et al., 2017).

There has thus far been no conclusive evidence regarding the teacher characteristics that governments should identify, select, or enhance to improve teacher and student outcomes. But educational policies that require teacher candidates to pass national standardized tests have spread even though very little research has been done to assess their effectiveness in raising teacher quality and student achievement, especially in developing countries. To help fill the gap, I evaluate the effectiveness of Ecuador's new competitive teacher recruitment process as a screening device implemented to raise teacher quality and student achievement.

I draw upon a unique survey data from Ecuador of a representative sample of schools in the academic year 2011-2012, which allows us to compare learning outcomes of students taught by teachers who were granted tenure through the new competitive recruitment process as well by teachers who did not go through it. As an extension, I also analyze the effect of test-screened teachers, regardless of their tenure status. Furthermore, I look at the effect of the policy on vulnerable students who live in poverty.

Using OLS and hierarchical linear models (HLM), I first estimate the explanatory power that is added to student achievement model so as to evaluate the effectiveness of Ecuador's new teacher recruitment policy. Then I implement a propensity score matching (PSM) approach to simulate a random assignment of students to teachers and estimate causal treatment effects. The evidence suggests teachers granted tenure through the new competitive recruitment system were not necessarily more effective in raising student achievement in reading or math. Nonetheless, the results also suggest that these teachers had a significant positive effect on reading achievement for students from poor households. Noteworthy, test-screened teachers, regardless of their tenure status, seem to have had positive significant effects on reading, particularly for students living in poverty. Contrary to previous findings, this study shows that the teacher recruitment reform had a positive impact on a specific group of vulnerable students in Ecuador.

The paper is organized as follows. Section II presents the main frameworks and findings of teacher quality research and a summary of Ecuador's competitive teacher recruitment policy as applied in the last decade. Section III formalizes the value-added to student achievement model, estimated with OLS, HLM and PSM. Section IV describes data sources and reports summary statistics. Finally, Sections V and VI present results and conclusions.

2. BACKGROUND AND EVIDENCE

2.1. Teacher Quality

The study of teacher quality began with the identification and quantification of the determinants of the educational production function with the earliest work generally traced back to the "Coleman Report" released in 1966 (Hanushek & Rivkin, 2012). From the production function literature evolved the value-added to student achievement model, developed by Hanushek (1971; 1979) and Murnane (1975). Hanushek tested a parametric model that attempts to estimate the effects of specific teacher characteristics on students' achievement gains, after controlling for family, peer, and school factors. Subsequently, the teacher value-added to achievement model emerged (Hanushek & Rivkin, 2012). It is a non-parametric approach used to identify the overall teacher ability to increase student learning, however that may be achieved (Hanushek & Rivkin, 2012; Jackson, Rockoff, & Staiger, 2014). Nowadays, both frameworks are applied in the study of teacher quality.

The evidence from this literature suggests that teacher quality is the key factor in student learning and even the most important asset of schools (Chetty, Friedman, & Rockoff, 2014; Hanushek, 2011; Hanushek & Rivkin, 2006a, 2012; Jackson et al., 2014; McKinsey & Company, 2007; Nye, Konstantopoulos, & Hedges, 2004; Rivkin, Hanushek, & Kain, 2005; Rockoff, 2004). Nevertheless, measuring teacher quality in economics has proved to be challenging. The effects of specific teacher characteristics on student achievement tend to be inconsistent across studies due to lack of adequate or sufficient data and the methods used to identify their impact.

On the one hand, research from the value-added to student achievement model suggests that teacher quality and student achievement is associated to teachers' observable characteristics such as years of experience, academic degree, certification and knowledge or competency tests (Boyd et al., 2008; Clotfelter, Ladd, & Vigdor, 2007; Goldhaber, 2007; Goldhaber & Anthony, 2007; Goldhaber & Brewer, 1997; Hill, Rowan, & Loewenberg Ball, 2005; McKinsey & Company, 2007; Metzler & Woessmann, 2010; Rockoff et al., 2011). On the other hand, several studies that use the non-parametric teacher value-added to achievement model have found little evidence that teachers' observable characteristics are strongly related to student performance (Angrist & Guryan, 2008; Hanushek, 2003, 2011; Hanushek & Rivkin, 2006b; Harris & Sass, 2007; Kane, Rockoff, & Staiger, 2008; Krueger, 1999; Phillips, 2010; Rivkin et al., 2005). These studies suggest that teachers have powerful effects on student achievement; nevertheless, little of the variation in teacher quality is explained by observable characteristics such as certification, educational degree or experience beyond the initial years.

Research, starting with the "Coleman Report", has shown that student background characteristics are significantly associated with student outcomes. However, most teacher quality studies do not specifically examine the effects of teacher characteristics on vulnerable students. Some evidence suggests that achievement gains of socioeconomically disadvantaged students are more affected by their teacher qualifications. For instance, Boyd et al. (2008) found that improvements in teacher qualifications, especially among the poorest schools, resulted in substantially improved student achievement in New York City. Similarly, Phillips (2010) found achievement gains of at-risk[1] students were more sensitive to teacher quality indicators than gains of non-risk students in the U.S.

High quality studies about the effects of specific teacher characteristics on student achievement are scarce in developing countries. In a meta-analysis, Glewwe et al. (2014) examined studies published between 1990 and 2010 in both education and economics literature to explore which specific school and teacher characteristics appeared to have strong positive impacts on learning in developing countries. From over 9.000 studies, the authors selected 43 high quality studies. They found little evidence that teacher's level of education had a positive significant effect on student learning, but some evidence that teacher experience had a positive impact. Noteworthy, they also found that teacher knowledge of the subjects they taught had a consistent positive significant effect on learning. In the Ecuadorian case, Araujo et al. (2016) examined the impact of teacher quality on learning outcomes in kindergarten, using data where two cohorts of children were assigned to different classes with a rule as good as random. Their results suggested that children assigned to teachers with higher classroom observation scores[2] had significantly higher achievement. Their results also indicated that children with inexperienced teachers had test scores that were significantly lower. None of the other teacher characteristics analyzed (tenure status, IQ, the Big five dimensions of personality, inhibitory control and attention, and early circumstances) were associated with student learning.

Even though there is no conclusive evidence regarding the teacher characteristics that have a significantly positive impact on student achievement, several Latin American countries have implemented teacher recruiting systems based on testing candidates' knowledge and competencies (Elacqua et al., 2017). The purpose of these reforms has been to recruit the most well-prepared teacher candidates for public schools in order to raise quality and equity. As mentioned before, Colombia (since 2002), Ecuador (2007), México (2008) and Peru (2012) have required teacher candidates to

[1] In this study, at-risk students fell at least in one of the categories designed by the U.S. "No Child Left Behind" (NCLB) Act of 2001: student lived in a single-parent home, the student's mother did not have a high school diploma, the student's home language was not English and student's family lived below the poverty line.
[2] The tool used was the Classroom Assessment Scoring System (CLASS).

pass mandatory tests before they can opt for long-term careers at public schools (Bruns & Luque, 2015; Elacqua et al., 2017).

Very little research has been done about the effects of these policies on teacher quality and student outcomes. To evaluate the Mexican case, Estrada (2015) used a six-year database of rural junior secondary schools that received either one new test-hired teacher or one new traditionally hired teacher in 2010. The author conducted a robust difference-in-difference analysis to isolate the effects of merit-based teacher hiring. His results showed that the introduction of test-hiring of teachers was associated with a significant and substantial increase in math and language student scores, despite the fact that the standardized teacher test had no power to predict teacher quality. For the Colombian case, Brutti and Sánchez (2017) estimated how new quality-screened teachers impacted student high school performance after the introduction of the selective entry competition for teachers. They took advantage of the fact that the regulation applied only to newly hired teachers, which created a mix of new-regulation and old-regulation teachers at schools. Using administrative data at the school level from 2008 to 2013, the authors found a modest positive and significant effect of new-regulation teachers on student performance.

Finally, Cruz-Aguayo, Ibarrarán and Schady (2017) used data from Ecuador on a sample of children in 2nd, 3rd and 4th grade to analyze whether children taught by teachers with higher scores in the new selective entry competition had higher achievement in language and math at the school year 2011-2012. The authors found no evidence that teachers with better scores were more effective and they concluded that the evaluation used to make tenure decisions in Ecuador did not predict how effective teachers were at increasing children's test scores. Although the study compared students' outcomes among teachers that had taken entry competition exams to assess teacher quality and tenure decisions, it did not attempt to compare students' outcomes of teachers that passed the whole new selective recruitment process to the outcomes of teachers who did not go through it. Consequently, there are still opened questions regarding the effectiveness of the screening device of Ecuador's policy. Furthermore, the study did not take into account the changes implemented in the selection process between 2007 and 2011 and its implications.

I address these questions and assess the effectiveness of Ecuador's new teacher recruitment process as a quality screening device, by incorporating information of teachers who were not recruited through the new selective entry competitions and were working at the same schools and grades during the 2011-2012 year. I also include unique information about the rules applied to each teacher's selection process to evaluate teachers' effects by type of competition. Moreover, I incorporate data of children's poverty condition in order to examine the effects of teacher characteristics on vulnerable students.

2.2. The New Teacher Recruitment Policy in Ecuador

In November 2007, the Ecuadorian government released Executive Order No. 708, requiring teacher candidates to pass national standardized tests, before they could participate in merit-based selection competitions for tenure[3] at public preschools, schools and high schools (MINEDUC, 2007). Ecuador's Education Law of 1990 (*Ley de Carrera Docente y Escalafón del Magisterio Nacional*) established that teachers should be selected through merit-based competitions; however, a national standardized examination for teacher candidates was not implemented until the release of the Executive Order No. 708[4]. The new regulation was applied to teachers seeking tenure in public schools starting in December 2007. Teachers who were granted tenure before the 2007 regulation were exempted from taking national entrance exams; however, tenured teachers who wanted to be transferred to another school were also required to take these exams and compete for an available position (MINEDUC, 2008). Moreover, local education authorities were allowed to hire teachers who had not gone through the new recruitment process only temporarily. Teacher vacancies should be filled permanently by tenured teachers through the merit-based selection competitions.

In March 2011, the National Assembly of Ecuador passed the new Intercultural Education Law (*Ley Orgánica de Educación Intercultural*, LOEI) that ratified national entrance exams as mandatory requirement for teacher candidates (Asamblea Nacional del Ecuador, 2011). The new recruitment rules not only modified the teacher career path that had been in place since 1990, but also removed the discretionary influence of the national teachers' union (UNE) over teacher selection in Ecuador (Bruns & Luque, 2015).

The Ministry of Education of Ecuador has regulated the new teacher recruitment process through several Ministerial Regulations (*Acuerdos Ministeriales*, AM). From 2007 to 2009, the recruitment process was regulated by the Ministerial Regulation AM No. 438-07 of December 2007, which divided the process into two stages. At the first stage, teacher candidates were required to take a logical-verbal reasoning test, a pedagogical knowledge test and a subject-specific knowledge test that added up to 45 points of the total merit-based competition score, equivalent to 45 percent of the total score. Also at this stage, teachers had to present a demonstration class in front of a school board, which was granted 20 points of the total merit-based competition score, (equivalent to 20 percent of the final evaluation). Teacher candidates had to achieve at least 39 out of the 65 possible points at the first stage in order to become eligible candidates (60 percent). The second stage of the recruitment process was the evaluation of the eligible candidates' credentials. At this stage, scores were assigned to academic degrees, teaching experience, additional training courses and academic publications. The credentials added up to 35 points equivalent to 35 percent of the total merit-based competition score (MINEDUC, 2007). The total score was used to rank teacher candidates who applied to opened

[3] In Ecuador, tenured teachers hold permanent job positions in public educational institutions.
[4] Prior to 2007, teacher selection processes were locally organized by Provincial Directorates of Education without national standards other than academic degree requirements.

vacancies at public schools. Tenure was granted to the teacher with the highest score among candidates.

In January 2010, the new teacher recruitment process was slightly changed and reorganized into three stages under the Ministerial Regulation AM No. 018-10 (MINEDUC, 2010). At the first stage, teacher candidates were required to take the previously mentioned tests, but the teaching demonstration class was excluded from this phase. Tests' results added up to 45 points of the total merit-based competition score, equivalent to 45 percent of it. Accordingly, teacher candidates had to achieve at least 27 points out of 45 possible in order to become eligible candidates for the next stages (60 percent). The second stage again represented the evaluation of the eligible candidates' credentials, but the score granted to teacher experience increased. Credentials therefore now added up to 40 points or 40 percent of the total merit-based competition score. Finally, the demonstration class was conducted in the third stage and represented 15 points equivalent to 15 percent of the total merit-based competition score.

The LOEI, approved in November 2011, made it harder for teacher candidates to become eligible[5]. The weight of tests' results in the competition increased, as well as the minimum scores required to pass the tests. Furthermore, from July 2013 onwards, teacher tests have been designed by the National Institute of Educational Evaluation (*Instituto Nacional de Evaluación Educativa,* INEVAL*)* created by the LOEI. The merit-based competitions' regulations and components are summarized in Table 1.

Along with the new recruitment regulation, the Ecuadorian government introduced strong economic incentives to attract highly competitive teacher candidates into the public educational system. The LOEI homogenized the teacher payment scale to the public service payment scale, which meant that the real salary of a teacher who started her career in the public sector raised 160 percent between 2006 and 2014 (Elacqua et al., 2017). The economic incentives were granted only to tenured teachers. Therefore, the incentives were very attractive for teachers working at public schools with temporary contracts, teachers working at private schools and recently graduated teachers. Moreover, the LOEI officially opened the teaching career to university graduates who did not hold teaching degrees but were specialists in subjects taught at schools and high schools.

The Ecuadorian new teacher recruitment process became highly competitive. In December 2012, the Ministry of Education reported that, since 2007, there were 320.000 teacher candidates registered for eligibility tests. Meanwhile, 34.250 teaching positions were made available through

[5] Since July 2013, teacher candidates must first pass psychometric tests of personality and reasoning to be allowed to take the subject-specific knowledge tests (MINEDUC, 2013; MINEDUC, 2015). Once they have passed the psychometric tests, teacher candidates are required to achieve a minimum score at the subject-specific knowledge test to become eligible candidates for a merit-based selection competition. Also, English teacher candidates have been required to take and achieve specific scores at international standardized tests such as TOEFL and IELTS in order to become eligible candidates.

public selection competitions, 21.200 eligible candidates passed entry tests and 18.820 successful candidates were granted a permanent teaching position (MINEDUC, 2012).

Ecuador’s teacher recruitment process has changed since its inauguration in late 2007, but mandatory teacher tests worked as the screening device for the process throughout the years. In this paper, I evaluate the effectiveness of the new recruitment process for teachers who were granted tenure between 2007 and 2011 (under the 2007 and 2010 Ministerial Regulations) and who were working during the school year 2011-2012.

Table 1: Regulations and Components of Ecuador’s Competitive Teacher Recruitment

	MINISTERIAL REGULATION							
	AM No. 438-07 December 2007		**AM No. 018-10 January 2010**		**AM No. 379-11 November 2011**		**AM No. 0249-13 July 2013**	
Competition Components	Weight	Use of score	Weight	Use of score	Weight	Use of score	Weight	Use of score
Tests	**45%**		**45%**		**55%**		**60%**	
− Psychometric Personality and Reasoning								Pass or fail
− Logical-Verbal Reasoning	15%	Eligibility	15%	Eligibility	15%	Eligibility		
− Pedagogical Knowledge	15%	Eligibility	15%	Eligibility	15%	Eligibility		
− Subject-Specific Knowledge	15%	Eligibility	15%	Eligibility	25%	Eligibility	60%	Eligibility
Demonstration Class	**20%**	Eligibility	**15%**	Ranking	**10%**	Ranking	**5%**	Ranking
Teacher Credentials	**35%**		**40%**		**35%**		**35%**	
− Academic Degree	20%	Ranking	20%	Ranking	20%	Ranking	25%	Ranking
− Training and publications	10%	Ranking	10%	Ranking	5%	Ranking	5%	Ranking
− Teaching experience	5%	Ranking	10%	Ranking	10%	Ranking	5%	Ranking
Minimum Eligibility Threshold	− 60% of Eligibility Instruments		− 60% of Eligibility Instruments		− 60% of Logical-verbal and Pedagogical Knowledge Tests − 70% of Subject-Specific Knowledge Test		− Passed Psychometric Personality and Reasoning test − 70% of Subject-Specific Knowledge Test	
Issued	Dec-07		Jan-10		Nov-11		Jul-13	
Abolished	Jan-10		Nov-11		May-13		Apr-15	

3. THEORETICAL FRAMEWORK AND ANALYTIC APPROACH

To assess the effectiveness of the screening device of the new teacher recruitment process in Ecuador, I estimate parameters of the following value-added model of student achievement:

$$A_{it} - A_{it-1} = \rho_0 + \rho_1 TMBC_{ijmt} + \rho_2 T_{ijmt} + \rho_3 S_{it} + \rho_4 X_{it} + \rho_5 C_{ijmt} + \alpha_m + u_{it}$$

The subscripts denote students (*i*), classrooms (*j*), schools (*m*) and time (*t*). The relevant variables or vector of variables are defined as follows:

A_{it}	is achievement of student *i* in year *t* as measured by normalized test scores in reading or math by grade.
A_{it-1}	is previous achievement of the student *i* as measured by normalized test scores in reading or math by grade.
$TMBC_{ijmt}$	is an indicator of whether the student's current teacher achieved tenure through the new merit-based competition process.
T_{ijmt}	is a vector of additional teacher characteristics such as gender, academic degree and teacher experience.
S_{it}	is a vector of measurable student characteristics such as gender, age and attendance to preschool.
X_{it}	is a vector of family inputs such as parents' education and economic status.
C_{ijmt}	is an indicator of class size.
α_m	is a school fixed component.

The main focus of interest is the estimation of ρ_1 which is identified by the comparison of teachers who passed mandatory standardized tests and were tenured by the new merit-based recruitment process to those who did not. Therefore, it is a measure of the average differential in student achievement between these two types of teachers, holding other teacher, student, family, classroom and school factors constant. I estimate the parameters of both OLS and hierarchical linear regression models (HLM). Estimations of the value-added to student achievement model with a specification that places previous student achievement (A_{it-1}) at the right-hand side of the equation as a control variable were also conducted for comparison reasons[6]. The results were rather confirmatory and are available upon request.

[6] It is also possible to estimate a value-added to student achievement model with a specification that uses student achievement in the previous year (A_{it-1}), at the right-hand side of the equation as a control variable. Hanushek (1979) has argued that A_{it-1} should be on the right-hand side of the equation because of three main reasons: (1) empirically both measures of student achievement may have different scaling; (2) levels of starting achievement may influence achievement gain; and (3) correlated errors in achievement measurement may suggest such a

In carrying out the analysis described, there is a potential source of bias. Current research suggests that students are not randomly assigned to teachers (Clotfelter, Ladd, & Vigdor, 2006; Jackson et al., 2014). Teachers with stronger credentials tend to be matched to more-advantaged students and schools. The nonrandom matching is likely to produce bias in teacher coefficient estimates. It is not clear whether this is the case at the Ecuadorian schools[7]. Nonetheless, I use four strategies to address this problem. First, the OLS regression takes into account student prior achievement, which eliminates unmeasured school and family factors from the past and minimizes individual specific differences (Chetty, Friedman, & Rockoff, 2014a; E. Hanushek, 1971). Second, the OLS estimation includes school fixed effects that control for all school specific characteristics and therefore eliminates bias of nonrandom matching to schools. Third, I estimate the same model with a hierarchical linear regression, which takes into account a possible problem of dependence between individual observations at the school and classroom level. The HLM also allows each classroom and school to have a different intercept, which is equivalent to a model with classroom and school fixed effects. Finally, I estimate the model using a matched sample based on a propensity score, where a random assignment of students to teachers will be simulated in order to find causal average treatment effects. The Propensity Score Matching (PSM) approach allows a comparison of outcomes from policy participants to nonparticipants similar in all relevant pretreatment observable characteristics. Under the PSM identification, potential outcomes are also independent of treatment and are conditional on a balancing score such as the probability for an individual to participate in the treatment given his observed covariate (Caliendo & Kopeinig, 2008).

4. DATA AND DESCRIPTIVE STATISTICS

In 2011, the Ministry of Education of Ecuador and the Inter-American Development Bank (IDB) conducted a school survey to analyze the attitudes and pedagogical practices of teachers recruited by the new competitive recruitment process and their impact on educational outcomes. A random sample of 240 primary public schools from the coastal region of Ecuador[8] was chosen. Originally, the sample was drawn from primary schools that had at least two teachers from 2nd to 4th

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formulation. However, recent research suggests that there are statistical problems that arise when the lagged achievement variable (A_{it-1}) is included as a control on the right-hand side of the equation, since any correlation of achievement over time would make the variable endogenous (Clotfelter et al., 2007).

[7] School principals who participated in this study were asked about their process of student assignment to teachers. A third of them exclusively applied rules close to random assignment of students to teachers, such as the sequence in the enrolment list. Two thirds of the principals, however, applied a combination of random assignment and rules in favor of advantaged or disadvantaged students.

[8] Ecuador has four natural regions: Coastal (*Costa*), Andean (*Sierra*), Amazon (*Amazonía*) and Insular (*Islas Galápagos)*. Because of particular weather conditions of each Region, the school year starts at different months. The 2011-2012 school year in the Coastal and Insular Regions stared in April 2011 and ended in January 2012. The same school year in the Andean and Amazon Regions started in September 2011 and ended in June 2012.

grades[9], who had received tenure throughout the new competitive recruitment process. Nonetheless, when schools were actually visited, information from teachers who had not gone through these process was also collected[10] (PUCE, 2012). Schools were visited twice in the 2011-2012 school year, at end of the second and third quarter.

In total, 476 teachers were interviewed at the 240 primary public schools. Using information from the surveys, variables of teacher characteristics such as gender, years of teaching experience and level of education were generated. With respect to the educational level, a binary variable of whether the teacher had a university degree was also built, because Ecuadorian teachers obtain their teaching degrees from Technical Institutes[11] as well as from Universities. Furthermore, additional information about teachers' recruitment process from administrative records of the Ministry of Education of Ecuador was obtained. I had access to information of all teachers who received tenure from the start of the merit-based selection competitions to the beginning of the 2011-2012 school year at the coastal region. Once the information from the teachers' recruitment process to the original survey was matched, I ascertained that approximately a third of teachers surveyed were not granted tenure under the new competitive selection process at the time of the survey. From these teachers, about 88 percent were working at schools with temporary contracts and 12 percent were tenured before the application of the 2007 regulation. Neither group of teachers was tenured by the national competitive selection process that started at the end of 2007. From the approximately two thirds of teachers who achieved tenure through the new selection process, around 95 percent participated in competitions ruled by the original Ministerial Regulation of December 2007 (AM No. 438-07), while just about 5 percent participated in competitions organized under the Ministerial Regulation of January 2010 (AM No. 018-10). The additional administrative information obtained from the Ministry of Education makes this data set unique. Although it is similar to the one used by Cruz-Aguayo et al. (2017), it incorporates information from teachers who have not been recruited through the new competitive selection process and differentiates newly tenured teachers by the type of competition they faced. Consequently, my analyses would allow inferring causal effects of the reform.

From the interviewed teachers' classrooms, around 10 students were randomly selected and tested in reading with an adaptation of the Early Grade Reading Assessment (EGRA)[12] and in math

[9] The Ecuadorian 2nd grade of Basic Education is equivalent to the 1st grade of primary school in the ISCED classification. Children start the 2nd grade of Basic Education when they are around 6 years old.

[10] Researchers found at field that some preselected schools did not have two merit-based recruited teachers at the specific grades, but one. In order to complete the sample, primary teachers in 2nd to 4th grades were randomly chosen at the moment of the survey's application. Thus, teachers tenured throughout the new competitive recruitment process are oversampled in the survey.

[11] Non-university tertiary education.

[12] The EGRA version applied in Ecuador contained eight tasks or subtests: (1) letter name knowledge; (2) phonemic awareness; (3) letter sound knowledge; (4) familiar word reading; (5) unfamiliar word reading; (6) oral reading fluency with comprehension; (7) listening comprehension; and (8) dictation (PUCE, 2012).

with an adaptation of the Early Grade Mathematics Assessment (EGMA)[13]. EGRA is a tool used to measure students' progress toward learning to read, and it is administered orally to individual students (RTI International, 2009b, 2016). EGRA has been adapted for use in more than 65 countries and in over a 100 languages, and can be used for program evaluation purposes (Dubeck & Gove, 2015). Likewise, EGMA is an international assessment of early mathematics learning, with emphasis on numbers and operations (RTI International, 2009a, 2014). It is also an oral assessment individually administered to students. Internationally, EGMA has been used to measure learning change over time usually during the course of an program intervention (RTI International, 2014). In total, 4,520 students completed both assessments of EGRA and EGMA in the second and third quarter of the 2011-2012 school year. Total EGRA and EGMA scores were calculated and standardized by grade[14]. From the student questionnaires, information about students' gender, age in years and class size was also obtained.

The Ministry's survey included a questionnaire applied to students' parents or representatives[15] about their socio-economic context. In total, parents and representatives of 3,937 students were surveyed at schools. From the family questionnaires, I generated a variable of parents' years of education, a binary variable of whether the student attended to an Early Childhood Development (ECD) program, a family living standard indicator[16], and a binary variable of whether the family received a monthly cash transfer from the government called Human Development Bond (*Bono de Desarrollo Humano,* BDH)[17], which is a strong indicator of poverty in Ecuador. I used either the poverty indicator (BDH) or the family living standard indicator in the regression analysis, since these variables broadly represent the same concept[18].

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[13] The EGMA adaptation applied in Ecuador had six components: (1) number identification; (2) quantity discrimination; (3) recognition of number patterns (missing number); (4) addition and subtraction; (5) word problems; and (6) geometry (PUCE, 2012).

[14] The EGMA and EGRA Toolkits' guidelines were followed to calculate the scores for each of their subtasks, as well as the global EGMA and EGRA scores for the first and second assessment (RTI International, 2009a, 2009b, 2014, 2016).

[15] This category included: stepmother, stepfather, grandmother, grandfather, brother, sister, uncle, aunt, other relative, other non-relative.

[16] The family living standard indicator was based on the Global Multidimensional Poverty Index (MPI) developed by the UNDP Human Development Report Office, in collaboration with the Oxford Poverty & Human Development Initiative (OPHI) for the Human Development Reports (HDRs) (Alkire et al., 2016). It aggregates the following households' characteristics: access to electricity, improved sanitation and safe drinking water, type of flooring, cooking fuel and assets ownership.

[17] The Human Development Bond (BDH) is the largest cash transfer program in Latin America for households living in poverty. A poverty score indicator is used to determine households' eligibility for BDH transfers in Ecuador. Information about household composition, education levels, work, dwelling characteristics and access to services is aggregated into the poverty score indicator by principal components. Poverty censuses to gather this information and update the indicator and households' eligibility have been conducted in 2000/02, 2007/08 and 2013/14 (Araujo, Bosh, & Schady, 2016)

[18] The main findings of the regression analyses estimated with the poverty indicator (BDH) did not differ from estimations conducted with the family living standard indicator instead.

Additional information about the schools' characteristics was provided by principals. The survey had information about: area, whether the school was multi-grade[19] or complete, enrolment, repetition and dropout rates, among others.

The final data set resulted from matching student, teacher, family and school surveys. I was able to match 4,347 students to their teachers and schools. Of these, 3,661 students (84.22 percent) provided complete family context information.

Table 2 reports sample statistics of selected student, teacher and school characteristics for the whole sample, as well as by whether the teacher was tenured through a merit-based competition (henceforth, TMBC) and by whether the child came from a poor household (BDH receiver). Approximately 69 percent of the students in the sample are taught by a TMBC teacher and about 75 percent can be considered poor. On average, students assigned to TMBC teachers have significantly lower reading (EGRA) and math (EGMA) scores at the base line tests, come from parents with less years of education and poorer families. There are no statistically significant differences regarding students' gender, age and attendance to ECD programs between the two groups. With respect to teacher characteristics, the proportion of TMBC teachers who have university degrees is significantly higher. Nonetheless, there is no significant difference in years of teaching experience. Finally, the class size of TMBC teachers is significantly smaller, but the proportion of TMBC teachers at multi-grade schools is significantly higher. The descriptive statistics presented do not support the assumption that teachers with stronger credentials were matched to more-advantaged students. We can rather see the opposite. Therefore, if there are indeed selection processes in the assignment of students to teachers, we would expect the estimates of teacher characteristics to be biased downwards instead of upwards.

Looking at students from poor households, Table 2 shows that they, on average, have significantly lower reading and math results at their base line tests. These students are also older, come from parents with less years of education and face lower living standard conditions. Also, the proportion of students from poor families assigned to TMBC teachers is significantly higher, their class size smaller and their attendance to multi-grade schools higher.

[19] Multi-grade schools are primary schools where teachers have to teach two or more student grades in the same class. Even though multi-grade schools are not prevalent in Ecuador, they can be found in rural and distant communities.

Table 2: Sample Characteristics

	Complete Sample	Tenured by New Merit-based Competition (TMBC)			Household is poor (BDH)		
		YES	NO	Difference	YES	NO	Difference
Student:							
Prior Reading Score	0.026	-0.018	0.122	-0.140***	-0.065	0.294	-0.359***
	(0.016)	(0.020)	(0.030)	(0.036)	(0.019)	(0.033)	(0.038)
Prior Math Score	0.021	-0.003	0.075	-0.078**	-0.061	0.261	-0.322***
	(0.016)	(0.020)	(0.030)	(0.036)	(0.019)	(0.032)	(0.037)
Female	0.492	0.487	0.503	-0.016	0.495	0.484	0.010
	(0.008)	(0.010)	(0.015)	(0.018)	(0.010)	(0.016)	(0.019)
Age (years)	7.942	7.946	7.933	0.012	7.999	7.773	0.226***
	(0.021)	(0.025)	(0.037)	(0.045)	(0.025)	(0.038)	(0.046)
Attended ECD	0.784	0.783	0.786	-0.004	0.779	0.798	-0.018
	(0.007)	(0.008)	(0.012)	(0.015)	(0.008)	(0.013)	(0.015)
Teacher:							
Female	0.882	0.881	0.885	-0.004	0.870	0.917	-0.047***
	(0.005)	(0.006)	(0.009)	(0.011)	(0.006)	(0.009)	(0.011)
University Degree	0.700	0.714	0.667	0.047***	0.693	0.719	-0.026
	(0.008)	(0.009)	(0.014)	(0.017)	(0.009)	(0.015)	(0.017)
Years of Experience	10.790	10.751	10.876	-0.126	10.873	10.545	0.328
	(0.104)	(0.117)	(0.212)	(0.242)	(0.120)	(0.208)	(0.240)
TMBC	0.691				0.721	0.602	0.119***
	(0.008)				(0.009)	(0.016)	(0.018)
Family:							
Parents years of education	8.812	8.553	9.390	-0.838***	8.214	10.568	-2.354***
	(0.061)	(0.072)	(0.113)	(0.134)	(0.065)	(0.132)	(0.147)
Family Living Standard Indicator	0.002	-0.076	0.176	-0.252***	-0.122	0.368	-0.490***
	(0.016)	(0.021)	(0.026)	(0.033)	(0.020)	(0.026)	(0.033)
Household is poor (BDH)	0.746	0.779	0.673	0.105***			
	(0.007)	(0.008)	(0.014)	(0.016)			
School:							
Class size	29.629	28.121	32.991	-4.870***	28.706	32.342	-3.637***
	(0.158)	(0.185)	(0.279)	(0.335)	(0.183)	(0.299)	(0.351)
Complete	0.812	0.800	0.837	-0.036***	0.791	0.872	-0.081***
	(0.006)	(0.008)	(0.011)	(0.014)	(0.008)	(0.011)	(0.013)
Observations	3661	2528	1133	.	2732	929	.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses

5. RESULTS

5.1. OLS and HLM Estimations of TMBC Teachers' Effects

Table 3 reports the estimated effects of TMBC teachers on student achievement gains in reading and math. Columns 1 and 5 present the result of the OLS model estimation for reading and math with student, family, classroom controls and school fixed effects. In this first estimation I do not take into account other teacher characteristics such as academic degree and experience, because one could argue that they were already part of the competitive recruitment process. Columns 2 and 6 present the OLS estimates for reading and math after including controls for teacher characteristics. These additional controls do not importantly change the estimates. Similarly, columns 3 and 7, and columns 4 and 8 present the results of the three-level HLM estimations for reading and math[20], first without and then with controls for other teacher characteristics. All the model specifications show that TMBC teachers do not have a statistically significant impact on student learning gains in reading or math, when compared to non-TMBC teachers. The only teacher characteristic that has a significant positive impact is whether the teacher holds a university degree, according to the HLM estimations.

The effectiveness of the new competitive teacher recruitment process in Ecuador may vary by student background. Several studies have found that differences in socioeconomic status are strongly associated with variations in children's cognitive and language outcomes. In Ecuador, Schady et al., (2015) found that the differences in language development between children of high and low socioeconomic status are statistically significant, substantially large and constant throughout elementary school[21]. Thus, there is an ongoing debate on how much highly qualified teachers can do to close the gap between socioeconomically advantaged and disadvantaged students (Borman & Kimball, 2005; Boyd et al., 2008; Phillips, 2010).

Table 4 presents the effect estimates of TMBC teachers on student achievement gains in reading, sorted by student households' poverty condition. Columns 1 and 5 present the result of the OLS estimation with student, family, classroom controls and school fixed effects, but without controls for other teacher characteristics, for poor and non-poor student households respectively. Columns 2 and 6 report OLS estimates with a full set of controls. Columns 3 and 7 report HLM estimates without additional teacher characteristic controls, and columns 4 and 8 present them with a full set of controls, for poor and non-poor student households respectively. We observe a marginally significantly positive effect of TMBC teachers on reading achievement gains for students who live in poverty in the HLM estimation without additional teacher controls. However, all other estimations show that TMBC teachers seem to have no significant effect on reading for students who come from either poor or non-poor households. The effect of whether the teacher has a university degree remains positive and significant in the HLM regression for students living in poverty, similar to the findings before. None of the other teacher characteristics have any significant effect on students from poor or non-poor households in reading.

Table 5 reports the results for student achievement gains in math sorted by student household's poverty condition, following the same structure of Table 4. There, again, appears to be no significant effect of TMBC teachers on math learning gains for students that come from poor or non-poor families. Consistently, the only teacher characteristic that has a positive significant effect on students' achievement from poor households is whether the teacher has a university degree. None of the teacher characteristics have any significant effect on students from non-poor households.

[20] I also introduce a school-specific effect in this model, which is an indicator of whether the school is complete or multi-grade. The effect improved model fitness, but overall results and significance levels do not change.

[21] For example, the difference in language development between children in the richest and poorest quartiles is 1.21 standard deviations in rural Ecuador.

Table 3: Estimates of the Effects of TMBC Teachers on Reading (EGRA) and Math (EGMA) Achievement Gains

	Reading				Math			
	(1) OLS	(2) OLS	(3) HLM	(4) HLM	(5) OLS	(6) OLS	(7) HLM	(8) HLM
Teacher:								
TMBC	0.085	0.092	0.058	0.048	-0.075	-0.074	-0.002	-0.009
	(0.091)	(0.090)	(0.049)	(0.049)	(0.066)	(0.065)	(0.046)	(0.047)
Female		-0.009		0.043		-0.104		-0.025
		(0.093)		(0.063)		(0.087)		(0.063)
University Degree		0.109		0.121**		0.073		0.095**
		(0.071)		(0.048)		(0.067)		(0.048)
Years of Experience		0.012		-0.002		0.008		0.004
		(0.016)		(0.010)		(0.014)		(0.010)
Years of Experience		-0.000		-0.000		-0.000		-0.000
Squared		(0.000)		(0.000)		(0.000)		(0.000)
Student:								
Female	0.034	0.037	0.031	0.031	-0.019	-0.016	-0.014	-0.013
	(0.033)	(0.033)	(0.031)	(0.031)	(0.035)	(0.035)	(0.033)	(0.033)
Age	0.034*	0.036**	0.020	0.020	-0.018	-0.019	-0.017	-0.016
	(0.018)	(0.018)	(0.016)	(0.015)	(0.016)	(0.016)	(0.014)	(0.014)
Attended ECD	0.103**	0.106**	0.114***	0.115***	0.029	0.032	0.019	0.021
	(0.048)	(0.047)	(0.043)	(0.043)	(0.045)	(0.045)	(0.041)	(0.041)
Family:								
Parents years of education	0.009	0.009	0.008	0.008	0.006	0.006	0.006	0.006
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Household is poor (BDH)	-0.020	-0.019	-0.015	-0.012	-0.006	-0.006	0.009	0.009
	(0.042)	(0.042)	(0.038)	(0.038)	(0.047)	(0.048)	(0.043)	(0.043)
School:								
Class size	0.003	0.002	-0.002	-0.003	0.000	-0.001	-0.004*	-0.005**
	(0.007)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
Complete			0.051	0.043			0.052	0.049
			(0.061)	(0.060)			(0.055)	(0.056)
var (School)			0.037***	0.033***			0.047***	0.045***
			(0.014)	(0.014)			(0.013)	(0.013)
var (Classroom)			0.074***	0.074***			0.023***	0.022***
			(0.019)	(0.019)			(0.014)	(0.014)
var (Residual)			0.855***	0.856***			0.914**	0.914**
			(0.035)	(0.035)			(0.042)	(0.042)
Observations	3661	3661	3661	3661	3661	3661	3661	3661
R^2	0.141	0.142			0.124	0.124		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard error

Table 4: Estimates of the Effects of TMBC Teachers on Reading (EGRA) Achievement Gains by Student Poverty Condition

	Poor Household				Non-poor Household			
	(1) OLS	(2) OLS	(3) HLM	(4) HLM	(5) OLS	(6) OLS	(7) HLM	(8) HLM
Teacher:								
TMBC	0.154	0.163	0.099*	0.088	-0.092	-0.109	-0.033	-0.028
	(0.103)	(0.101)	(0.055)	(0.054)	(0.197)	(0.200)	(0.074)	(0.074)
Female		-0.020		0.011		-0.039		0.136
		(0.105)		(0.068)		(0.168)		(0.114)
University Degree		0.126		0.146***		-0.058		0.042
		(0.087)		(0.054)		(0.142)		(0.075)
Years of Experience		0.006		-0.006		0.007		-0.010
		(0.019)		(0.011)		(0.026)		(0.017)
Years of Experience Squared		-0.000		0.000		-0.000		0.000
		(0.001)		(0.000)		(0.001)		(0.001)
Student:								
Female	0.061	0.065*	0.058	0.058	0.006	0.006	-0.049	-0.048
	(0.039)	(0.038)	(0.036)	(0.036)	(0.079)	(0.080)	(0.063)	(0.063)
Age	0.056***	0.057***	0.037**	0.037**	-0.077	-0.079	-0.070**	-0.069**
	(0.018)	(0.018)	(0.016)	(0.016)	(0.052)	(0.053)	(0.032)	(0.032)
Attended ECD	0.083	0.085	0.099**	0.099**	0.134	0.133	0.144*	0.142*
	(0.054)	(0.054)	(0.049)	(0.049)	(0.108)	(0.108)	(0.077)	(0.077)
Family:								
Parents years of education	0.006	0.006	0.004	0.004	0.018	0.018	0.016*	0.016*
	(0.007)	(0.007)	(0.006)	(0.006)	(0.012)	(0.012)	(0.008)	(0.008)
School:								
Class size	0.003	0.001	-0.001	-0.001	0.012	0.012	-0.006	-0.006
	(0.008)	(0.008)	(0.003)	(0.003)	(0.011)	(0.011)	(0.004)	(0.004)
Complete			0.030	0.020			0.106	0.091
			(0.062)	(0.060)			(0.122)	(0.123)
var (School)			0.042***	0.036***			0.044***	0.036***
			(0.018)	(0.018)			(0.038)	(0.040)
var (Classroom)			0.068***	0.067***			0.046**	0.051**
			(0.019)	(0.019)			(0.062)	(0.063)
var (Residual)			0.866***	0.867***			0.827***	0.827***
			(0.041)	(0.041)			(0.051)	(0.051)
Observations	2732	2732	2732	2732	929	929	929	929
R^2	0.162	0.163			0.326	0.326		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard errors

Table 5: Estimates of the Effects of TMBC Teachers on Math (EGMA) Achievement Gains by Student Poverty Condition

	Poor Household				Non-poor Household			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	HLM	HLM	OLS	OLS	HLM	HLM
Teacher:								
TMBC	-0.096	-0.079	0.019	0.018	-0.091	-0.173	-0.065	-0.067
	(0.066)	(0.067)	(0.050)	(0.051)	(0.173)	(0.178)	(0.077)	(0.077)
Female		-0.056		-0.006		-0.233		-0.104
		(0.090)		(0.061)		(0.207)		(0.168)
University Degree		0.143*		0.114**		-0.171		0.038
		(0.079)		(0.053)		(0.142)		(0.081)
Years of Experience		0.011		0.002		0.008		0.010
		(0.015)		(0.012)		(0.034)		(0.021)
Years of Experience Squared		-0.000		0.000		-0.001		-0.001
		(0.000)		(0.000)		(0.001)		(0.001)
Student:								
Female	0.002	0.007	0.006	0.006	-0.057	-0.057	-0.058	-0.059
	(0.039)	(0.039)	(0.036)	(0.036)	(0.092)	(0.092)	(0.072)	(0.071)
Age	-0.010	-0.009	-0.009	-0.008	-0.037	-0.050	-0.034	-0.035
	(0.017)	(0.017)	(0.015)	(0.015)	(0.046)	(0.045)	(0.029)	(0.029)
Attended ECD	0.046	0.049	0.034	0.034	0.028	0.034	-0.033	-0.028
	(0.051)	(0.050)	(0.046)	(0.046)	(0.116)	(0.115)	(0.083)	(0.083)
School:								
Class size	-0.001	-0.003	-0.004*	-0.005**	-0.006	-0.009	-0.005	-0.005
	(0.005)	(0.006)	(0.002)	(0.002)	(0.013)	(0.013)	(0.004)	(0.004)
Family:								
Parents years of education	0.008	0.008	0.008	0.008	-0.002	-0.004	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.009)	(0.009)
Complete			0.032	0.022			0.114	0.129
			(0.054)	(0.054)			(0.112)	(0.117)
var (School)			0.041***	0.040***			0.078***	0.083***
			(0.017)	(0.017)			(0.040)	(0.040)
var (Classroom)			0.023***	0.021***			0.018*	0.011
			(0.020)	(0.020)			(0.041)	(0.041)
var (Residual)			0.894**	0.894**			0.963	0.962
			(0.048)	(0.048)			(0.066)	(0.066)
Observations	2732	2732	2732	2732	929	929	929	929
R^2	0.142	0.144			0.296	0.304		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard errors

5.2. OLS and HLM Estimations of TMBC Teachers' Effects, accounting for Competition's Ministerial Regulation

As mentioned before, almost 95 percent of the TMBC teachers of the sample participated in competitions regulated by the original Ministerial Regulation of December 2007. The remaining 5 percent participated in competitions organized under the Ministerial Regulation of January 2010, which mainly differs from the 2007 Regulation by the timing and weight of the candidates' demonstration class. Table 6 reports the estimated effects of TMBC teachers on reading and math student achievement gains, differentiating by the Competition's Ministerial Regulation[22].

All the model specifications show that TMBC teachers who participated in competitions organized under the 2007 Regulation do not have a statistically significant effect on student learning gains in reading or math, when compared to non-TMBC teachers. Once again, the HLM estimates suggests that the only teacher characteristic that has a significant positive impact in reading and math achievement gains is whether the teacher holds a university degree.

Similar to the model estimations outlined before, the results in Table 7 and Table 8 differentiate by the household's poverty status. Results for reading achievement gains are presented in Table 7. We do observe that TMBC teachers of the 2007 Regulation have a positive effect on reading for students that come from poor households in both OLS and HLM regressions, at the 10 percent significance level. The results hold when additional teacher characteristics are taking into account as controls in the OLS and HLM estimations. For students living in poverty, having a TMBC teacher tenured under the 2007 Regulation is associated with between a 0.099 and 0.198 standard deviation gain in reading achievement over three months of instruction. In addition, the effect of whether the teacher has a university degree remains positive and significant in the HLM estimation for students living in poverty. By contrast, none of the teacher characteristics have any significant effect on students from non-poor households in reading. These results are in line with the findings of Boyd et al. (2008) and Phillips (2010) in the U.S. that showed that achievement gains of particularly socioeconomically disadvantaged students are more affected by their teacher qualifications.

This finding, however, is only observed for reading, not for math. From Table 8 we can see that there is no significant effect of having a TMBC teacher, irrespective of the type of competition. Once again, the only teacher characteristic that has a positive significant effect on math achievement gains is whether the teacher has a university degree, for students from poor households.

[22] Since there are very few observations from TMBC teachers who were granted tenure under the 2010 Regulation, the purpose of these estimations is to isolate the effect of the TMBC teachers granted tenure under the 2007 Regulation. Estimates of TMBC teachers that participated in competitions organized under the 2010 Rule cannot be considered robust because of the lack of a sufficient sample and should be taken with caution.

Table 6: Estimates of the Effects of TMBC Teachers on Reading (EGRA) and Math (EGMA) Achievement Gains, accounting for Competition's Ministerial Regulation

	Reading				Math			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	HLM	HLM	OLS	OLS	HLM	HLM
Teacher:								
TMBC Rule 438-07	0.141	0.148	0.072	0.060	-0.068	-0.068	0.005	-0.004
	(0.104)	(0.102)	(0.051)	(0.050)	(0.075)	(0.074)	(0.047)	(0.048)
TMBC Rule 018-10	-0.205*	-0.190	-0.126	-0.096	-0.109	-0.107	-0.090	-0.065
	(0.114)	(0.122)	(0.125)	(0.126)	(0.133)	(0.132)	(0.137)	(0.138)
Female		-0.015		0.044		-0.105		-0.025
		(0.094)		(0.064)		(0.087)		(0.063)
University Degree		0.103		0.113**		0.072		0.092*
		(0.070)		(0.049)		(0.068)		(0.047)
Years of Experience		0.013		-0.003		0.009		0.003
		(0.016)		(0.010)		(0.014)		(0.010)
Years of Experience Squared		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Student:								
Female	0.035	0.038	0.032	0.031	-0.019	-0.016	-0.013	-0.013
	(0.033)	(0.033)	(0.031)	(0.031)	(0.035)	(0.035)	(0.033)	(0.033)
Age	0.036**	0.038**	0.020	0.020	-0.018	-0.019	-0.017	-0.016
	(0.018)	(0.018)	(0.016)	(0.015)	(0.016)	(0.016)	(0.014)	(0.014)
Attended ECD	0.104**	0.107**	0.113***	0.114***	0.029	0.032	0.019	0.020
	(0.048)	(0.047)	(0.043)	(0.043)	(0.045)	(0.045)	(0.041)	(0.041)
Family:								
Parents years of education	0.009	0.009	0.008	0.008	0.006	0.006	0.006	0.006
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Household is poor (BDH)	-0.018	-0.018	-0.019	-0.015	-0.006	-0.006	0.007	0.008
	(0.042)	(0.042)	(0.038)	(0.038)	(0.047)	(0.048)	(0.043)	(0.043)
School:								
Class size	0.003	0.002	-0.002	-0.002	0.000	-0.001	-0.004*	-0.005**
	(0.007)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
Complete			0.053	0.046			0.054	0.050
			(0.060)	(0.059)			(0.054)	(0.055)
var (School)			0.037***	0.033***			0.046***	0.045***
			(0.014)	(0.014)			(0.013)	(0.013)
var (Classroom)			0.073***	0.073***			0.023***	0.022***
			(0.019)	(0.019)			(0.014)	(0.014)
var (Residual)			0.855***	0.856***			0.914**	0.914**
			(0.035)	(0.035)			(0.042)	(0.042)
Observations	3661	3661	3661	3661	3661	3661	3661	3661
R^2	0.142	0.143			0.124	0.124		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard error

Table 7: Estimates of the Effects of TMBC Teachers on Reading (EGRA) Achievement Gains by Student Poverty Condition, accounting for Competition's Ministerial Regulation

	Poor Household				Non-poor Household			
	(1) OLS	(2) OLS	(3) HLM	(4) HLM	(5) OLS	(6) OLS	(7) HLM	(8) HLM
Teacher:								
TMBC Rule 438-07	0.192*	0.198*	0.111**	0.099*	-0.028	-0.045	-0.013	-0.010
	(0.112)	(0.111)	(0.056)	(0.055)	(0.267)	(0.270)	(0.079)	(0.079)
TMBC Rule 018-10	-0.174	-0.140	-0.168	-0.123	-0.207	-0.222	-0.173	-0.156
	(0.112)	(0.118)	(0.145)	(0.143)	(0.233)	(0.232)	(0.153)	(0.156)
Female		-0.020		0.015		-0.046		0.134
		(0.106)		(0.069)		(0.169)		(0.115)
University Degree		0.118		0.136**		-0.052		0.032
		(0.087)		(0.055)		(0.142)		(0.077)
Years of Experience		0.006		-0.006		0.008		-0.011
		(0.019)		(0.011)		(0.026)		(0.017)
Years of Experience Squared		-0.000		0.000		-0.000		0.000
		(0.001)		(0.000)		(0.001)		(0.001)
Student:								
Female	0.061	0.065*	0.057	0.057	0.009	0.009	-0.046	-0.045
	(0.039)	(0.038)	(0.036)	(0.036)	(0.080)	(0.081)	(0.063)	(0.063)
Age	0.057***	0.058***	0.037**	0.037**	-0.075	-0.076	-0.070**	-0.069**
	(0.018)	(0.018)	(0.016)	(0.016)	(0.052)	(0.053)	(0.032)	(0.032)
Attended ECD	0.083	0.085	0.097**	0.097**	0.135	0.135	0.145*	0.143*
	(0.054)	(0.054)	(0.049)	(0.049)	(0.108)	(0.108)	(0.077)	(0.077)
Family:								
Parents years of education	0.006	0.006	0.004	0.004	0.018	0.018	0.017*	0.017**
	(0.007)	(0.007)	(0.006)	(0.006)	(0.012)	(0.012)	(0.009)	(0.009)
School:								
Class size	0.002	0.001	-0.000	-0.001	0.012	0.011	-0.005	-0.005
	(0.008)	(0.008)	(0.003)	(0.003)	(0.011)	(0.011)	(0.004)	(0.004)
Complete			0.033	0.023			0.110	0.096
			(0.062)	(0.059)			(0.121)	(0.122)
var (School)			0.041***	0.036***			0.046***	0.038***
			(0.018)	(0.018)			(0.037)	(0.039)
var (Classroom)			0.067***	0.067***			0.045**	0.050**
			(0.019)	(0.019)			(0.061)	(0.061)
var (Residual)			0.866***	0.867***			0.825***	0.825***
			(0.041)	(0.041)			(0.050)	(0.050)
Observations	2732	2732	2732	2732	929	929	929	929
R^2	0.163	0.164			0.326	0.327		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard errors.

Table 8: Estimates of the Effects of TMBC Teachers Math (EGMA) Achievement Gains by Student Poverty Condition, accounting for Competition's Ministerial Regulation

	Poor Household				Non-poor Household			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	HLM	HLM	OLS	OLS	HLM	HLM
Teacher:								
TMBC Rule 438-07	-0.109	-0.095	0.024	0.020	-0.042	-0.143	-0.060	-0.065
	(0.070)	(0.071)	(0.051)	(0.052)	(0.212)	(0.223)	(0.081)	(0.080)
TMBC Rule 018-10	0.017	0.058	-0.071	-0.024	-0.179	-0.225	-0.103	-0.080
	(0.148)	(0.174)	(0.167)	(0.166)	(0.302)	(0.284)	(0.173)	(0.167)
Female		-0.056		-0.005		-0.237		-0.104
		(0.090)		(0.061)		(0.208)		(0.168)
University Degree		0.147*		0.112**		-0.168		0.037
		(0.079)		(0.053)		(0.144)		(0.079)
Years of Experience		0.011		0.002		0.008		0.010
		(0.015)		(0.012)		(0.034)		(0.021)
Years of Experience Squared		-0.000		0.000		-0.001		-0.001
		(0.000)		(0.000)		(0.001)		(0.001)
Student:								
Female	0.002	0.007	0.006	0.006	-0.055	-0.056	-0.057	-0.059
	(0.039)	(0.039)	(0.036)	(0.036)	(0.092)	(0.093)	(0.072)	(0.072)
Age	-0.011	-0.009	-0.009	-0.008	-0.035	-0.049	-0.034	-0.035
	(0.018)	(0.017)	(0.015)	(0.015)	(0.047)	(0.046)	(0.029)	(0.029)
Attended ECD	0.046	0.049	0.033	0.034	0.029	0.035	-0.032	-0.028
	(0.051)	(0.050)	(0.047)	(0.046)	(0.116)	(0.115)	(0.083)	(0.083)
Family:								
Parents years of education	0.008	0.008	0.008	0.008	-0.002	-0.004	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.009)	(0.009)
School:								
Class size	-0.001	-0.003	-0.004*	-0.005*	-0.006	-0.009	-0.005	-0.005
	(0.005)	(0.006)	(0.002)	(0.002)	(0.013)	(0.013)	(0.004)	(0.004)
Complete			0.033	0.022			0.115	0.129
			(0.054)	(0.054)			(0.112)	(0.117)
var (School)			0.041***	0.040***			0.078***	0.083***
			(0.017)	(0.017)			(0.040)	(0.040)
var (Classroom)			0.023***	0.021***			0.019*	0.011
			(0.020)	(0.020)			(0.041)	(0.041)
var (Residual)			0.894**	0.894**			0.963	0.962
			(0.048)	(0.048)			(0.066)	(0.066)
Observations	2732	2732	2732	2732	929	929	929	929
R^2	0.142	0.144			0.297	0.304		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard errors.

5.3. OLS and HLM Estimations of Test-Screened Teachers

As previously describe, teacher candidates in Ecuador are required to pass national entrance tests before they can participate in merit-based selection competitions for tenure at public schools since 2007. Teacher candidates who pass entrance examinations become eligible candidates allowed to compete for teacher vacancies. In our school sample, approximately 67 percent of teachers had won merit-based competitions and consequently achieved tenure; however, almost 78 percent of teachers had already passed national entrance tests. This means that a group of non-tenured teachers were test-screened candidates in the process of applying to merit-based competitions for vacancies at public schools. In this section I analyze whether eligible candidates or test-screened teachers, regardless of their tenure status, produced significantly different results in reading or math compared to their peers who had not taken or passed the national entrance examinations.

Table 9 reports the estimated effects of test-screened teachers on reading and math student achievement gains. The OLS and HLM estimations that do not control for other teacher characteristics find a positive and marginally significantly effect of test-screened teachers on reading achievement gains. However, the effect disappears once additional teacher characteristics are controlled for. By contrast, no effect is found on math achievement gains. Once again, the HLM estimations suggests that the only teacher characteristic that has a significantly positive impact in reading and math achievement gains is whether the teacher holds a university degree.

The effects of test-screened teachers on reading and math achievement gains of students from poor and non-poor households were also estimated. Results of reading achievement gains are reported in Table 10 and those for math in Table 11. We do observe that test-screened teachers have a marginally significant positive effect on reading learning gains for students that come from poor households in both OLS and HLM regressions. For students living in poverty, having a test-screened teacher is associated with between a 0.100 and a 0.172 standard deviation gain in reading achievement over three months of instruction. The size of this effect is substantial, but the significance is just found at the 10 percent level.

By contrasts, results presented in Table 11 show that there is no significant effect of having a test-screened teacher on math learning gains for students from poor households and non-poor households. Once more, the effect of whether the teacher has a university degree remains positive and significant for reading and math in the HLM estimations for students living in poverty. None of the teacher characteristics have any significant effect on students from non-poor households in reading or math achievement gains.

Overall, results are similar to the ones observed in the estimations for TMBC teachers.

Table 9: Estimates of the Effects of Test-Screened Teachers on Reading (EGRA) and Math (EGMA) Achievement Gains

	Reading				Math			
	(1) OLS	(2) OLS	(3) HLM	(4) HLM	(5) OLS	(6) OLS	(7) HLM	(8) HLM
Teacher:								
Test-Screened	0.145*	0.141	0.093*	0.078	-0.036	-0.046	-0.023	-0.030
	(0.084)	(0.087)	(0.052)	(0.053)	(0.058)	(0.061)	(0.046)	(0.049)
Female		-0.012		0.039		-0.104		-0.024
		(0.094)		(0.063)		(0.087)		(0.063)
University Degree		0.092		0.120**		0.080		0.096**
		(0.070)		(0.049)		(0.068)		(0.048)
Years of Experience		0.012		-0.003		0.008		0.004
		(0.016)		(0.010)		(0.014)		(0.010)
Years of Experience Squared		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Student:								
Female	0.036	0.038	0.032	0.031	-0.019	-0.016	-0.014	-0.013
	(0.033)	(0.033)	(0.031)	(0.031)	(0.035)	(0.035)	(0.033)	(0.033)
Age	0.035*	0.036**	0.021	0.021	-0.018	-0.019	-0.017	-0.016
	(0.018)	(0.018)	(0.016)	(0.015)	(0.016)	(0.016)	(0.014)	(0.014)
Attended ECD	0.104**	0.107**	0.115***	0.115***	0.029	0.032	0.019	0.021
	(0.048)	(0.047)	(0.043)	(0.043)	(0.045)	(0.045)	(0.041)	(0.041)
Family:								
Parents years of education	0.009	0.009	0.008	0.008	0.006	0.006	0.006	0.006
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Household is poor (BDH)	-0.019	-0.019	-0.013	-0.011	-0.006	-0.006	0.009	0.009
	(0.042)	(0.042)	(0.038)	(0.038)	(0.047)	(0.047)	(0.043)	(0.043)
School:								
Class size	0.004	0.003	-0.002	-0.003	0.000	-0.001	-0.004**	-0.005**
	(0.007)	(0.007)	(0.003)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
Complete			0.054	0.046			0.052	0.049
			(0.061)	(0.060)			(0.055)	(0.056)
var (School)			0.038***	0.034***			0.047***	0.045***
			(0.014)	(0.014)			(0.013)	(0.013)
var (Classroom)			0.072***	0.073***			0.023***	0.022***
			(0.019)	(0.019)			(0.014)	(0.014)
var (Residual)			0.855***	0.856***			0.914**	0.914**
			(0.035)	(0.035)			(0.042)	(0.042)
Observations	3661	3661	3661	3661	3661	3661	3661	3661
R^2	0.142	0.143			0.123	0.124		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard errors.

Table 10: Estimates of the Effects of Test-Screened Teachers on Reading (EGRA) Achievement Gains by Student Poverty Condition

	Poor Household				Non-poor Household			
	(1) OLS	(2) OLS	(3) HLM	(4) HLM	(5) OLS	(6) OLS	(7) HLM	(8) HLM
Teacher:								
Test-Screened	0.173*	0.172*	0.116*	0.100*	0.050	0.051	0.023	0.021
	(0.097)	(0.101)	(0.059)	(0.060)	(0.186)	(0.189)	(0.079)	(0.078)
Female		-0.022		0.007		-0.022		0.137
		(0.107)		(0.068)		(0.164)		(0.113)
University Degree		0.106		0.145***		-0.042		0.039
		(0.089)		(0.054)		(0.146)		(0.075)
Years of Experience		0.005		-0.006		0.008		-0.012
		(0.019)		(0.012)		(0.026)		(0.017)
Years of Experience Squared		-0.000		0.000		-0.000		0.000
		(0.001)		(0.000)		(0.001)		(0.001)
Student:								
Female	0.062	0.065*	0.058	0.057	0.005	0.005	-0.048	-0.047
	(0.038)	(0.038)	(0.036)	(0.036)	(0.079)	(0.079)	(0.063)	(0.063)
Age	0.056***	0.057***	0.038**	0.037**	-0.077	-0.078	-0.070**	-0.069**
	(0.018)	(0.018)	(0.016)	(0.016)	(0.051)	(0.053)	(0.032)	(0.032)
Attended ECD	0.084	0.086	0.100**	0.099**	0.133	0.132	0.145*	0.143*
	(0.054)	(0.054)	(0.048)	(0.048)	(0.107)	(0.107)	(0.076)	(0.076)
Family:								
Parents years of education	0.006	0.006	0.004	0.004	0.018	0.018	0.016*	0.017*
	(0.007)	(0.007)	(0.006)	(0.006)	(0.012)	(0.012)	(0.009)	(0.008)
School:								
Class size	0.003	0.002	-0.001	-0.001	0.014	0.013	-0.005	-0.005
	(0.008)	(0.008)	(0.003)	(0.003)	(0.011)	(0.011)	(0.004)	(0.004)
Complete			0.035	0.024			0.108	0.093
			(0.062)	(0.060)			(0.122)	(0.123)
var (School)			0.043***	0.038***			0.044***	0.036***
			(0.018)	(0.018)			(0.038)	(0.040)
var (Classroom)			0.066***	0.066***			0.046**	0.051**
			(0.019)	(0.019)			(0.061)	(0.062)
var (Residual)			0.866***	0.867***			0.827***	0.828***
			(0.041)	(0.041)			(0.051)	(0.051)
Observations	2732	2732	2732	2732	929	929	929	929
R^2	0.163	0.164			0.326	0.326		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard errors.

Table 11: Estimates of the Effects of Test-Screened Teachers on Math (EGMA) Achievement Gains by Student Poverty Condition

	Poor Household				Non-poor Household			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	HLM	HLM	OLS	OLS	HLM	HLM
Teacher:								
Test-Screened	-0.023	-0.019	-0.001	0.004	-0.154	-0.203	-0.102	-0.125
	(0.056)	(0.062)	(0.047)	(0.050)	(0.165)	(0.167)	(0.091)	(0.092)
Female		-0.059		-0.006		-0.228		-0.101
		(0.091)		(0.062)		(0.201)		(0.167)
University Degree		0.147*		0.115**		-0.134		0.040
		(0.080)		(0.054)		(0.137)		(0.081)
Years of Experience		0.011		0.002		0.009		0.010
		(0.016)		(0.011)		(0.034)		(0.021)
Years of Experience Squared		-0.000		0.000		-0.001		-0.001
		(0.000)		(0.000)		(0.001)		(0.001)
Student:								
Female	0.002	0.007	0.006	0.006	-0.057	-0.058	-0.060	-0.062
	(0.039)	(0.039)	(0.036)	(0.036)	(0.092)	(0.092)	(0.072)	(0.071)
Age	-0.009	-0.008	-0.009	-0.008	-0.039	-0.053	-0.036	-0.038
	(0.017)	(0.017)	(0.015)	(0.015)	(0.046)	(0.045)	(0.029)	(0.029)
Attended ECD	0.045	0.048	0.034	0.034	0.026	0.032	-0.035	-0.030
	(0.051)	(0.050)	(0.046)	(0.046)	(0.116)	(0.116)	(0.083)	(0.083)
School:								
Class size	-0.000	-0.003	-0.004*	-0.005**	-0.007	-0.009	-0.005	-0.005
	(0.005)	(0.006)	(0.002)	(0.002)	(0.013)	(0.013)	(0.004)	(0.004)
Family:								
Parents years of education	0.008	0.008	0.008	0.008	-0.002	-0.003	0.001	0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.009)	(0.009)
Complete			0.032	0.023			0.104	0.117
			(0.054)	(0.054)			(0.111)	(0.116)
var (School)			0.042***	0.040***			0.079***	0.084***
			(0.017)	(0.017)			(0.039)	(0.039)
var (Classroom)			0.023***	0.020***			0.017*	0.009
			(0.020)	(0.020)			(0.041)	(0.041)
var (Residual)			0.894**	0.894**			0.963	0.961
			(0.048)	(0.048)			(0.065)	(0.065)
Observations	2732	2732	2732	2732	929	929	929	929
R^2	0.142	0.144			0.297	0.305		

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. OLS Models (1) (2) (5) and (6) estimated with school fixed effects and cluster standard errors at the school level. HLM Models (3) (4) (7) and (8) estimated with robust standard errors.

5.4. Propensity Score Matching (PSM) Estimations of TMBC Teachers' Effects

As previously discussed, TMBC teachers were not randomly allocated to students as a rule. Thus there is a potential source of bias in the previously presented estimations. In order to deal with the selection problem, I apply a PSM approach to estimate causal treatment effects by balancing the probability for a student to be assigned to a TMBC teacher based on observed characteristics. Furthermore, the PSM approach also undertakes the problematic over-representation of TMBC teachers in the sample.

For the PSM identification, I consider TMBC teachers are the "treatment." In a first model specification, I further consider that treatment selection is on the student, family and school observable characteristics of my original value-added model[23]. Under this model specification, TMBC teachers are the "treatment" regardless of their individual teacher characteristics such as gender, educational level and experience. The first model aims to reproduce a randomized experiment where TMBC teachers are a pure treatment. This model is going to be referred as the unconditional to teacher characteristics' model or unconditional model. In a second model specification, I consider that treatment selection is not only on the student, family and school observable characteristics, but also on other teacher observable characteristics. Under the second model specification, I intend to reproduce a randomized experiment where the treatment (TMBC teacher) was blocked by teacher observed characteristics. This model is going to be referred as full model.

In order to implement the PSM for both model specifications, first I estimate the probability of participation into the treatment with logit regressions, presented in Table A1 of the Appendix. According to both propensity score estimations, students whose parents had less years of education and came from poor households were more likely to be assigned to TMBC teachers. Once again, the evidence supports the idea that more vulnerable students were assigned to TMBC teachers.

In a second step of the PSM estimation for both model specifications, I apply three matching algorithms: i) nearest neighbour matching with replacement using one neighbour, ii) nearest neighbour matching with replacement using five neighbours and imposing a caliper, and iii) Gaussian Kernel matching. The algorithms group the most comparable students into treatment and control groups in order to estimate average treatment effects of TMBC teachers on student achievement gains in reading and math. The PSM algorithms also reduce imbalance in the pre-treatment covariates between the treated and control groups, thereby reducing the degree of model dependence and potential for bias. In order to assess whether the matching procedures have been successful in balancing the distribution of the observable relevant pre-treatment covariates in both the control and treatment groups, I estimate the following quality indicators: mean standardized bias, pseudo-R2 and joint significance before and after matching (Caliendo & Kopeinig, 2008).

[23] This assumption is referred to as unconfoundedness or conditional independence assumption (CIA).

Table 12 reports the PSM quality indicators for reading and math achievement gains for both model specifications. Colum 1 reports the unmatched sample indicators. Subsequently, column 2 reports quality indicators of the one nearest neighbour matching; column 3 of the five nearest neighbours matching and column 4 of the Gaussian Kernel matching. All matching algorithms reduce the mean standardized bias below 5 percent after matching, which is a sufficient balance measure. The pseudo-R2, which indicates how well the observable characteristics explain the participation probability, is smaller after matching for all procedures. Finally, the likelihood ratio test on the joint significance of all regressors in the logit model is rejected in all matching approaches after matching with the exception of the one nearest neighbour matching. Overall, the Gaussian Kernel matching outperforms the other approaches for reading and for math.

Table 12: PSM Quality Indicators before and after Matching for Reading and Math

	(1)	(2) PSM Nearest Neighbour (1)	(3) PSM Nearest Neighbour (5)	(4) PSM Kernel
Sample	Unmatched	Matched	Matched	Matched
Unconditional Model				
Mean Bias	16,1	3,8	2,2	1,7
Pseudo R2	0,051	0,003	0,001	0,000
LR chi2	231,42	20,03	5,09	3,47
p >chi2	0,000	0,006	0,649	0,838
Full Model				
Mean Bias	12.3	3.0	1.5	1.3
Pseudo R2	0.069	0.004	0.001	0.001
LR chi2	311.74	25.81	9.21	3.59
p >chi2	0.000	0.007	0.603	0.980

Table 13 reports the average treatment effects on the treated (ATT) and the average treatment effects (ATE) of TMBC teachers on reading and math achievement gains estimated with the three matching algorithms, for both model specifications. We do not find consistent evidence of a causal effect of TMBC teachers on reading or math achievement gains from the PSM estimations, either for the unconditional to teacher characteristics' model or for the full model.

Table 13: PSM Effects of TMBC Teacher on Reading (EGRA) and Math (EGMA) Achievement Gains

	Reading			Math		
	(1) PSM Nearest Neighbour (1)	(2) PSM Nearest Neighbour (5)	(3) PSM Kernel	(4) PSM Nearest Neighbour (1)	(5) PSM Nearest Neighbour (5)	(6) PSM Kernel
Unconditional Model						
ATT	0.091*	0.037	0.056	0.005	0.021	0.011
	(0.051)	(0.049)	(0.043)	(0.060)	(0.046)	(0.038)
ATE	0.076	0.044	0.058	-0.018	0.020	0.010
	(0.046)	(0.044)	(0.039)	(0.045)	(0.039)	(0.037)
Full Model						
ATT	0.015	0.045	0.050	-0.013	0.004	0.011
	(0.052)	(0.045)	(0.041)	(0.055)	(0.047)	(0.039)
ATE	0.008	0.049	0.048	-0.003	0.003	0.008
	(0.040)	(0.041)	(0.033)	(0.048)	(0.037)	(0.038)
N	3661	3661	3661	3661	3661	3661

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Bootstrapped standard errors for ATT and ATE. Unconditional model does not include additional teacher characteristics in PSM.

In order to identify causal effects of TMBC teachers on reading and math achievement gains of students from poor and non-poor households, I next construct a stratified PSM estimation with the same three matching algorithms for both model specifications. PSM quality indicators for reading and math achievement gains of students from poor and non-poor household samples are presented in Table A2 of the Appendix. Once again, the Gaussian Kernel matching outperforms the other approaches in both samples for reading and math in the unconditional and full model[24]. The one nearest neighbour matching does not meet the PSM quality indicators for balance; therefore, it results should be taken with caution.

Table 14 presents the ATT and the ATE of TMBC teachers on reading and math stratified by student poverty condition. Interestingly, among poor students, the ATT on reading achievement of having a TMBC teacher is positive and significant in both the unconditional and full models, according to the matching algorithms that balance the pre-treatment covariates of treated and control groups. A marginally significant ATE for reading is also consistently found by most matching algorithms in both models. Thus, the ATE of being assigned to a TMBC teacher rages between a 0.083 and a 0.093 standard deviation gain in reading achievement for a student living in poverty, under the Gaussian Kernel matching. Remarkably, the effect is similar in magnitude to the one found by the HLM estimations, but significant. Besides, no significant effect is found on students from non-poor households in reading, and no significant effect is found in math either for students from poor households or for students from non-poor households.

[24] That is, this algorithm obtains the lowest mean standardized bias, the lowest pseudo-R^2, and rejects joint significance of the regressors after matching.

Table 14: PSM Effects of TMBC Teacher on Reading (EGRA) and Math (EGMA) Achievement Gains, Stratified by Student Poverty Condition

	Poor Household			Non-Poor Household		
	(1) PSM Nearest Neighbour (1)	(2) PSM Nearest Neighbour (5)	(3) PSM Kernel	(4) PSM Nearest Neighbour (1)	(5) PSM Nearest Neighbour (5)	(6) PSM Kernel
			Reading			
Unconditional Model						
ATT	0.029	0.108**	0.092**	0.088	-0.003	-0.054
	(0.056)	(0.050)	(0.038)	(0.100)	(0.090)	(0.067)
ATE	0.043	0.093*	0.093*	0.062	-0.010	-0.040
	(0.046)	(0.048)	(0.048)	(0.090)	(0.077)	(0.070)
Full Model						
ATT	0.139**	0.094*	0.084*	-0.065	-0.069	-0.037
	(0.069)	(0.051)	(0.046)	(0.097)	(0.087)	(0.073)
ATE	0.109*	0.081	0.083*	-0.031	-0.045	-0.025
	(0.056)	(0.051)	(0.044)	(0.075)	(0.076)	(0.078)
			Math			
Unconditional Model						
ATT	0.062	0.049	0.033	-0.131	-0.071	-0.070
	(0.061)	(0.053)	(0.042)	(0.102)	(0.081)	(0.079)
ATE	0.052	0.041	0.033	-0.092	-0.044	-0.061
	(0.057)	(0.051)	(0.048)	(0.093)	(0.094)	(0.068)
Full Model						
ATT	0.050	0.031	0.038	-0.064	-0.072	-0.063
	(0.070)	(0.052)	(0.047)	(0.095)	(0.090)	(0.087)
ATE	0.037	0.027	0.033	-0.033	-0.030	-0.042
	(0.051)	(0.048)	(0.049)	(0.085)	(0.077)	(0.076)
N	2732	2732	2732	929	929	929

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Bootstrapped standard errors for ATT and ATE. Unconditional model does not include additional teacher characteristics in PSM.

The causal effects of TMBC teachers who participated in competitions ruled by the 2007 Regulation are also estimated for the unconditional and full models. In this case, students of TMBC teachers tenured under the 2007 Regulation are the treatment group and the control group corresponds to students assigned to other teachers that have not been tenured under any of the new merit-based competitions[25]. Table A3 of the Appendix reports the PSM quality indicators for reading and math achievement gains. Overall, the Gaussian Kernel matching outperforms the other approaches.

Table 15 presents the ATT and ATE of TMBC teachers tenured under the 2007 Regulation on reading and math achievement gains. The PSM estimations of the unconditional model show some evidence of a positive and significant ATT and ATE of these TMBC teachers on reading, however, the effects are not hold in the full model estimations. In contrast, we do not find any evidence of a causal effect of the corresponding TMBC teachers on math achievement gains.

[25] TMBC teachers tenured under the Ministerial Regulation of January 2010 and their students are not taken into account. They constitute a different treatment.

Table 15: PSM Effects of TMBC Teacher (2007 Regulation) on Reading and Math Achievement Gains

	Reading			Math		
	(1) PSM Nearest Neighbour (1)	(2) PSM Nearest Neighbour (5)	(3) PSM Kernel	(4) PSM Nearest Neighbour (1)	(5) PSM Nearest Neighbour (5)	(6) PSM Kernel
Unconditional Model						
ATT	0.074	0.095**	0.065	0.010	0.025	0.015
	(0.051)	(0.045)	(0.040)	(0.052)	(0.040)	(0.042)
ATE	0.053	0.088*	0.069*	0.028	0.022	0.015
	(0.039)	(0.045)	(0.036)	(0.047)	(0.043)	(0.038)
Full Model						
ATT	0.026	0.051	0.057	-0.020	0.024	0.016
	(0.053)	(0.047)	(0.039)	(0.066)	(0.045)	(0.048)
ATE	0.049	0.060	0.055	-0.012	0.022	0.013
	(0.048)	(0.045)	(0.036)	(0.049)	(0.042)	(0.044)
N	3548	3548	3548	3548	3548	3548

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Bootstrapped standard errors for ATT and ATE. Unconditional model does not include additional teacher characteristics in PSM

A stratified PSM estimation by poverty condition is also implemented to identify the causal effects of TMBC teachers tenured by the 2007 Regulation. Table A4 of the Appendix reports the PSM quality indicators for reading and math achievement gains. The Gaussian Kernel matching, again, outperforms the other approaches for reading and for math, for both samples of students from poor and non-poor households and in the two model specifications. Estimations of the one nearest neighbour matching algorithm should be taken with caution, since it does not achieve quality balance standards.

The ATT and ATE effects on reading and math achievement gains stratified by poverty condition are presented in Table 16. Noteworthy, all algorithms find positive and significant ATT and ATE effects in the unconditional model. Under the Gaussian Kernel matching, the ATT and ATE of having a TMBC teacher tenured under the 2007 Regulation on reading among poor students are positive, significant and substantial in both model specifications. The ATE of being assigned to this type of TMBC teacher rages between a 0.088 and a 0.099 standard deviation gain in reading achievement for a student living in poverty. The size of this effect is almost identical to the one found by the HLM estimation, but stronger in terms of significance. In addition, no significant effect is found on students from non-poor households in reading achievement and no significant effect is found in math.

Table 16: PSM Effects of TMBC Teacher (2007 Regulation) on Reading (EGRA) and Math (EGMA) Achievement Gains, Stratified by Student Poverty Condition

	Poor Household			Non-Poor Hosehold		
	(1) PSM Nearest Neighbour (1)	(2) PSM Nearest Neighbour (5)	(3) PSM Kernel	(4) PSM Nearest Neighbour (1)	(5) PSM Nearest Neighbour (5)	(6) PSM Kernel
			Reading			
Unconditional Model						
ATT	0.148***	0.108**	0.097**	-0.122	-0.086	-0.048
	(0.055)	(0.052)	(0.045)	(0.118)	(0.097)	(0.075)
ATE	0.118**	0.099**	0.099**	-0.097	-0.052	-0.030
	(0.055)	(0.049)	(0.047)	(0.083)	(0.075)	(0.069)
Full Model						
ATT	0.089	0.081	0.089*	0.021	-0.016	-0.031
	(0.062)	(0.049)	(0.050)	(0.112)	(0.095)	(0.082)
ATE	0.084	0.085	0.088**	0.018	-0.007	-0.022
	(0.056)	(0.052)	(0.042)	(0.083)	(0.076)	(0.066)
			Math			
Unconditional Model						
ATT	0.108	0.047	0.037	-0.126	-0.081	-0.054
	(0.068)	(0.055)	(0.052)	(0.105)	(0.096)	(0.084)
ATE	0.098**	0.051	0.036	-0.090	-0.060	-0.044
	(0.049)	(0.049)	(0.045)	(0.073)	(0.078)	(0.072)
Full Model						
ATT	0.011	-0.000	0.043	-0.091	-0.068	-0.064
	(0.068)	(0.059)	(0.045)	(0.110)	(0.095)	(0.089)
ATE	0.003	0.000	0.038	-0.021	-0.003	-0.034
	(0.063)	(0.050)	(0.043)	(0.092)	(0.080)	(0.084)
N	2680	2680	2680	868	868	868

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Bootstrapped standard errors for ATT and ATE. Unconditional model does not include additional teacher characteristics in PSM such as gender, university degree and teaching experience

Finally, I use the PSM approach to estimate the causal effect of test-screened teachers, regardless of their tenure status, on reading and math achievement gains for the unconditional and full models. Under this scenario, test-screened teachers are the “treatment.” Table A5 of the Appendix reports the PSM quality indicator for reading and math. All matching algorithms achieve sufficient balance measures, but the five nearest neighbours matching outperforms the other approaches.

Table 17 presents the ATT and ATE of test-screened teachers for reading and math achievement gains, estimated with the three matching algorithms. Interestingly, we do find strong evidence of a significantly positive causal effect of test-screened teachers on reading achievement gains, particularly for the fully specified model. The ATE of being assigned to a test-screened teacher rages between a 0.082 and a 0.098 standard deviation in reading, under the five nearest neighbours matching algorithm. By contrast, no significant effect is found in math.

Table 17: PSM Effects of Test-Screened Teacher on Reading (EGRA) and Math (EGMA) Achievement Gains

	Reading			Math		
	(1) PSM Nearest Neighbour (1)	(2) PSM Nearest Neighbour (5)	(3) PSM Kernel	(4) PSM Nearest Neighbour (1)	(5) PSM Nearest Neighbour (5)	(6) PSM Kernel
Unconditional Model						
ATT	0.065	0.084*	0.079*	-0.028	-0.019	-0.016
	(0.068)	(0.045)	(0.044)	(0.056)	(0.055)	(0.040)
ATE	0.062	0.082*	0.080**	-0.032	-0.024	-0.018
	(0.051)	(0.043)	(0.041)	(0.057)	(0.046)	(0.042)
Full Model						
ATT	0.087	0.108*	0.100**	0.057	0.054	0.014
	(0.069)	(0.058)	(0.043)	(0.059)	(0.052)	(0.050)
ATE	0.088*	0.098**	0.094**	0.035	0.037	0.007
	(0.049)	(0.048)	(0.044)	(0.050)	(0.049)	(0.047)
N	3661	3661	3661	3661	3661	3661

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Bootstrapped standard errors for ATT and ATE. Unconditional model does not include additional teacher characteristics in PSM.

I also implement a stratified PSM estimation by poverty condition to identify the causal effects of test-screened teachers for both the unconditional and full model. Table A6 of the Appendix reports the PSM quality indicators for reading and math achievement gains. The Gaussian Kernel matching outperforms the other approaches for the unconditional to teacher characteristics' model, for both samples of students from poor and non-poor households. The five nearest neighbours matching is the algorithm that outperforms the other approaches in the full model, for both samples of students from poor and non-poor households. The algorithm that performs the worst is the one nearest neighbour matching, particularly for the sample of students from poor households.

Table 18 reports the ATT and ATE effects of test-screened teachers on reading and math achievement gains stratified by poverty condition. Significantly positive ATT and ATE are found for reading. For a student living in poverty, the ATE of being assigned to a test-screened teacher rages between a 0.097 and a 0.107 standard deviation in reading achievement gains under the Gaussian Kernel matching, and between a 0.090 and a 0.110 standard deviation under the five nearest neighbours matching. These effects are very similar in magnitude to the ones found by the HLM estimations. No significant effect is found on students from non-poor households.

Likewise, no significant effect is consistently found on math achievement, either for students of poor households or for students of non-poor households.

Table 18: PSM Effects of Test-Screened Teacher on Reading (EGRA) Achievement Gains, Stratified by Student Poverty Condition

	Poor Household			Non-Poor Household		
	(1) PSM Nearest Neighbour (1)	(2) PSM Nearest Neighbour (5)	(3) PSM Kernel	(4) PSM Nearest Neighbour (1)	(5) PSM Nearest Neighbour (5)	(6) PSM Kernel
			Reading			
Unconditional Model						
ATT	0.061	0.088	0.106**	0.092	0.011	-0.006
	(0.069)	(0.057)	(0.045)	(0.112)	(0.083)	(0.072)
ATE	0.071	0.090*	0.107**	0.073	0.013	-0.003
	(0.062)	(0.054)	(0.047)	(0.089)	(0.079)	(0.081)
Full Model						
ATT	0.141*	0.120*	0.101**	0.159	0.074	0.047
	(0.074)	(0.064)	(0.045)	(0.112)	(0.102)	(0.081)
ATE	0.127*	0.110*	0.097*	0.108	0.046	0.040
	(0.067)	(0.058)	(0.050)	(0.094)	(0.087)	(0.068)
			Math			
Unconditional Model						
ATT	0.102	0.012	0.016	-0.134	-0.146	-0.147
	(0.063)	(0.046)	(0.048)	(0.130)	(0.099)	(0.090)
ATE	0.084	0.009	0.013	-0.142	-0.125	-0.130
	(0.053)	(0.055)	(0.055)	(0.108)	(0.097)	(0.083)
Full Model						
ATT	0.105	0.102	0.052	-0.195*	-0.130	-0.115
	(0.080)	(0.068)	(0.052)	(0.112)	(0.105)	(0.096)
ATE	0.080	0.079	0.043	-0.185*	-0.127	-0.106
	(0.085)	(0.065)	(0.053)	(0.110)	(0.101)	(0.096)
N	2732	2732	2732	929	929	929

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Bootstrapped standard errors for ATT and ATE. Unconditional model does not include additional teacher characteristics in PSM such as gender, university degree and teaching experience

6. CONCLUSIONS

In order to improve teacher quality, the Ecuadorian government requires teacher candidates to pass national standardized tests since 2007. Passing these exams was necessary to participate in Ecuador's merit-based selection competitions for tenure at public schools. Was the new competitive teacher recruitment process effective as a screening device? Different estimations of a value-added to student achievement model show that, overall, teachers who were granted tenure through the new recruitment process were *not* more effective in raising student achievement in reading or math at the 2011-2012 academic year in the first grades of primary school. However, merit-based and competitive tenure substantially improved reading skills for students living in poor households (BDH receivers). The finding is consistent in OLS, HLM as well as PSM estimations, particularly for teachers that were granted tenure through competitions organized under the Ministerial Regulation of December 2007.

The PSM estimations show that students from poor families had a ATE of at least a 0.083 standard deviation gain in reading achievement when taught by a teacher tenured under the new recruitment system, and a 0.088 standard deviation gain when taught by a teacher tenured under the 2007 Regulation, over three months of instruction.

The effects on reading and math of test-screened teachers, regardless of their tenure status, are also explored. OLS, HLM as well as PSM estimations suggest that test-screened teachers were more effective in raising student achievement in reading, particularly for students living in poverty. The ATE of a test-screened teacher was at least a 0.080 standard deviation gain in reading achievement for a regular student, and at least a 0.090 standard deviation gain in reading achievement for a student living in a poor household, according to the PSM estimations.

In contrast to earlier findings (Cruz-Aguayo et al., 2017), this study offers crucial evidence of positive and significant effects of teachers selected and tenured through Ecuador's new competitive recruitment policy on the outcomes of students living in poverty. The sizes of these effects are substantial when compared to other studies conducted in Ecuador[26].

Some policy implications can be drawn from the research results. On the one hand, the results show that the Ecuadorian reform partially succeeded in raising the quality and equity of the educational system between 2007 and 2011. The policy had a positive significant and substantial effect on reading achievement gains for students living in poverty. This particular population should not be ignored because it is concentrated among public schools. On the other hand, the results suggest that the policy was unable to recruit candidates that outperformed their peers in raising students' math achievement or in producing better results for non-poor students in primary schools. Thus, the quality of the tests and instruments used in the merit-based selection process should be carefully evaluated in order to improve the process and it effectiveness. Further research is needed to evaluate the policy effects beyond its first four years of implementation.

In the context of Latin America, this study helps to inform the current debate about teacher quality and the effectiveness of competitive recruitment based on candidates' knowledge and competencies tests. The results suggest that a competitive teacher recruitment policy could lead to improve academic outcomes, particularly of socioeconomically disadvantaged students.

[26] In their study about teacher quality in Kindergarten in Ecuador, Araujo et al., (2016) found that teacher's lagged class observation score (CLASS) was associated with between a 0.05 and 0.07 standard deviation higher end of year tests scores in; children with inexperienced (less than 3 years of experience) teachers had test scores that were 0.17 standard deviation lower; none of the other teacher characteristics analyzed (tenure status, IQ, the Big five dimensions of personality, inhibitory control and attention, and early circumstances) were associated with student learning.

REFERENCES

Alkire, S., Conconi, A., Robles, G., Roche, J. M., Santos, E., Seth, S., & Vaz, A. (2016). The Global Multidimensional Poverty Index (MPI): 5-year methodological note.

Angrist, J. D., & Guryan, J. (2008). Does teacher testing raise teacher quality? Evidence from state certification requirements. *Economics of Education Review*. https://doi.org/10.1016/j.econedurev.2007.03.002

Araujo, M. C., Bosh, M., & Schady, N. (2016). *Can cash transfers help households escape an inter-generational poverty trap? NBER Working Paper Series*. Cambridge, MA. https://doi.org/10.3386/w22670

Araujo, M. C., Carneiro, P., Cruz-Aguayo, Y., & Schady, N. (2016). Teacher Quality and Learning Outcomes in Kindergarten. *The Quarterly Journal of Economics*, *131*(3), 1415–1453. https://doi.org/10.1093/qje/qjw016

Asamblea Nacional del Ecuador. LEY ORGÁNICA DE EDUCACIÓN INTERCULTURAL, Pub. L. No. N° 417, Registro Oficial Segundo Suplemento (2011).

Borman, G. D., & Kimball, S. M. (2005). Teacher Quality and Educational Equality: Do Teachers with Higher Standards-Based Evaluation Ratings Close Student Achievement Gaps? *The Elementary School Journal*, *106*(1), 3–20. https://doi.org/10.1086/496904

Boyd, D., Lankford, H., Loeb, S., Rockoff, J., & Wyckoff, J. (2008). The narrowing gap in New York City teacher qualifications and its implications for student achievement in high-poverty schools. *Journal of Policy Analysis and Management*, *27*(4), 793–818. https://doi.org/10.1002/pam.20377

Bruns, B., & Luque, J. (2015). *Great Teachers: How to raise student learning in Latin American and the Caribbean*. Washington D.C.: The World Bank. https://doi.org/10.1596/978-1-4648-0151-8

Brutti, Z., & Sánchez, F. (2017). *Does Better Teacher Selection Lead to Better Students? Evidence from a Large Scale Reform in Colombia* (No. 11). *Documentos CEDE*. Bogotá: Centro de Estudios sobre Desarrollo Económico. Retrieved from https://ideas.repec.org/p/col/000089/015350.html

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014a). Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates. *American Economic Review*, *104*(9), 2593–2632. https://doi.org/10.1257/aer.104.9.2593

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014b). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review*, *104*(9), 2633–2679. https://doi.org/10.1257/aer.104.9.2633

Clotfelter, C. T., Ladd, H. F., & Vigdor, J. L. (2006). Teacher-Student Matching and the Assessment of Teacher Effectiveness. *Journal of Human Resources*, *41*(April 2005), 778–820. https://doi.org/10.2307/40057291

Clotfelter, C. T., Ladd, H. F., & Vigdor, J. L. (2007). Teacher credentials and student achievement: Longitudinal analysis with student fixed effects. *Economics of Education Review*, *26*(6), 673–682. https://doi.org/10.1016/j.econedurev.2007.10.002

Cruz-Aguayo, Y., Ibarrarán, P., & Schady, N. (2017). Do tests applied to teachers predict their effectiveness? *Economics Letters*, *159*, 108–111. https://doi.org/10.1016/J.ECONLET.2017.06.035

Dubeck, M. M., & Gove, A. (2015). The early grade reading assessment (EGRA): Its theoretical foundation, purpose, and limitations. *International Journal of Educational Development*, *40*, 315–322. https://doi.org/10.1016/j.ijedudev.2014.11.004

Elacqua, G., Hincapié, D., Vegas, E., & Alfonso, M. (2017). *Profesión: Profesor en América Latina. ¿Por qué se perdió el prestigio docente y cómo recuperarlo?* Inter-American Development Bank. https://doi.org/10.18235/0000901

Estrada, R. (2015). *Rules Rather than Discretion : Teacher Hiring and Rent Extraction* (EUI Working Paper No. MWP 2015/14). San Domenico di Fiesole: European University Institute. Retrieved from http://cadmus.eui.eu/handle/1814/36535

Glewwe, P. W., Hanushek, E. A., Humpage, S. D., & Ravina, R. (2014). School Resources and Educational Outcomes in Developing Countries: A review of the literature from 1990 to 2010. In Paul Glewwe (Ed.), *Education Policy in Developing Countries* (pp. 13–64). Chicago and London: The University of Chicago Press. https://doi.org/10.3386/w17554

Goldhaber, D. (2007). Everyone's Doing It, but What Does Teacher Testing Tell Us about Teacher Effectiveness? *The Journal of Human Resources*, *XLII*(4), 765–794. https://doi.org/10.2307/40057329

Goldhaber, D., & Anthony, E. (2007). Can Teacher Quality Be Effectively Assessed? National Board Certification as a Signal of Effective Teaching. *The Review of Economics and Statistics*, *89*(1), 134–150. https://doi.org/10.1162/rest.89.1.134

Goldhaber, D. D., & Brewer, D. J. (1997). Why Don't Schools and Teachers Seem to Matter? Assessing the Impact of Unobservables on Educational Productivity. *Journal of Human Resources*, *32*(3), 505–523. https://doi.org/10.2307/146181

Hanushek, E. (1971). Teacher Characteristics and Gains in Student Achievement: Estimation Using Micro Data. *The American Economic Review*. American Economic Association. https://doi.org/10.2307/1817003

Hanushek, E. A. (1979). Conceptual and Empirical Issues in the Estimation of Educational Production Functions. *The Journal of Human Resources*, *14*(3), 351–388. Retrieved from http://www.jstor.org/stable/145575

Hanushek, E. A. (2003). The Failure of Input-based Schooling Policies*. *The Economic Journal*, *113*(485), F64–F98. https://doi.org/10.1111/1468-0297.00099

Hanushek, E. A. (2011). The economic value of higher teacher quality. *Economics of Education Review*, *30*(3), 466–479. https://doi.org/10.1016/j.econedurev.2010.12.006

Hanushek, E. A., & Rivkin, S. G. (2006a). Chapter 18 Teacher Quality. *Handbook of the Economics of Education*, *2*, 1051–1078. https://doi.org/10.1016/S1574-0692(06)02018-6

Hanushek, E. A., & Rivkin, S. G. (2006b). Teacher Quality. In E. Hanushek and F. Welch (Ed.), *Handbook of the Economics of Education* (pp. 1052–1075). North-Holland. https://doi.org/10.1016/S1574-0692(06)02018-6

Hanushek, E. A., & Rivkin, S. G. (2012). The Distribution of Teacher Quality and Implications for Policy. *Annual Review of Economics*, *4*(1), 131–157. https://doi.org/10.1146/annurev-economics-080511-111001

Hanushek, E. A., & Woessmann, L. (2012). Schooling, educational achievement, and the Latin American growth puzzle. *Journal of Development Economics*, *99*, 497–512. https://doi.org/10.1016/j.jdeveco.2012.06.004

Harris, D. N., & Sass, T. R. (2007). The effects of NBPTS- Certified Teachers on Student. *Journal of Policy Analysis and Management*. WileyAssociation for Public Policy Analysis and Management. https://doi.org/10.2307/29738986

Hill, H. C., Rowan, B., & Loewenberg Ball, D. (2005). Effects of Teachers' Mathematical Knowledge for Teaching on Student Achievement. *American Educational Research Journal; Summer*, *42*(2), 371–406.

Jackson, C. K., Rockoff, J. E., & Staiger, D. O. (2014). Teacher Effects and Teacher-Related Policies. *Annual Review of Economics*, *6*, 801–25. https://doi.org/10.1146/annurev-economics-080213-040845

Kane, T. J., Rockoff, J. E., & Staiger, D. O. (2008). What does certification tell us about teacher effectiveness? Evidence from New York City. *Economics of Education Review*, *27*, 615–631. https://doi.org/10.1016/j.econedurev.2007.05.005

Krueger, A. B. (1999). Experimental estimates of education production functions. *The Quarterly Journal of Economics*, *114*(2), 497–532. Retrieved from https://academic.oup.com/qje/article-abstract/114/2/497/1844226

McKinsey & Company. (2007). How the world's best-performing schools come out on top. Retrieved December 13, 2017, from http://mckinseyonsociety.com/how-the-worlds-best-performing-schools-come-out-on-top/

Metzler, J., & Woessmann, L. (2010). *The impact of teacher subject knowledge on student achievement: Evidence from within-teacher within-student variation* (CESinfo working paper Economics of Education No. 3111). *ECONSTOR*. Retrieved from http://www.sciencedirect.com/science/article/pii/S0304387812000478

Ministerio de Educación del Ecuador (MINEDUC). Acuerdo Ministerial 438_07: NORMAS DE LOS CONCURSOS DE MÉRITOS Y OPOSICIÓN PARA EL INGRESO AL MAGISTERIO NACIONAL, Pub. L. No. 438_07, Acuerdos Ministeriales 10 (2007). Quito: Ministerio de Educación del Ecuador.

Ministerio de Educación del Ecuador (MINEDUC). Acuerdo Ministerial 363: NORMAS PARA LLENAR VACANTES A TRAVÉS DEL SISTEMA DE RUEDAS DE CAMBIOS, Pub. L. No. 363, Acuerdos Ministeriales 6 (2008). Ministerio de Educación del Ecuador.

Ministerio de Educación del Ecuador (MINEDUC). Acuerdo Ministerial 018-10: NORMATIVA PARA LOS CONCURSOS DE MÉRITOS Y OPOSICIÓN PARA LLENAR VACANTES DEL MAGISTERIO NACIONAL, Pub. L. No. 0118, Acuerdos Ministeriales 12 (2010). Ministerio de Educación del Ecuador.

Ministry of Education of Ecuador (MINEDUC). (2012). Ecuador 2007-2012 a Transformation in Education, presentation at the Inter-American Development Bank. Washington: 2012.

Murnane, R. J. (1975). *The impact of school resources on the learning of inner city children*. Ballinger Pub. Co.

Nye, B., Konstantopoulos, S., & Hedges, L. V. (2004). How Large Are Teacher Effects? *Educational Evaluation and Policy Analysis*, *26*(3), 237–257. https://doi.org/10.3102/01623737026003237

Organisation for Economic Co-Operation and Development (OECD). Programme for International Student Assessment (PISA). (2014). *PISA 2012 Results in Focus*. Retrieved from http://www.oecd-ilibrary.org/education/pisa_19963777

Organisation for Economic Co-Operation and Development (OECD). Programme for International Student Assessment (PISA). (2016). *PISA 2015 Results in Focus*. Retrieved from http://www.oecd.org/pisa/

Phillips, K. J. R. (2010). What Does “Highly Qualified” Mean for Student Achievement? Evaluating the Relationships between Teacher Quality Indicators and At-Risk Students’ Mathematics and Reading Achievement Gains in First Grade. *Elementary School Journal*, *110*(4), 464–493. https://doi.org/10.1086/651192

Pontificia Universidad Católica del Ecuador (PUCE). (2012). *Informe Final: Levantamiento de Datos en Establecimientos Educacionales para Estudio sobre Prácticas Pedagógicas, Características y Actitudes del Docente y Mejoras en el Proceso Educativo del Ecuador*.

Rivkin, S. G., Hanushek, E. A., & Kain, J. F. (2005). Teachers, Schools, and Academic Achievement. *Econometrica*, *73*(March, 2005), 417–458. https://doi.org/10.2307/3598793

Rockoff, J. E. (2004). The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data. *The American Economic Review*, *94*(2), 247–252. Retrieved from http://www.jstor.org/stable/3592891

Rockoff, J. E., Jacob, B. A., Kane, T. J., & Staiger, D. O. (2011). *CAN YOU RECOGNIZE AN EFFECTIVE TEACHER WHEN YOU RECRUIT ONE?* (Vol. 6). Association for Education Finance and Policy.

RTI International. (2009a). *Early Grade Mathematics Assessment (EGMA): A Conceptual Framework Based on Mathematics Skills Development in Children*. Retrieved from https://www.globalpartnership.org/content/early-grade-mathematics-assessment-egma-conceptual-framework-based-mathematics-skills

RTI International. (2009b). *Early Grade Reading Assessment Toolkit*. Retrieved from https://globalreadingnetwork.net/eddata/early-grade-reading-assessment-toolkit-2009

RTI International. (2014). *Early Grade Mathematics Assessment (EGMA) Toolkit*. Retrieved from https://shared.rti.org/content/early-grade-mathematics-assessment-egma-toolkit

RTI International. (2016). *Early Grade Reading Assessment (EGRA) Toolkit*. Washington D.C. Retrieved from https://www.globalreadingnetwork.net/resources/early-grade-reading-assessment-egra-toolkit-second-edition

Schady, N., Behrman, J., Araujo, M. C., Azuero, R., Bernal, R., Bravo, D., … Vakis, R. (2015). Wealth Gradients in Early Childhood Cognitive Development in Five Latin American Countries. *Journal of Human Resources*, *50*(2), 446–463. https://doi.org/10.3368/jhr.50.2.446

APPENDIX

Table A1: Propensity Score Estimation of Assignment to TMBC Teacher, Unconditional to Teacher Characteristics' Model and Full Model

	TMBC Propensity Score	
	(1)	(2)
	Unconditional Model	Full Model
Teacher:		
Female		0.071
		(0.117)
University Degree		0.278^{***}
		(0.082)
Years of Experience		0.143^{***}
		(0.020)
Years of Experience Squared		-0.005^{***}
		(0.001)
Student:		
Female	-0.068	-0.079
	(0.074)	(0.075)
Age	-0.005	0.007
	(0.031)	(0.031)
Attended ECD	0.019	0.043
	(0.092)	(0.093)
Family:		
Parents years of education	-0.022^{**}	-0.019^{*}
	(0.011)	(0.011)
Household is poor (BDH)	0.336^{***}	0.337^{***}
	(0.085)	(0.086)
School:		
Class size	-0.052^{***}	-0.057^{***}
	(0.004)	(0.004)
Complete	0.114	0.211^{**}
	(0.101)	(0.103)
Constant	2.309^{***}	1.240^{***}
	(0.328)	(0.371)
N	3661	3661
chi2	232.010^{***}	311.532^{***}
bic	4363.628	4316.928

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses. Propensity Score estimated with logit

Table A2: PSM Quality Indicators before and after Matching for Reading and Math by Student Poverty Condition

	Poor Household				Non-Poor Household			
		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel
Sample	Unmatched	Matched	Matched	Matched	Unmatched	Matched	Matched	Matched
Unconditional Model								
Mean Bias	12,8	6,3	4,3	2,2	14,5	3,8	2,9	1,8
Pseudo R2	0,042	0,005	0,002	0,001	0,043	0,002	0,002	0,000
LR chi2	135,38	28,80	13,32	4,04	53,67	3,36	2,48	0,76
p >chi2	0,000	0,000	0,038	0,672	0,000	0,763	0,870	0,993
Full Model								
Mean Bias	11.9	5.1	2.6	1.9	15.5	5.1	3.6	1.5
Pseudo R2	0.063	0.006	0.002	0.001	0.066	0.008	0.003	0.001
LR chi2	205.24	30.05	9.05	5.21	82.77	12.25	5.10	1.51
p >chi2	0.000	0.001	0.527	0.877	0.000	0.269	0.884	0.999

Table A3: PSM Quality Indicators before and after Matching for Reading and Math, when Treatment is TMBC Teacher (2007 Regulation)

		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel
Sample	Unmatched	Matched	Matched	Matched
Unconditional Model				
Mean Bias	17,9	4,3	2,1	1,8
Pseudo R2	0,06	0,002	0,001	0,001
LR chi2	268,28	16,48	7,18	4,01
p>chi2	0,000	0,021	0,411	0,779
Full Model				
Mean Bias	13,9	3,2	2,5	1,5
Pseudo R2	0,081	0,004	0,002	0,001
LR chi2	361,36	28,88	11,42	3,92
p>chi2	0,000	0,002	0,408	0,972

Table A4: PSM Quality Indicators before and after Matching for Reading and Math by Student Poverty Condition, when Treatment is TMBC Teacher (2007 Regulation)

	Poor Household				Non-Poor Household			
		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel
Sample	Unmatched	Matched	Matched	Matched	Unmatched	Matched	Matched	Matched
Unconditional Model								
Mean Bias	13,7	5,6	3,0	2,3	18,1	4,8	2,6	2,2
Pseudo R2	0,045	0,005	0,001	0,001	0,059	0,005	0,001	0,001
LR chi2	144,94	26,48	7,04	4,20	69,50	6,50	1,27	0,75
p >chi2	0,000	0,000	0,317	0,650	0,000	0,369	0,973	0,993
Full Model								
Mean Bias	12,6	3,6	1,8	1,8	18,1	6,6	2,8	2,2
Pseudo R2	0,069	0,005	0,001	0,001	0,089	0,008	0,002	0,001
LR chi2	220,07	25,71	6,08	4,56	105,37	10,77	2,70	1,64
p >chi2	0,000	0,004	0,809	0,919	0,000	0,376	0,988	0,998

Table A5: PSM Quality Indicators before and after Matching for Reading and Math, when Treatment is Test-Screened Teachers

		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel
Sample	Unmatched	Matched	Matched	Matched
Unconditional Model				
Mean Bias	15,3	3,6	1,6	1,8
Pseudo R2	0,040	0,003	0,000	0,001
LR chi2	147,26	20,05	3,07	6,45
p>chi2	0,000	0,005	0,879	0,488
Full Model				
Mean Bias	16,4	2,8	2,3	2,9
Pseudo R2	0,075	0,002	0,002	0,002
LR chi2	277,95	19,30	12,31	17,05
p>chi2	0,000	0,056	0,341	0,106

Table A6: PSM Quality Indicators before and after Matching for Reading and Math by Student Poverty Condition, when Treatment is Test-Screened Teachers

	Poor Household				Non-Poor Household			
		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel		PSM Nearest Neighbour (1)	PSM Nearest Neighbour (5)	PSM Kernel
Sample	Unmatched	Matched	Matched	Matched	Unmatched	Matched	Matched	Matched
Unconditional Model								
Mean Bias	13,9	6,4	2,9	1,7	21,2	3,8	4,2	4,1
Pseudo R2	0,036	0,006	0,002	0,001	0,057	0,003	0,003	0,004
LR chi2	96,64	34,85	11,25	4,07	57,20	5,52	4,89	7,58
p >chi2	0,000	0,000	0,081	0,667	0,000	0,479	0,558	0,270
Full Model								
Mean Bias	17,2	4,6	2,5	3,4	16,1	5,2	2,8	3,5
Pseudo R2	0,082	0,006	0,003	0,003	0,071	0,008	0,003	0,005
LR chi2	220,01	35,24	15,18	14,98	71,54	14,95	5,43	9,37
p >chi2	0,000	0,000	0,126	0,133	0,000	0,134	0,861	0,497

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