UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ

Colegio de Administración y Economía

Natural Disasters and Secondary School Performance: Evidence from the Coastal-Ecuadorian Earthquake

Valeria Anabel Garcés Padilla

Economía

Trabajo de fin de carrera presentado como requisito

para la obtención del título de

Economista

Quito, 10 de mayo de 2021

UNIVERSIDAD SAN FRANCISCO DE QUITO USFQ
Colegio de Administración y Economía

HOJA DE CALIFICACIÓN
DE TRABAJO DE FIN DE CARRERA

Natural Disasters and Secondary School Performance: Evidence from the Coastal-Ecuadorian Earthquake

Valeria Anabel Garcés Padilla

Nombre del profesor, Título académico **Sergio Parra-Cely, Ph.D.**

Quito, 10 de mayo de 2021

© DERECHOS DE AUTOR

Nombres y apellidos: Valeria Anabel Garcés Padilla

Código: 00200811

Cédula de identidad : 1722314638

Lugar y fecha: Quito, 10 de mayo de 2021

ACLARACIÓN PARA PUBLICACIÓN

UNPUBLISHED DOCUMENT

AGRADECIMIENTOS

Agradezco a mi tutor de tesis Sergio Parra, quién con su guía y compromiso contribuyó a este trabajo de investigación, la culminación de mi proceso de aprendizaje en la Universidad San Francisco de Quito. A Pablo Vega, por su apoyo incondicional, enseñanzas, motivación, tiempo y trabajo que me brindó desde mi primer día de universidad. Agradezco especialmente a mis padres por su amor infinito y esfuerzo diario, me han concedido la oportunidad de cumplir mis metas y sueños, son mi motivación para superarme a en todo lo que hago. A mi hermana, tío y abuelos por confiar en mí y compartir mis aventuras de universidad como si fueran suyas. Finalmente, a mis amigos y futuros colegas, que han hecho de la universidad, la mejor etapa de mi vida. Entre risas, fiestas, preocupaciones y llantos, me llevo los mejores recuerdos y a mi mejor amigo, quién me enseñó a amar.

RESUMEN

Se emplea una estrategia empírica de diferencias en diferencias con emparejamiento para determinar el impacto del terremoto ecuatoriano de 2016 sobre el desempeño de los estudiantes graduados de secundaria pertenecientes a la región costa. Escuelas con características sociodemográficas similares se vincularon a través de pareamiento por puntaje de propensión para garantizar el supuesto de tendencias paralelas requerido dentro de este contexto. Después del shock, el efecto se distingue por año y difiere según la fuente de financiamiento de las escuelas. Los puntajes estandarizados del examen de egreso de la escuela secundaria implementado a nivel nacional (*Ser Bachiller*), fueron utilizados para cuantificar el efecto sobre el desempeño de los estudiantes, así como el ausentismo registrado. Debido a la redistribución de estudiantes en las escuelas, su rendimiento empeoró en escuelas privadas y mixtas después del terremoto, sin embargo, los estudiantes de las escuelas públicas, mejoraron levemente sus puntajes promedio. El nivel de educación de los padres es un determinante clave en la composición demográfica de las escuelas después del terremoto. El absentismo sigue siendo insignificante, mientras que los puntajes estandarizados se reducen significativamente en escuelas privadas y mixtas después de 2016. Este estudio proporciona evidencia de los efectos negativos potencialmente heterogéneos sobre los desastres naturales en la acumulación de capital humano.

Palabras clave: *terremoto, examen Ser Bachiller, puntaje del examen, escuelas públicas, escuelas privadas, escuelas fiscomisionales, absentismo, puntajes del examen*

ABSTRACT

A matching difference-in-differences empirical strategy is used to asses the impact of the 2016 Ecuadorian earthquake on high school graduate student performance within the coastal region. Schools with similar socio-demographic characteristics were linked through Propensity Score Matching in order to guarantee the parallel trend assumption required in this setting. After the shock, the effect is distinguished per year and differs according to the schools' funding source. The standardized scores of the nationwide implemented high-school exit exam (*Ser Bachiller*) were used to quantify the effect on student performance as well as registered absenteeism. Due to educational sorting, student performance worsened in private and mixed schools after the earthquake, nevertheless, students from public schools slightly improved their average scores. Parental level of education is a key determinant in school demographic composition post-earthquake. Absenteeism remains insignificant, while the standardized scores get significantly reduced in private and mixed schools after 2016. This study provides further evidence of potential heterogeneous negative effects of natural disasters on human capital accumulation.

Key words: *earthquake, SB exam, exam scores, school performance, public schools, private schools, mixed schools, absenteeism, exam scores*

TABLE OF CONTENTS

1 Introduction

Natural disasters do not only provoke short-run economic crashes, but also generate long-lasting effects on poverty reduction, urban safety, prosocial behavior, infrastructure development, and educational attainments (Benson & Clay, 2003). There is no doubt that unforeseen natural disasters cause permanent consequences in cognitive development and human stress levels (Human Factors and Ergonomics Society, 2012). However, the mechanisms and changes behind those negative shocks remain uncertain because they diverge depending on the type of natural shock and people's level of exposition. For instance, there is an ongoing discussion about the magnitude of negative vs. positive social outcomes after an earthquake (Fergusson et al., 2014; Filipski et al., 2019; Ripoll Gallardo, 2018).

In April 16th of 2016, an unexpected shock temporarily changed the lifestyle of thousands of Ecuadorian students. An earthquake with a severe Mercalli intensity of VIII and a Moment magnitude scale of 7,8 hit the country. Its epicenter was approximately 17 miles (27 km) from Pedernales and Muisne, towns belonging to Manabí and Esmeraldas provinces, respectively. The seism not only affected the Ecuadorian coast in a strong way, but also it was felt in the Andean region. More than 10.000 people were injured, and hundreds perished. As this natural disaster severely damaged infrastructure and the provision of public goods and services in the region, it is natural to question the extent by which this earthquake affected schooling outcomes of students directly exposed to such negative shock.

The most common response taken into action by governments is reallocation, hence public policies and resource distribution play a key role during the seism's aftermath. Understanding the different effects produced by an earthquake is essential for developing countries due to the universal and unexpected hazard vulnerability. Accidents can occur globally at any moment; education can eventually be interrupted. Therefore, it is important to acknowledge the intensity of an earthquake as a major factor when determining differences in youth development across the distinct geographical areas impacted by it. As a result, the research outcomes and conclusions do not only result useful for Ecuadorian authorities, but also for risk and education policy makers in terms of public policy design and prevention.

This research project focuses on identifying the causal effect of an exogenous natural disaster in education through the educational test scores of the Ecuadorian national standardized exam “Ser Bachiller” from 2014 to 2019. The key heterogeneity factors include global and per subject exam performance and absenteeism. This study implements a matching difference-in-differences (DID) approach to measure the effect of an earthquake’s exposure (a natural experiment) on schooling outcomes. The students’ sample comes from a combined repeated cross-sectional data that was obtained from 1) Ecuador’s National Institute of Educational Evaluation (test scores and socio-economic mandatory survey) and 2) the National Geophysical Institute (reports of the earthquake’s intensity per canton).

The quasi-experimental DID design was chosen because of its approach for obtaining the causal effect of an exogenous intervention (the earthquake) within a population (senior high school students), that includes treated schools that were the most affected by the earthquake vs. control schools that were not affected. In this study, omitted variables changing over time and the preexisting differences within the coastal schools before the 2016 earthquake represent an empirical challenge. Both features may violate the parallel trend assumption required for the DID estimator methodology and omitted variables may generate selection bias on the results.

To overcome the empirical challenge aforementioned, treated and control units are also linked through Propensity Score Matching. The PSM technique constructs a more reliable counterfactual (through a Probit model) using information gathered at cantonal level from the 2010 Ecuadorian National Census including school identifiers per canton. The matching aligns most of the parallel trends of public schools, eliminates omitted variables fixed in time, and reduces the bias due to cofounding variables. Still, some differences remain within the trends of private and mixed schools.

Regardless of the challenge previously described, the results show evidence of educational sorting in public, private, and mixed schools after the seism. There are no significant effects on the average exam scores and absenteeism rates in schools under the coastal regime at an aggregate level. Differentiating schools per funding source helps to unmask heterogeneous effects otherwise not evident. Students from non-public schools (private and mixed funded schools) significantly worsened their global average performance 2 deciles relative to students enrolled in public schools after the shock. Private school students significantly performed worse in Mathematics, Language and Natural Sciences, while mixed school students performed poorly in Natural and Social Sciences. Absenteeism of the SB Exam increased during the year of the earthquake, although there are no significant differences in this outcome between public, private, and mixed schools.

The mechanisms behind these results suggest sorting interpreted as positive selection towards public schools of students coming from families with higher socio-economic status after 2016. When classifying schools per funding source, the causal effect of the seism on exam scores is revealed.

The scheme of this paper unfolds as follows. Section 2 accounts relevant research about the impact of natural disasters among different educational contexts. Section 3 describes the Ecuadorian earthquake of 2016, the country's educational system, and the consequences of the shock on coastal education. Section 4 reports the sources of information, final data, sample selection, and summary statistics. Section 5 explains the empirical strategy in depth. Section 6 discusses the main results of the model and its specifications. Section 7 analyzes the possible transmission mechanisms. Last, section 8 concludes.

2 Related Literature

This research fits in the literature that studies the effects of natural disasters on academic performance. If there is an exogenous, unexpected event that impacts the economy, this reflects on education, school dropouts, academic scores, and collective well-being. Several contributions suggest that exposure to natural disasters influences human capital formation (Baez et al., 2011; Cuaresma, 2010; McDermott, 2012; Paudel & Ryu, 2018). Not only governments, but also international organizations like the Asian Development Bank and the World Bank (2005) have studied post-disaster effects for education policy making (Andrabi et al., 2020). Therefore, authorities require this information, especially in developing countries with modest probabilities of recovery from a natural catastrophe, to reduce the impact of natural disasters.

For this purpose, it is relevant to acknowledge the different effects between primary vs. secondary education after unavoidable causalities. Regarding primary schooling outcomes, previous research has documented a negative link between natural disasters and academic scores (Gibbs et al., 2019; Kousky, 2016). Children's test scores certainly get worse after an earthquake; this is shown with a DID model (Sulistyaningrum, 2017). Between 6 and 12 years old, social, cognitive, and in-class behaviour is found to be negatively associated after shocks like floods, explosions, and hurricanes (Conteh, 2015; Imberman et al., 2012; Smilde-van den Doel et al., 2006). Primary education is an important group which is left with long-term effects and it is not analyzed in this study.

Secondary education is as important as primary education. After graduating from high school, students may choose to integrate into the labor force of a society or continue their education in a tertiary level. Educational attainment on secondary schooling can be negatively influenced by extreme climate change and natural disasters worldwide, in a significant way (for evidence on this, see Espinoza et al., 2015; Hermida, 2011; Kim, 2010; Onigbinde, 2018; and Santos, 2010). For example, school closings may be unexpected and during winter season exam performance may be marginally reduced (Marcotte, 2007; Marcotte & Hemelt, 2008). Like the first results presented in this paper, Beaglehole et al. (2017) could not detect evidence of school disengagement and lower academic grades after the Canterbury earthquakes. This does not occur in higher education, where Di Prieto estimated a DID that shows that the L'Aquila earthquake altered factors as academic continuity, university access and house availability at L'Aquila University, the shock reduced the probability of on-time graduation by 6,6% on average (2018).

Inside the Ecuadorian context, Rosales-Rueda studied prenatal exposure to the "El Niño" phenomenon between 1997-1998 on children's cognition, health, and capital formation, also through a DID estimation (2018). Focusing on the repercussion of the 2016 Ecuadorian earthquake there is a qualitative analysis which covers basic to secondary schooling, proving increased absenteeism of teachers and students (Medina, 2019). Accordingly, the study that most closely relates in spirit with recent research on the impact of the 2016 Ecuadorian earthquake on school attendance is Arias (2019). He points out that school enrollment dropped the following academic year after the shock using a DID and a Tobit model approach. Nevertheless, his study does not address changes in school cognitive achievement measured through an standardized exam and does not acknowledge the potential heterogeneity effects across different types of schools.

Definitely, there is no concluding evidence around the globe which determines that earthquakes have a significant negative effect on educational results because of national and worldwide heterogeneity present among educational systems. This study demonstrates that in developing countries (i.e. Ecuador), natural shocks impact schools gradually depending on their type of funding. Relative to other studies in which the effect of natural disasters is slightly negative and non-significant, during the earthquake of April 16th it is confirmed that it did not affect students in the same way because of their different socio-economic backgrounds. This research shows that the global effect in Ecuadorian schools is masked by certain socioeconomic mechanisms which stroke schools heterogeneously through self-selection (*sorting*); it congested public schools after the seism and improved their average scores relative to private and mixed schools as observed in the data. The evidence presented in this paper shows that government intervention after a natural disaster is key in education and should be formulated and implemented differently across all schools. In addition, the results are relevant because investment in education is key for Ecuador's future growth, development, and student access to equal opportunities.

3 Background Information

One of Ecuador's most destructive catastrophes occurred in 2016 and its devastating impact in several areas of the coastal region is visible even to this day. Education, health, and living standards are some of the institutional pillars that were affected by the earthquake which occurred on Saturday, April 16th at 18:58:34 local time, lasting 42 seconds. The magnitude of the event was of 7,8 (Mw – moment magnitude scale) and its epicenter was detected at Manabí and Esmeraldas provinces. Ecuador is a country located in South America and its educational system differs among its geographical regions: Sierra, Coast, Amazon, and Galapagos archipelago. The educational system handles 2 working calendars: coastal (beginning in April and ending in January) and Sierra-Amazonía (from September to July), this research focuses on schools operating during the coastal working schedule as it was the most affected by the earthquake.

3.1 The Ecuadorian Educational System

Education in Ecuador is managed and regulated by the Ministry of Education and schools can be public, municipal, private, religious, secular, or bilingual; all are classified in accordance to their funding sources. Ecuador's program of compulsory education lasts 13 years. Students complete their secondary education at 17-18 years old. The progressive school system culminates with the obtention of a certificate or degree. Every educational entity has a school year with a calendar, a curriculum, and educational fees defined by the Ministry of Education in accordance with the National Plan of Education which offers initial, basic, and secondary levels. The supply of educational services is regulated and administrated by the government.

Schools can be managed by public authorities (fiscal, municipal, police, or military), secular, and religious congregations, or by private non-profit organizations. Private education average tuition ranges from $10 to $2000 per month depending on compliance with the educational quality standards according to the Organic Law of Intercultural Education (LOEI, Art. 118, 2017). Mixed, municipal, police and military schools charge their fees from $8 to $300 depending on the approval of the National Educational Authority through the Ministry of Education as stated by the LOEI (Ministerio de Educación, s./f.).

This study analyzes the impact of the 2016 earthquake on high-school exit exam scores. The "Examen Nacional Ser Bachiller" (SB hereafter), is a national standardized exam administered by the INEVAL (National Institute of Educational Evaluation), established by the government from 2014 to January 2020. Until January of 2020, the SB exam assessed proficiency in cognitive skills on four academic subjects that a high-school senior needs to master in order to obtain a high-school diploma.

The exam was also required for people seeking to enroll in tertiary education programs. In 2020, the "Examen Nacional Ser Bachiller" approximately determined a third part of the final high school grade needed for receiving a diploma, while, previous to 2016, it only determined one tenth of the final grade. Indeed, its relevance grew from 10% in 2014 to 30% through time.

3.2 Impact of the Earthquake on the Coastal Educational System

The 2016 earthquake mostly impacted in the towns of Pedernales, Muisne, Portoviejo, San Vicente, Jama, and Manta located at Manabí and Esmeraldas provinces within the coastal region. From April 16th to May 9th schools under the coastal calendar were closed, implying that the instruction of roughly 120.000 pupils was interrupted. Three weeks after the catastrophe only 75,5% of schools in the most affected zones still were operating (Arcos, 2016). The remaining 24,5% were severely damaged and they could not resume their activities. More than 650 people died and over 17.000 people were injured. A foreshock of 4,8 Mw occurred 11 minutes before the earthquake, followed by more than fifty aftershocks in a day and more than 3.000 during the next week (El Comercio, 2016).

In 2015, Manabí and Esmeraldas were among the six provinces with more schools, 3.239 in the first one and 1.264, respectively. The average years of schooling in Esmeraldas were 9,58 and 8,66 in Manabí in 2014. After the earthquake, six out of twenty-four provinces were declared in emergency (Esmeraldas, Manabí, Los Ríos, Santa Elena, Guayas, and Santo Domingo de los Tsáchilas). An executive decree ordered that every public institution (mainly Armed Forces, National Police, and Decentralized Autonomous Governments) of the most affected provinces, "should coordinate and take action to avoid and prevent any safety risk and improve the adverse conditions generated due to the disaster" (Secretaría de Gestión de Riesgos, 2016). Around 55.000 students returned to schools after a month of the seism and approximately 88.000 children were affected by the destruction of 119 schools and the severe damage of 325 establishments (CNN Español, 2017). As a result, the impact of the earthquake in education might have been reflected on the SB exam scores taken by students from January 2017 onwards.

4 Data Overview

To identify the causal effect of the 2016 earthquake on students' high school exit exam, the test scores must be available at the student level and the seism's data must be accessible before and after the exogenous shock. The SB exam data is available from 2014 to 2019 exam years from the INEVAL (National Institute for Educational Evaluation) which is the government agency in charge to design and implement the test nationwide.

In addition of global test results, the INEVAL database contains scores per academic subject, as well as students' socio-demographic information. Before taking the exam, students must complete the "Survey of Associated Factors" which tracks socio-demoghraphic information at the household and student levels, such as parental education, ethnicity, gender, classroom environment, culture, employment status, religion, etc. The survey has 100 questions that are answered online; its purpose is to know the determinants that may influence on students' exam scores (INEVAL, 2018). The shock and its effects can be observed on the years following the earthquake, after January of 2017, and the 5-year data allows us to standardize the exam results and adopt a matching difference-in-differences approach to identify the impact of the seismic event on the high-school exit test scores.

The second dataset was compiled by the British Red Cross from Ecuador's "Instituto Nacional Geofísico – EPN" (National Geophysical Institute of Ecuador), which is the institution in charge of measuring the intensity of Ecuador's seismic and volcanic activity. It mainly presents data regarding to the earthquake's intensity per canton containing values in moment magnitude scale (beginning at 0 and ending in 10 Mw points, approximately). Then, these values these were classified into a dichotomic variable that in equivalence with the moment magnitude scale, takes the value of "0" for less than 6,9 and "1" for more than 7 Mw.

4.1 Sources of Information and Sample Selection

The sample is a combined repeated cross-section from two sources. The Ser Bachiller 2014-2019 dataset that comes from the Instituto Nacional de Educación Educativa (INEVAL, 2020). It is a micro-level data downloadable from the INEVAL website with 1.344.415 students who took the exam between 2014 and 2019 at the end of their 13th year of education. The SB national standardized exam was taken online or on paper (cellphones and calculators were prohibited) and it evaluated 4 main subjects (Mathematics, Social Sciences, Language and Natural Sciences).

The first two exam years the "Ser Bachiller Exam" was administered (2014-2015 and 2015-2016) it included 129 questions and it represented 10% of the final graduation grade. During the next three academic cohorts, the exam included the field of abstract reasoning, the questions increased to 155 and it represented 30% of the final graduation grade. The exam was taken at student's individual level and in this research, it is used to determine the earthquake's impact on student performance under the coastal education regime.

Until 2016, the students received a single test score of the Ser Bachiller. This graduation exam was graded in a scale from 400 to 1000 points (minimum 700 required for approval), and it was a requisite for a higher public education application and acceptance. To validate this exam as 10% of the final grade, the exam score was converted on a scale from 4 to 10. During the next three exam years included in this dataset, the students received two differentiated test scores that came from the Ser Bachiller national standardized exam: the first one was a partial note needed for a postulation to the public higher education and graded in a scale from 400 to 1000 points (minimum 700 required for approval), and the second was its conversion to the final graduation exam score from 4 to 10 with a ponderation of 30% of every student's final grades (INEVAL, 2020, p.7). In this study, the exam scores are standardized.

The duration of the exam was 150 minutes and disabled students were given 210 minutes. Every student enrolled in an Ecuadorian school had to take the SB exam a month before their graduation, ending high school. Students under the coastal regime took it in January and the exam scores were posted in February through an online platform. During the academic years covered, the number of thematic groups and evaluated topics changed in each subject. Even though the exam was modified after the second academic year, the difference-in-differences estimator eliminates these changes because the central specification of this study, exploits variation across time and cantons in earthquake exposure. Thus, any nationwide change in the exam can be accounted by the inclusion of fixed effects per exam year.

It is important to mention more deeply the topics evaluated inside the main five fields. Abstract reasoning refers to the student's capacity to structure and organize thoughts logically. The subjects evaluated in Mathematics were algebra, functions, geometry, measurement, statistics, and probability. In Language and Literature, the questions focused on Spanish language and culture, oral communication, lecture, writing, and common literature. For Natural Sciences, the areas of human body, health, chemistry language and action, force and movement, energy conservation and transfer, earth and the universe, living things evolution, cellular and molecular biology, and animal and vegetable biology were evaluated. On Social Sciences, the global knowledge focused on the origins and primary cultures of humanity, the medium and modern ages, miscegenation and liberation, work and society, citizenship and rights, modern democracy, democracy and the construction of a pluricultural state, the state and its organization, argumentation, and construction of the logical oral and written speech, the individual, and the community (Cofre et al., 2020, p.9). The SB exam was calculated by counting the number of correct answers, then this number was divided by 80, the result of this division was multiplied by 600 and sum 400 points that the INEVAL assigns automatically (Educar Plus, s./f.).

To evidence the impact of the earthquake on the SB exam scores, the first dataset was combined with the earthquake damage and the severity index, publicly reported by the British Red Cross Maps Team on April 18th, 2016. It was a census collected by Ecuador's National Risk and Emergency Management Service (Servicio Nacional de Gestión de Riesgos y Emergencias, 2016) through the National Geophysical Institute in real time of the event. The National Geophysical Institute objectively measured the seism's intensity using peak ground vertical acceleration, known as PVA which presents an earthquake's ground shaking scale (Seismic Resilience, s./f). It includes 1.040.829 observations and the data matches with the exam scores at 71,42% of all national schools during the studied period. Four cantons are not included in the severity index: Las Golondrinas, Manga Del Cura, El Piedrero, and La Concordia.

Regarding our sample selection the dataset focuses on the students educated under the coastal calendar attending to schools in the Coastal region for three reasons. First, schools located in both the Sierra and Amazonía regions were unaffected. Second, the academic calendars differ among regions. Nonetheless, this method differentiates the effect between students attending school within the most affected coastal provinces (above 7 Mw) in comparison to students of the coastal provinces less affected (below 7 Mw). Third, in the Sierra region, the exam scores are on average superior relative to the coastal region. While the Sierra students obtained an average of 700 points over 1000, the Coast students got an average of 600 points over 1000 from 2012 to 2016 (El Universo, 2017). Thus, the differences among regions and cantons are not due to the seism, but to socio-demographic factors and cultural differences.

The unit of observation is a student-exam year combination. Independently from the school's type of funding, every student took the exam as a requisite for graduation and as an option to enroll at a public university. It may be useful to consider that the unit of observation refers to students within schools that 1) operate under the coastal school calendar from 2014 to 2019, 2) are located at the cantons of the coastal region, and 3) were linked based on their canton and student socio-demographic background. The final repeated cross-section dataset contains 1.336.270 observations from the earthquake and the SB test scores.

4.2 Common Trends

The main challenge of constructing the DID model is that the cantons or zones where the earthquake had a higher impact of more than 7 Mw are not completely comparable with the cantons where it was not strongly felt, and these differences persist even before the seism. To overcome this issue, a Propensity Score Matching (PSM) is run with socio-demographic variables obtained from the 2010 Ecuadorian Census to match schools per canton in control and treatment zones that are relatively similar before the shock.

The PSM was obtained through a Probit regression that classifies the treated and non-treated schools in accordance with the socio-demographic characteristics of the schools during the first two years of the repeated cross-section. As a result, the Probit uses PSM to choose treated and non-treated schools weighted by their socio-demographic characteristics. The data includes school identifiers that result in a matched sample and it is complied with the original database, obtaining: 1) a non-restricted sample 1720 schools and 2) a restricted and matched sample with 156 schools. The PSM generates average results by year, treatment, and funding conditions. Even though the resemblance is not entirely satisfactory due to the PSM assumption that the treatment assignment must be based on observable characteristics, it is easier to perform an analysis using schools that satisfy the common parallel trend assumption. Thus, the schools may not seem comparable at a global level but the differentiation between public, private, and mixed funding lets a comparison within groups.

In Annex A, figures 1 to 20 in panel (a) show the trends of the variables of interest for public (71,78%), private (20,48%) and mixed schools (7,74%) classified by their funding source without the Propensity Score Matching. On the contrary, panel (b) of the same figures shows the matched sample through the Propensity Score Matching of the variables of interest for the three types of school. These variables include the main SB global exam score, scores per evaluated subject, the students' decile performance, average number of absent students and the percentage of absent students.

Regardless that the graphs shown on column (b) do not show a perfectly matching common trend in every selected variable, the PSM allows us to implement the difference-in-differences empirical strategy. For instance, the estimator will show the effect of the earthquake on the SB Exam scores in order to explore the mechanisms behind these results.

4.3 Summary Statistics

Tables 1 to 4 present the summary statistics for the unmatched sample and the (PSM) matched sample used to estimate the model's results. The tables are split between outcome variables (Tables 1 and 3) and control variables (Tables 2 and 4). Every table details the mean, standard deviation, and the maximum and minimum values for the variables of interest.

In tables 1 and 2 it is shown that the unmatched sample includes a total of 663.105 observations vs the PSM matched sample with 51.468 observations. Furthermore, tables 3 and 4 are important in order to differentiate the observations prior the earthquake *"Before"* versus post-earthquake *"After"*. The *Before* group shows a larger composition for the standardized SB Exam Scores, performance, absence and control variables (e.g. number of female students, schools' economic attributes, parents' education, students' interpersonal performance) relative to the *After* group. Under the matched sample, the treatment group shows that, on average, the standardized SB Exam Scores are higher, more deviated, and with a shorter range of values after the seism. On the contrary, absenteeism increases after the shock in comparison to the *Before* group.

Regarding school and students' characteristics, in the PSM sample of interest, fourteen variables that make the results more comparable between the *Before* and *After* groups are listed. Post-earthquake there are less students belonging to ethnic minorities, whereas a female increase of students is noted. Most of the conditions of the school facilities were not affected except for the internet availability which worsened and some interpersonal abilities also improved.

The PSM sample and the inclusion of the control variables presented in tables 2 and 4 intend to reduce the gap between the control and treatment groups through fixed effects in the DID empirical strategy. The main concern of this study is the contrast between schools' institutional conditions prior to the earthquake. However, the model states three specifications controlling the differences through the PSM sample with the purpose of identifying the earthquake's effect in the SB Exam scores, ranked performance and rate of absenteeism.

5 Empirical Strategy

This research focuses on measuring the impact of the 2016 earthquake on the SB exam results of students in the coastal region, before and after the seism. For this purpose, the chosen empirical strategy is a matching difference-in-differences (DID) model which overcomes the concern for omitted variables. "It is popular in empirical economics, to estimate the effects of certain policy interventions and policy changes that do not affect everybody at the same time and in the same way" (Lechner, 2010). The data meets almost all the requirements of the model because the exam was taken pre and post-intervention (a repeated cross-sectional data followed through 5 years at individual exam scores level). Both differentiations and the PSM eliminate most of the bias generated between the control group and the treatment group as well as time or trend divergence. The causal effect of the treatment group will be obtained with adequate controls.

The main identification assumption of the DID model is that in absence of the natural disaster shock, in this case, the earthquake, trends on outcomes for treated and control units would have exhibit a parallel evolution throughout the period of study. Each regression is run for the eight variables of interest mentioned previously.

The baseline matching difference-in-differences model specification implemented is:

$$Y_{isct} = \beta(Treated_{ci} \cdot After_t) + \delta_s + \alpha_t + (\lambda_s \cdot t) + X_{it}^T \gamma + \varepsilon_{isct}, \tag{1}$$

in which Y_{isct} stands for the SB global and per subject standardized Exam scores or absenteeism rates for i student of school s located at coastal canton c during exam year t. δ_s and α_t are fixed effects by school and exam year, respectively. $Treated_{ci}$ is a dummy variable that takes the value of zero for schools in the control group and the value of 1 for schools in the treatment group (10 particular cantons and several schools where the earthquake was about 7 Mw or more). $After_t$ is a dummy 1 if the school year is "2016-2017" onwards and zero otherwise. The interaction term $(Treated_{ci} * After_t)$ is included to estimate the variation of the SB Exam scores and absenteeism that causally occurs due to the earthquake's impact since the 2016-2017 school year, it is the average treatment effects on the treated group (ATT). X_{it}^T indicates a set of control variables at school and student level so there is no multicollinearity and ε_{isct} is the standard error term at student level.

To account for the dynamic evolution of the effect, an alternative specification is:

$$Y_{isct} = \sum_{\substack{t=1 \\ t\neq 3}}^{5} \beta_t(Treated_c \cdot (Year = t)) + \delta_s + \alpha_t + (\lambda_s \cdot t) + X_{it}^T \gamma + \varepsilon_{isct}, \tag{2}$$

The purpose of this equation is to prove that the differences between control and treatment groups before the earthquake are not significantly different from zero in the first two exam years. β_t estimates the effect of the earthquake in four different exam years, relative to the academic cohort 2016-2017, where t stands for 2014-2019 exam years. Nevertheless, this assumption is non-significant after the shock and so, a third specification is formulated; an heterogeneity analysis to explore the differences of the effect between public, private, and mixed schools.

The following specification accounts for heterogeneous treatment effects per type of school:

$$
\begin{aligned}
Y_{isct} = \beta_0(Treated_c \cdot After_t) + \beta_1(Treated_c \cdot After_t \cdot Type_s) \\
+ \delta_s + \alpha_t + (\lambda_s \cdot t) + X_{it}^T \gamma + \varepsilon_{isct}.
\end{aligned} \tag{3}
$$

Equation (3) includes the dummy variable $Type_s$ that takes the value of 1 when schools are private or mixed, respectively (51.468 observations in total). Schools are classified by their funding source and the reference group is public schools. β_1 measures the differences of the impact of the seism on the student's exam scores by comparing private and mixed schools with public schools.

6 Results

Tables 5 and 6 present all results on the eight outcomes of interest using the DID with the PSM for all three specifications. A set of time variant student attributes is included for a more precise estimation of the earthquake's impact on the test scores and absenteeism. On average, public schools were not affected (they performed better than private and mixed schools) and had a positive and non-significant impact probably due to mechanisms of positive selection post seism, this will be tested in the next section. At an aggregate level, most of the results of the studied variables are positive and non-significant, but when desegregating schools per funding source, in specification (3) it is noted that the earthquake had a negative and significant effect for private and mixed schools.

Private schools were the most negatively affected on the global SB Exam scores (5% significance), likely because their student composition was altered. In Natural Sciences, negative and significant effects are found for private and mixed schools. Mixed schools performed worse in Social Sciences (10% significance). Regarding general rankings, students from private and mixed schools obtained approximately 2 deciles on average less relative to students from public schools. There are no relevant results for absenteeism and the percentage of absent students.

6.1 The Effect of the 2016 Earthquake on the SB Global Exam Scores and Absenteeism

In this section, the standardized exam average (1), performance decile (2), number of absent students (3), and the percentage of absence (4) of the SB Exam are explored via the three specifications alluded in Table 5. Again, the first specification shows a positive and non-significant effect after the seism in (1), (2), and (4). There is a slightly and non-significant decrease in the number of absent students (3). Succeeding the earthquake, the percentage of absent students dropped and had a non-significant effect shown in column (4).

Accordingly, specification (2) differences the effects per academic year and also, shows the same positive and non-significant results two years after in columns (1) and (2), meanwhile two years before the earthquake presents a negative and non-significant effect in (1) and (2). Following the year of the natural disaster, students improve their average standardized SB Exam score in more than 2,30 deciles relative to the year of the earthquake. Specification (2) also reports non-significant effects for the variables displayed in columns (3) and (4). The exam years before and after 2016-2017, the number of absent students per school and the percentage of absence of students taking the SB Exam was less than in 2016-2017. During this scholar period, the percentage of absenteeism reached its highest with a negative non-significant effect.

However, specification (3) includes more interesting outcomes for public, private, and mixed schools, taking public schools as reference group. The earthquake has negative and statistically significant effects on average standardized scores and performance decile of the exam taken at private and mixed schools. Students from private schools averaged 0,824 SD less than public schools students (5% significance). Private and mixed schools performed worse on the SB exam obtaining on average 2,43 deciles (5% statistical significance) and 2,85 deciles (10% statistical significance) less than public schools, respectively. The impact of the shock was very high in terms of magnitude, approximately, 2 points less on average over a 10 point test.

Notably, the results of specification (3) in absenteeism are also positive and non-significant after the exogenous event, this indicates certain desertion mechanisms, yet not a remarkable difference among schools. Private and public schools decreased their percentage of attending students taking the SB Exam after 2016-2017, on the contrary, mixed schools increased the number of attending regular students in comparison with students from public schools. Column (4) shows a higher and non-significant increase of absenteeism for public and mixed schools. All schools approximately had the same volume of absenteeism, apparently the differences between their results are indistinguishable from zero. The SB exam performance decile and average SD coefficients report variation in a significant magnitude, still there are no important differences in the exam's percentage of absenteeism and number of absent students.

6.2 The Effect of the 2016 Earthquake on the SB Exam Scores per Subject

Scores per subject were also standardized. Columns (5), (6), (7) and (8), of Table 6 show results per subject including: Mathematics (5), Language (6), Natural Sciences (7), and Social Sciences (8). The first specification demonstrates that at a global level, the earthquake had a positive but imprecise impact on the standardized test scores per subject. Actually, after the shock, Natural Sciences and Mathematics standardized scores of the SB Exam were the most improved for all of the students under the coastal education regime.

In specification (2), the conclusion is similar to the one of the previous specification. Analyzing the effect per year, relative to the year of the earthquake, shows again, a positive and non-significant impact during the aftermath. Mathematics is the subject with the greatest standardized score increase one year after the event and Language gets the higher raise a year succeeding that. In contrast, some parallel trends are violated two years before the seism, Natural Sciences standardized scores were worse with a significance of 10% and approximately 0,220 SD less than in 2016-2017. Thus, the third specification must be studied more thoroughly.

For the last specification, the goal is to measure how heterogeneous is the change of the SB standardized scores between public, private, and mixed schools after the earthquake year. The baseline group is compared with private and mixed schools. The results suggest that the earthquake had a significant and negative impact on average in private schools for Mathematics (5% significance) with 0,711 SD, Language (5% significance) with 0,564 SD and Natural Sciences (1% significance) 0,877 SD less than what students from public schools obtained. Meanwhile, for mixed schools the shock had a negative and significant impact on average of Natural Sciences (5% significance) 0,912 SD and Social Sciences (10% significance) 0,872 SD less relative to public school students. Mixed schools were not affected in (1) an (2) likely because they are the smallest group of schools in the sample.

Although, public schools still present a positive and non-significant increase on all four evaluated subjects, this does not necessarily suggest that these schools improved their teaching practices or other determinants of student's performance. If the performance of public school students had improved, the coefficients would be significant. They increased their scores due to a global student recomposition which brought students from private and mixed schools into the public school system.

7 Potential Mechanisms

After discussing the main results, it is important to analyze the transmission mechanisms that may have mediated the heterogeneous effects aforementioned. At a global level, the earthquake had no significant impact on the SB Exam scores, but when schools are classified based on their type of funding (public, private, or mixed schools), non public schools were relatively harmed by the seism. Why private and mixed schools performed worse on the SB Exam relative to public schools? Are there any predetermined characteristics at student level that have a positive or negative association with school performance? In order to answer these questions, the next step is to measure the correlation of key predetermined socio-demographic factors at the student level that influence test scores. Statistical differences in these attributes across different types of schools, may indicate the presence of educational sorting.

Furthermore, specification (3) is restated to test positive selection. The variables of interest are the following dummies: *students belonging to an ethnic minority group* (1 for students identified with ethnic minorities and 0 if not), *students' gender* (1 if the student is female and 0 for male students), and *students' mother highest level of education* (1 if the mother has reached third-level or more education and 0 for the opposite). These regressions focus on the differences in student composition per school to quantify the changes in test scores that depend on student socio-demographic background.

Table 7 presents the results for this section. There is a broad field of literature that studies the impact of ethnic diversity on student school performance and achievement. Vast research shows that an increase of ethnic diversity in schools leads to better performance (shown by Braster & Dronkers, 2015; Dronkers & van der Velden, 2013; Maestri, 2016), while (Angrist & Lang, 2004; Hanushek, Kain, & Rivkin, 2009), suggest the contrary and find no remarkable differences. In this context, column (1) shows that the percentage of students belonging to ethnic minorities fell in public schools, while it increased in private and mixed schools. Although the effects are non-significant for the three types of schools, there is evidence of an increase in the number of ethnic minority students in private and mixed schools, both performing worse in the evaluated subjects relative to public schools. Although this feature is not significant, the signs of the coefficients align with the hypothesis that an increase in ethnic diversity, leads to inferior performance.

In column (2) of table 7 women's participation is the second determinant taken into account as a potential mechanism. The gender gap is a relevant factor when analyzing student achievement. Studies reveal that boys perform better in STEM, while girls perform higher in reading and language (to name a few, Bacharach, Baumeister & Furr, 2003; Cobb-Clark & Moschion, 2017; Tsai, Smith & Hauser, 2018; Han, 2016; Glenn E., & Swanson A., 2010). Although in recent years, mainly in developed countries, there is evidence that the gap is closing slowly (Autor et al., 2019; Cabeza-García, Del Brio & Oscanoa-Victorio, 2018). After the SB Exam, there were less female students in public schools and this difference is non-significant. On the contrary, in private and mixed schools, women's SB Exam participation increased in 1% and 10.6%, respectively. The effect on mixed schools has a 10% level of significance after the earthquake. These results clearly suggest the existence of gender gaps in some evaluated components of the SB test present in Ecuadorian mixed schools.

In particular, column (3) shows the key determinant that may thrive the relationship between the SB exam scores and the 2016 earthquake. There is an increase of students in public schools with mothers that have accomplished third-level education with a statistical significance of 10%. However, private schools report a 9% average decrease of students with highly educated families after the earthquake at a 5% level of significance. In mixed schools, this kind of students decreased in 3.8%, the effect remains insignificant. The evidence proves the theory of schools' recomposition after the earthquake. Students from private and mixed schools probably transferred to the public education system (this shows a positive coefficient). More educated parents had their income reduced, private and mixed schools were greatly affected, or the investment towards public schools increased, resulting in positive selection into public schools and negative selection into mixed and private schools. Therefore, sorting after the seism confirms, well-known theories of advantages of additive parental education (Pit-ten Cate & Glock, 2018; Sheppard & Monden, 2018).

Overall, the evidence proves that public schools performed better due to the students' educational sorting after the natural shock. Students were enrolled from private and mixed schools into public education with socioeconomic factors such as their mother's level of education, gender and ethnic minority self-identification as key determinants of such group recomposition. These predetermined characteristics affected the students' SB Exam performance after the earthquake. Therefore, the aggregate effect remains unclear, despite when it is examined according to the type of school. In this case, the effects are differentiated and the main mechanism by which this occurred is self-selection towards different schools.

8 Concluding Remarks

This research project studied the effect of the 2016 Ecuadorian earthquake on student performance using proficiency measures in numeracy and literacy from the national high school exit exam "Ser Bachiller". The study exploits repeated cross-sectional data from students under the coastal education regime and combines it with the seism's records from Ecuador's National Geophysical Institute. A matching difference-in-differences is the empirical strategy implemented which determines the effect of the exogenous shock on the exam scores. By the use of a combined propensity score matching algorithm with a classical difference in difference approach, the empirical design is valid as parallel trends on outcomes are shared between both affected and unaffected schools.

The findings of this research imply that the earthquake led to a drop in scores heterogeneously across schools with different funding schemes. While students from private and mixed schools were negatively impacted by the shock, those from public schools performed marginally better. On average, graduate students of private and mixed schools obtained 2 deciles in performance less relative to students within the public education system after the seism. A potential explanation suggests student sorting from private and mixed schools towards a congested public system during and after the natural disaster. To confirm this transmission channel, the SB scores variation is analyzed considering student background such as parental level of education. Since there are no significant effects in schools at a global overview, the impact is evidenced when the estimation is performed, classifying schools according to their type of funding.

Undoubtedly, the major contribution of this study is to show that the earthquake's impact in coastal schools affected public, private, and mixed schools differently and this occurred through an self-selection mechanism. There is a clear effect of the seism when decomposing schools per funding source. Nevertheless, the data does not perfectly fit under the parallel trend assumption and omitted variables may bias the estimations. For further confirmation, a Synthetic Control Method is suggested to build a control group that surely matches the treated group during the pre-treatment period to corroborate these findings.

9 References

Andrabi, T., Daniels, B., & Das, J. (2020). Human Capital Accumulation and Disasters: Evidence from the Pakistan Earthquake of 2005. *RISE Working Paper Series.* 20, 39.

Angrist, D. & Lang, K. (2004). Does School Integration Generate Peer Effects? Evidence from Boston's Metco Program. *American Economic Review*, 94(5), 1613-1634.

Arcos, S. (2016, April 26). *El terremoto de Ecuador deja fuera de la escuela a 120.000 niños: UNICEF.* Noticias ONU. https://news.un.org/es/story/2016/04/1355911

Arias, F. (2019). *¿Cúal fue el impacto del terremoto de 2016 sobre los estudiantes reprobados el año lectivo?* USFQ. http://repositorio.usfq.edu.ec/handle/23000/8261

Asian Development Bank and World Bank. (2005). *Pakistan 2005 Earthquake Preliminary Damage and Needs Assessment.* Asian Development Bank and World Bank, Islamabad.

Autor, D., Figlio, D., Karbownik, K., Roth, J., & Wasserman, M. (2019). Family Disadvantage and the Gender Gap in Behavioral and Educational Outcomes. *American Economic Journal: Applied Economics*, 11(3), 338–381.

Bacharach, V., Baumeister, A. & Furr, R. (2003). Racial and Gender Science Achievement Gaps in Secondary Education. *The Journal of Genetic Psychology*, 164(1), 115–126.

Baez, J. E., de la Fuente, A., & Santos, I. (2011). Do Natural Disasters Affect Human Capital? an Assessment Based on Existing Empirical Evidence. *Institute for the Study of Labor (IZA).* IZA Discussion Papers 5164. http://www.ftp.iza.org/dp5164.pdf

Beaglehole, B., Bell, C., Frampton, C., & Moor, S. (2017). The Impact of the Canterbury Earthquakes on Successful School Leaving for Adolescents. *Australian and New Zealand Journal of Public Health*, 41(1), 70-73.

Benson, C. & Clay, E. (2003). Economic and Financial Impacts of Natural Disasters: an Assessment of Their Effects and Options for Mitigation: Synthesis Report. *London: Overseas Development Institute (ODI)*, 7-8.

Braster, S., & Dronkers, J. (2015). The Positive Effects of Ethnic Diversity in Classrooms on the Educational Performance of Pupils in a Multi-Ethnic European Metropole. *Education and Society*, 33(2), 25–49.

British Red Cross Maps Team. (2016). *Ecuador Earthquake-April 2016-Severity index.* https://data.humdata.org/dataset/ecuador-earthquake-april-2016-severity-index

British Red Cross Maps Team. (2016). *Ecuador Earthquake damage - April 2016.* https://data.humdata.org/dataset/ecuador-earthquake-damage-april-2016

CNN Español. (2017, April 13). Ecuador: ¿Qué ha pasado desde el terremoto? *CNN Español.* https://cnnespanol.cnn.com/2017/04/13/a-un-ano-de-la-tragedia-que-sacudio-a-ecuador-que-ha-pasado-desde-el-terremoto/

Cobb-Clark, D. A., & Moschion, J. (2017). Gender Gaps in Early Educational Achievement. *Journal of Population Economics*, 30(4), 1093–1134.

Conteh, I. K. (2015). *Natural Hazards and Education : the Impact of Floods on Primary School Education in Zambia.* Boekenplan.

Cuaresma, J. C. (2010). Natural Disasters and Human Capital Accumulation. *The World Bank*

Economic Review, 24(2), 280–302.

Di Pietro, G. (2018). The Academic Impact of Natural Disasters: Evidence from L'Aquila Earthquake. *Education Economics*, 26(1), 62-77.

Dronkers, J., & van der Velden, R. (2013). Positive but also Negative Effects of Ethnic Diversity in Schools on Educational Performance? An Empirical Test Using PISA Data. *Integration and Inequality in Educational Institutions*, 71–98.

Educar Plus. (s./f.). *Conoce tu puntaje en las pruebas Ser Bachiller – EAES y Nota de Grado.* https://educarplus.com/2018/12/conoce-tu-puntaje-en-las-pruebas-ser-bachiller-y-nota-de-grado.html

El Comercio. (2016, May). En 42 segundos. *Grupo El Comercio*. https://especiales.elcomercio.com/2016/05/terremoto/

El Universo. (2017, September 24). Promedio para cupo universitario, mejor en la Sierra que en la Costa. *Grupo El Universo*. https://www.eluniverso.com/noticias/2017/09/24/nota/6396667/promedio-cupo-universitario-mejor-sierra-que-costa/

Espinoza, R., Urzúa, S., & Claro, S. (2015). *Natural disasters, academic performance and reconstruction: Evidence from Chile's 2010 earthquake and tsunami.*

Fergusson, D. M., Boden, J. M., Horwood, L. J., & Mulder, R. T. (2014). Perceptions of distress and positive consequences following exposure to a major disaster amongst a well-studied cohort. *Australian & New Zealand Journal of Psychiatry*, 49(4), 351–359.

Filipski, M., Jin, L., Zhang, X., & Chen, K. (2019). Living Like There's No Tomorrow: The Psychological Effects of an Earthquake on Savings and Spending Behavior. *European*

Economic Review, 116, 107-128.

Gibbs, L., et al. (2019). Delayed Disaster Impacts on Academic Performance of Primary School Children. *Child Development*, 90(4), 1402-1412.

Glenn, E. & Swanson, A. (2010). The Gender Gap in Secondary School Mathematics at High Achievement Levels: Evidence from the American Mathematics Competitions. *Journal of Economic Perspectives*, 24(2), 109-128.

Han, S. W. (2016). National Education Systems and Gender Gaps in STEM Occupational Expectations. *International Journal of Educational Development*, 49, 175–187.

Hanushek, E., Kain, J., & Rivkin, S. (2002). New Evidence about Brown v. Board of Education: The Complex Effects of School Racial Composition on Achievement. *Journal of Labor Economics*, 27, 3.

Hermida, P. (2011). The Long-term Effect of Natural Disasters: Health and Education in Guatemala After the 1976 Earthquake. *Fifth Annual PopPov Conference on Population, Reproductive Health, and Economic Development*.

Human Factors and Ergonomics Society. (2012). Human cognitive performance suffers following natural disasters. *ScienceDaily.* https://www.sciencedaily.com/releases/2012/02/120211095351.htm

Imberman, S. A., Kugler, A. D., & Sacerdote, B. I. (2012). Katrina's Children: Evidence on the Structure of Peer Effects from Hurricane Evacuees. *American Economic Review*, 102(5), 2048–2082.

Instituto Nacional de Evaluación Educativa – INEVAL. (2020). *Bases de datos Ser Bachiller.*

http://evaluaciones.evaluacion.gob.ec/BI/bases-de-datos-ser-bachiller/

Instituto Nacional de Evaluación Educativa – INEVAL. (2020). *Informe de Resultados Evaluación Costa 2019 - 2020.* p, 7. Quito - Ecuador.

Instituto Nacional de Evaluación Educativa – INEVAL. (2018). *Hasta el 6 de diciembre se podrá realizar la Encuesta de Factores Asociados del examen Ser Bachiller.* https://www.evaluacion.gob.ec/hasta-el-6-de-diciembre-se-podra-realizar-la-encuesta-de-factores-asociados-del-examen-ser-bachiller/

Jaramillo, L. (2016). Resolución de Emergencia N°SGR-001-2016. *Secretaría de Gestión de Riesgos.* https://www.gestionderiesgos.gob.ec/wp-content/uploads/downloads/2016/04/Resoluci%C3%B3n-de-Emergencia-SGR-001-2016.pdf

Kim, N. (2010). Impact of Extreme Climate Events on Educational Attainment: Evidence from Cross-Section Data and Welfare Projection. *Risk, Shocks, and Human Development.* Palgrave Macmillan, London, 185-206.

Kousky, C. (2016). Impacts of Natural Disasters on Children. *The Future of Children*, 26(1), 73-92.

Lechner, M. (2010). The Estimation of Causal Effects by Difference-in-Difference Methods Estimation of Spatial Panels. *Foundations and Trends® in Econometrics*, 4(3), 165–224.

Ley Orgánica de Educación Intercultural [LOEI]. (2017). *Reglamento general a la LOEI.* Art. 118, p. 39. https://educacion.gob.ec/wp-content/uploads/downloads/2017/05/Reglamento-General-Ley-Organica-Educacion-Intercultural.pdf

Marcotte, D. E. (2007). Schooling and Test Scores: A Mother-Natural Experiment. *Economics* *of Education Review*, 26(5), 629–640.

Marcotte, D. E., & Hemelt, S. W. (2008). Unscheduled School Closings and Student Performance. *Education Finance and Policy*, 3(3), 316–338.

Maestri, V. (2016). Can Ethnic Diversity Have a Positive Effect on School Achievement? *Education Economics*, 25(3), 290–303.

McDermott, T.K.J. (2012). The Effects of Natural Disasters on Human Capital Accumulation. *SSRN Electronic Journal.*

Medina, F. (2019). *Efectos del terremoto del 16 de abril de 2016 sobre la educación inicial, básica y bachillerato en Esmeraldas y Manabí.* USFQ. http://repositorio.usfq.edu.ec/handle/23000/8467

Ministerio de Educación. (s./f.). *Cobros autorizados a instituciones particulares y fiscomisionales.* https://educacion.gob.ec/cobros-autorizados-a-instituciones-particulares-y-fiscomisional

Onigbinde, L. (2018). *The Impacts of Natural Disasters on Educational Attainment: Cross-Country Evidence from Macro Data.* Master's Theses. 1078. https://repository.usfca.edu/thes/1078

Paudel, J., & Ryu, H. (2018). Natural Disasters and Human Capital: The Case of Nepal's Earthquake. *World Development*, 111, 1–12.

Pit-ten Cate, I. M., & Glock, S. (2018). Teachers' Attitudes Towards Students With High- and Low-educated Parents. *Social Psychology of Education*, 21(3), 725–742.

Ripoll Gallardo, A. et al. (2018). Medium- and long-term health effects of earthquakes in high-income countries: a systematic review and meta-analysis. *International Journal of Epidemiology.*

Rosales-Rueda, M. (2018). The Impact of Early Life Shocks on Human Capital Formation: Evidence from El Niño Floods in Ecuador. *Journal of Health Economics*, 62(C), 13-44.

Santos, I. V. (2010). The Effects of Earthquakes on Children and Human Development in Rural El Salvador. *Risk, Shocks, and Human Development*, 128–151.

Seismic Resilience. (s./f.). *Measuring earthquakes.* http://www.seismicresilience.org.nz/topics/seismic-science-and-site-influences/measuring-earthquakes/

Servicio Nacional de Gestión de Riesgos y Emergencias. (2016). *Informes de Situación: Terremoto 7.8. Pedernales (16/04/2016) / Réplicas Esmeraldas (18/05/2016).* https://www.gestionderiesgos.gob.ec/informes-de-situacion-actual-terremoto-magnitud-7-8/

Sheppard, P., & Monden, C. (2018). The Additive Advantage of Having Educated Grandfathers for Children's Education: Evidence from a Cross-National Sample in Europe. *European Sociological Review*, 34(4), 365–380.

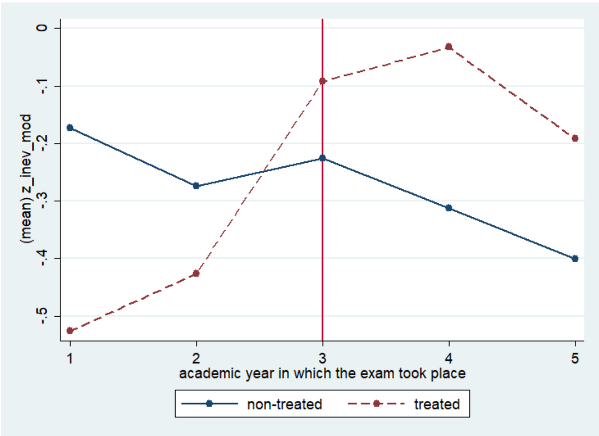
Smilde-van den Doel, D. A., Smit, C., & Wolleswinkel-van den Bosch, J. H. (2006). School Performance and Social-Emotional Behavior of Primary School Children Before and After a Disaster. *PEDIATRICS*, 118(5), e1311–e1320.

Sulistyaningrum, E. (2017). The Impact of Earthquake on Child Test Score. *Journal of Indonesian Economy and Business*, 32(2), 104–120.

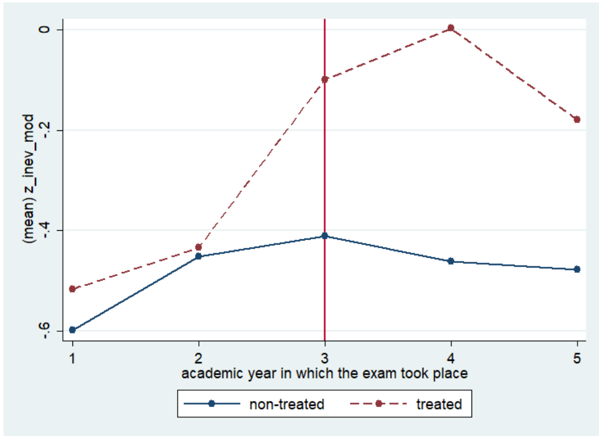
Tsai, S.-L., Smith, M. L., & Hauser, R. M. (2018). Gender Gaps in Student Academic Achievement and Inequality. *Research in the Sociology of Education*, 20, 181–218.

10 Annex A: Figures

Figure 1: SB Exam Global Scores of Public Schools 2014-2019

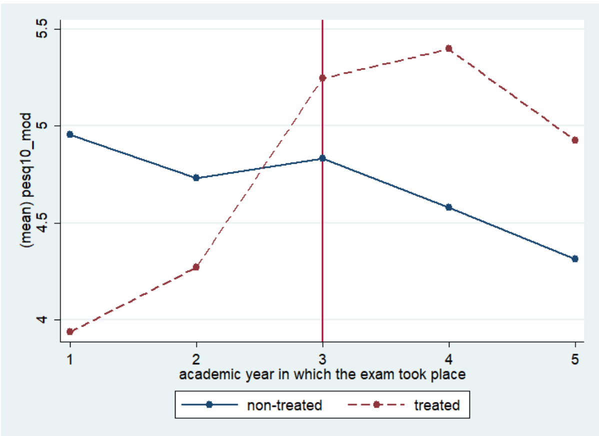


(a) Unmatched sample

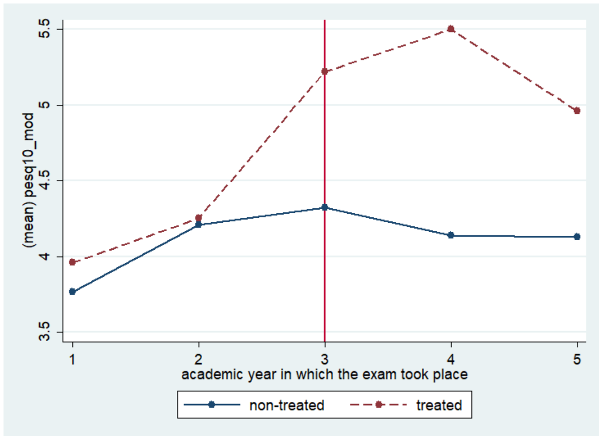


(b) Matched sample (PSM)

Figure 2: Students' SB Exam Performance Decile of Public Schools 2014-2019

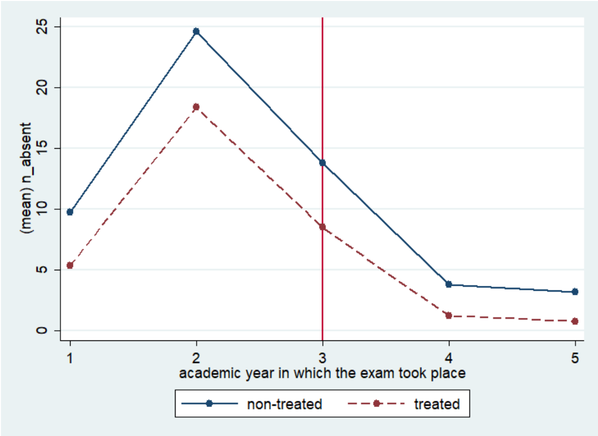


(a) Unmatched sample

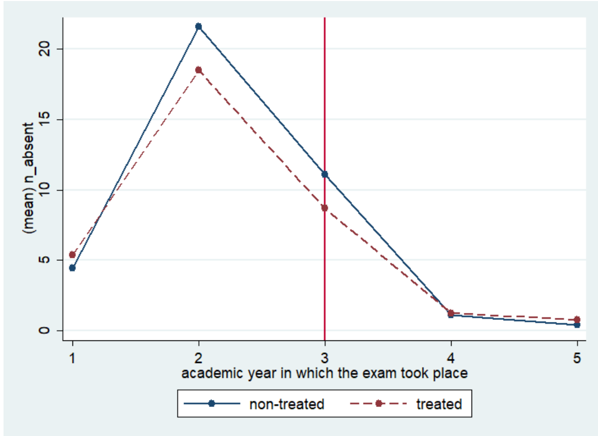


(b) Matched sample (PSM)

Figure 3: SB Exam Average Number of Absent Students of Public Schools 2014-2019

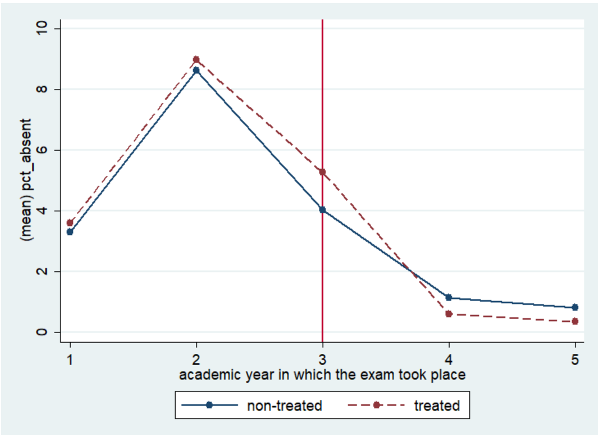


(a) Unmatched sample

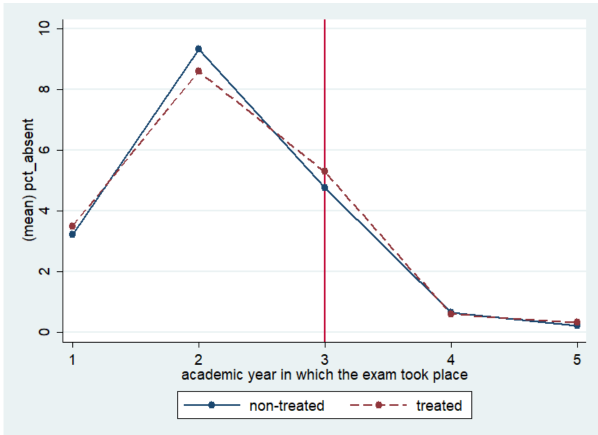


(b) Matched sample (PSM)

Figure 4: SB Exam Percentage of Absent Students of Public Schools 2014-2019

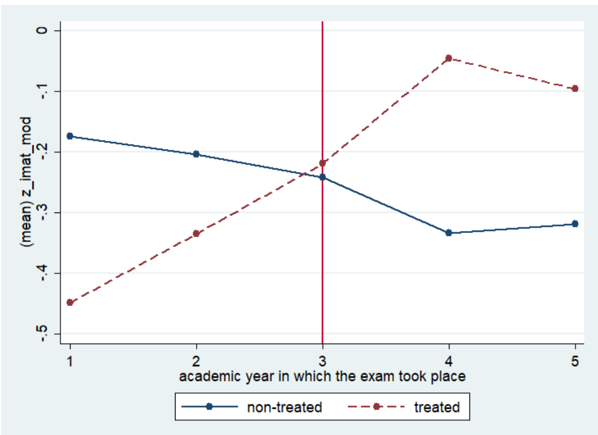


(a) Unmatched sample

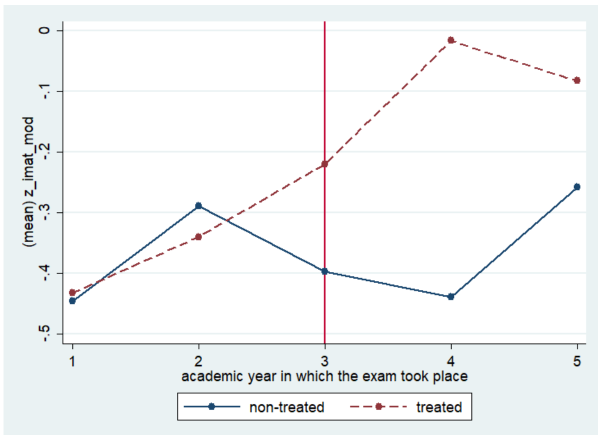


(b) Matched sample (PSM)

Figure 5: SB Exam Mathematics Scores of Public Schools 2014-2019

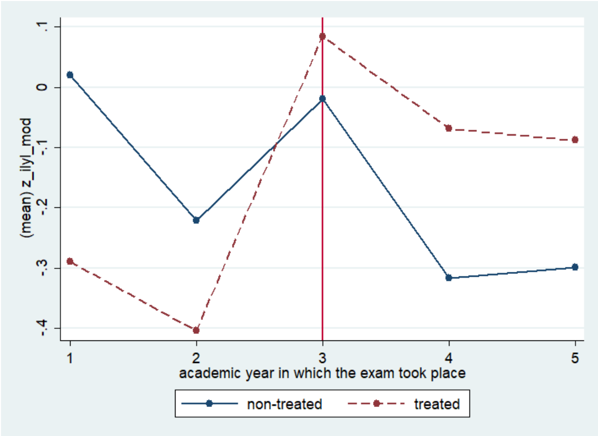


(a) Unmatched sample

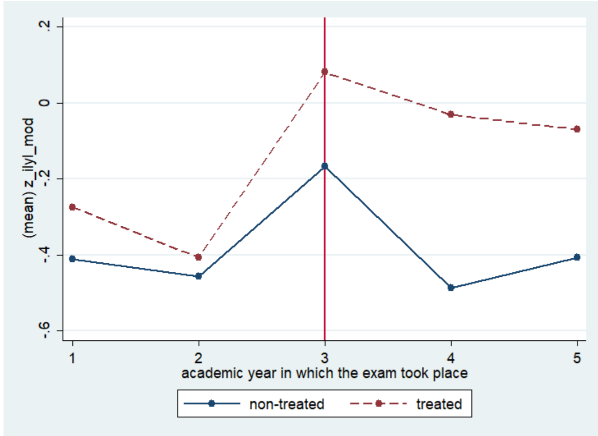


(b) Matched sample (PSM)

Figure 6: SB Exam Language Scores of Public Schools 2014-2019

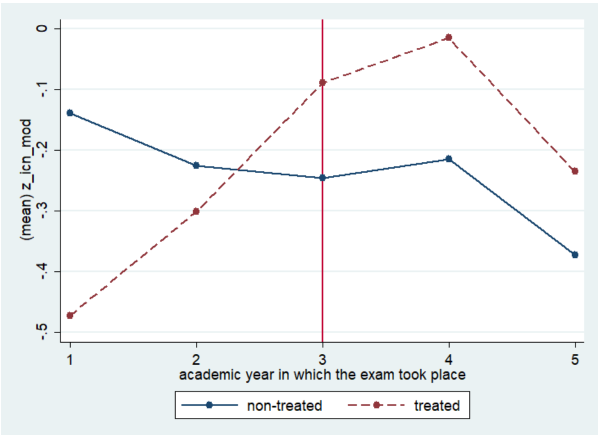


(a) Unmatched sample

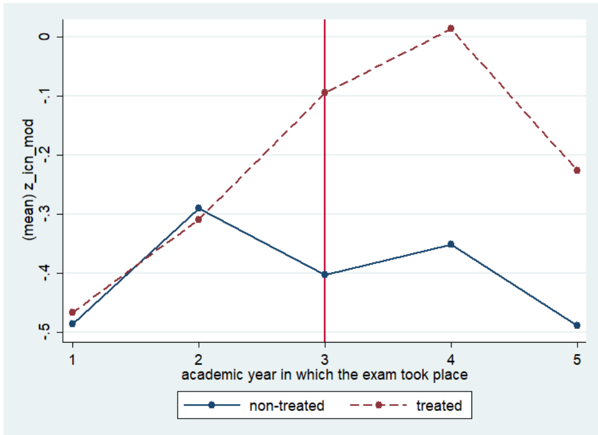


(b) Matched sample (PSM)

Figure 7: SB Exam Natural Sciences Scores of Public Schools 2014-2019

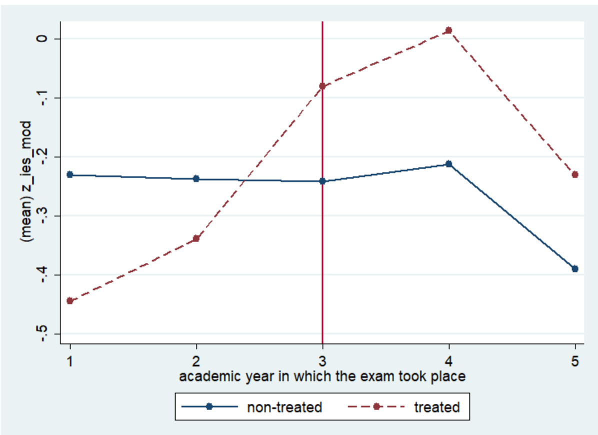


(a) Unmatched sample

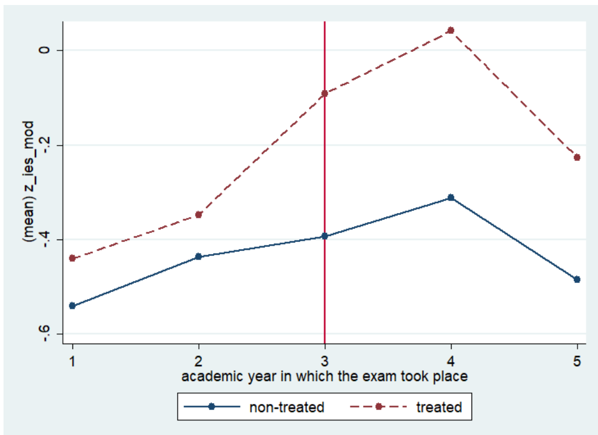


(b) Matched sample (PSM)

Figure 8: SB Exam Social Sciences Scores of Public Schools 2014-2019

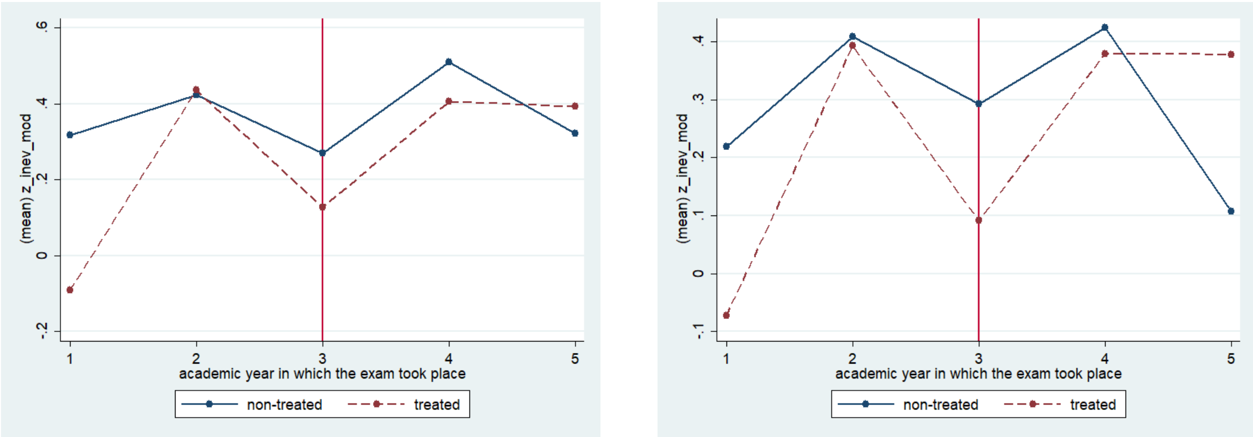


(a) Unmatched sample



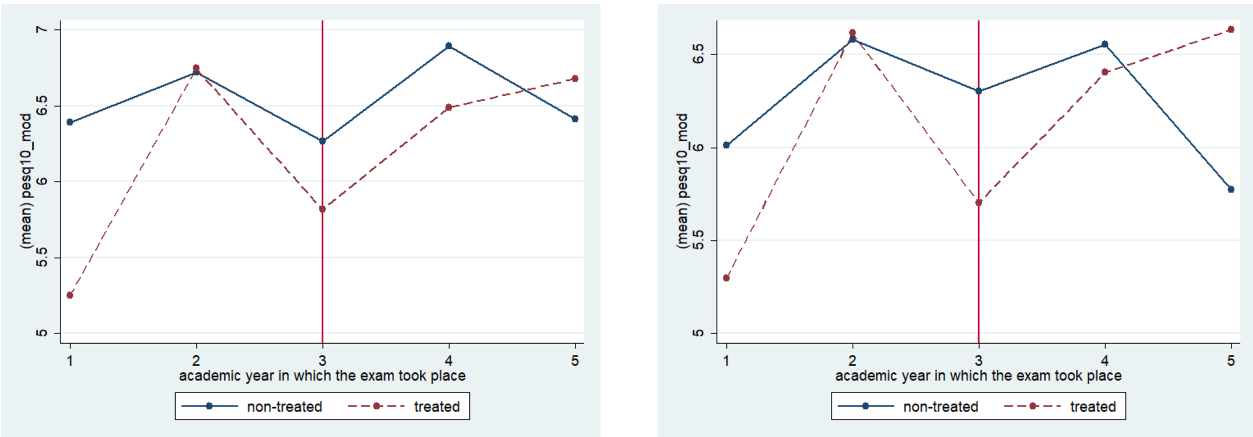
(b) Matched sample (PSM)

Figure 9: SB Exam Global Scores of Private Schools 2014-2019



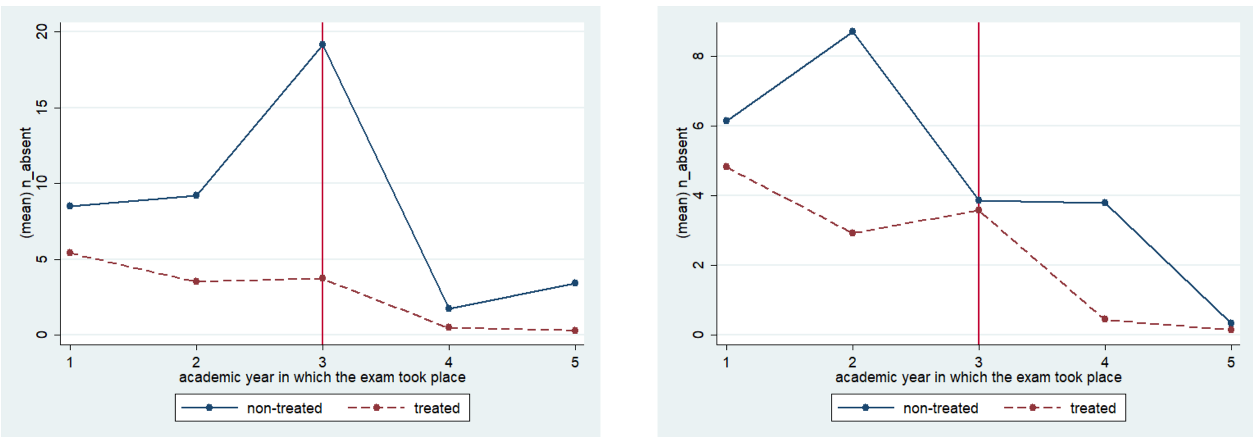
(a) Unmatched sample (b) Matched sample (PSM)

Figure 10: Students' SB Exam Performance Decile of Private Schools 2014-2019



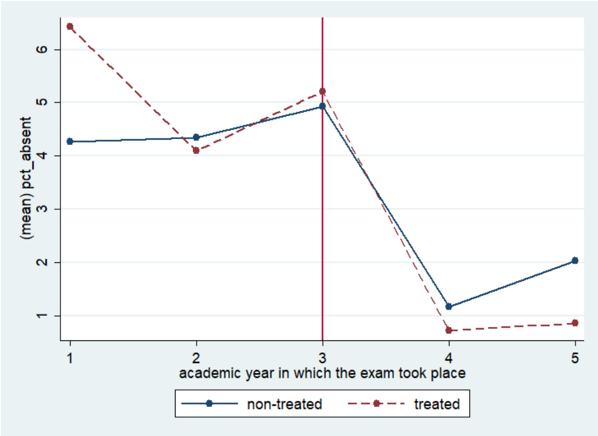
(a) Unmatched sample (b) Matched sample (PSM)

Figure 11: SB Exam Average Number of Absent Students of Private Schools 2014-2019

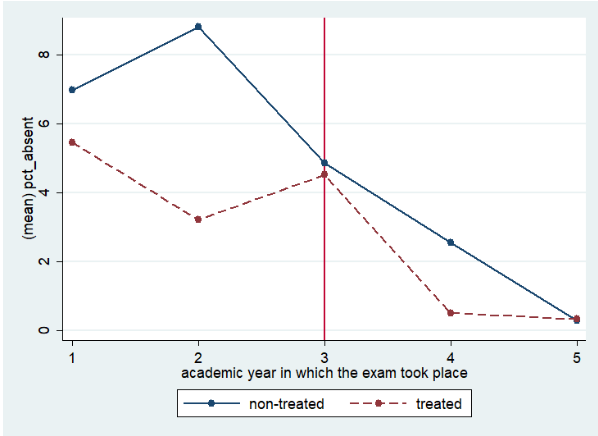


(a) Unmatched sample (b) Matched sample (PSM)

Figure 12: SB Exam Percentage of Absent Students of Private Schools 2014-2019

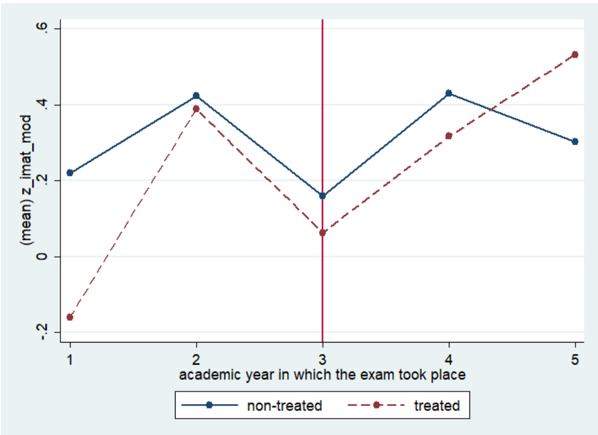


(a) Unmatched sample

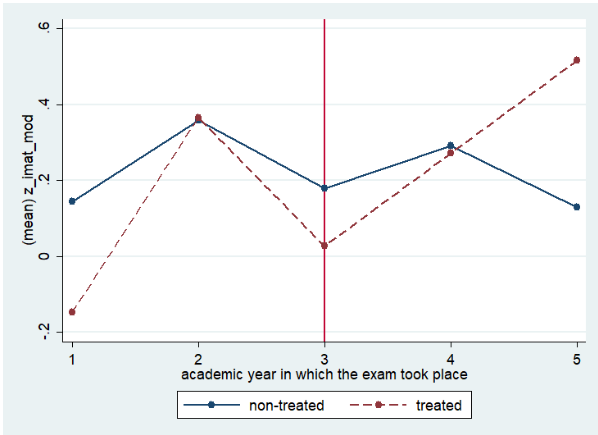


(b) Matched sample (PSM)

Figure 13: SB Exam Mathematics Scores of Private Schools 2014-2019

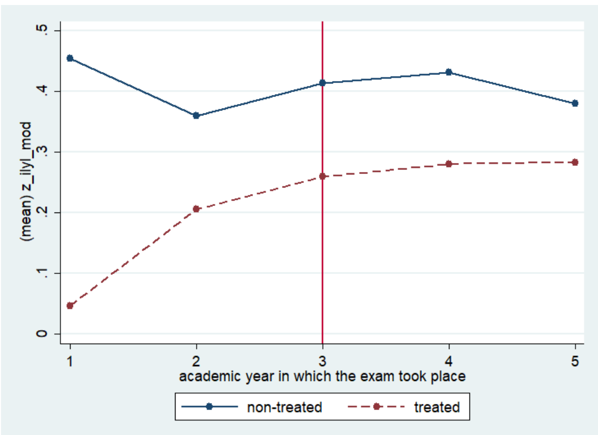


(a) Unmatched sample

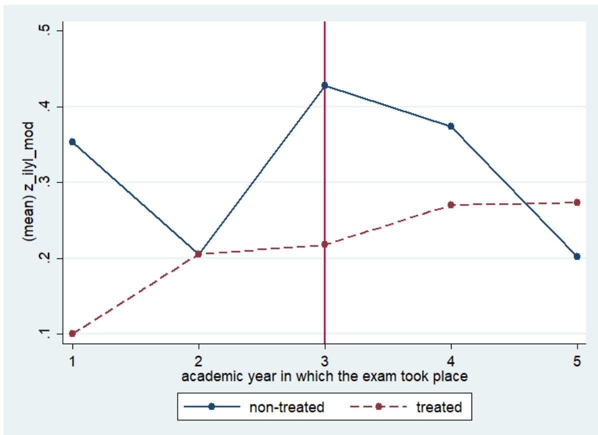


(b) Matched sample (PSM)

Figure 14: SB Exam Language Scores of Private Schools 2014-2019

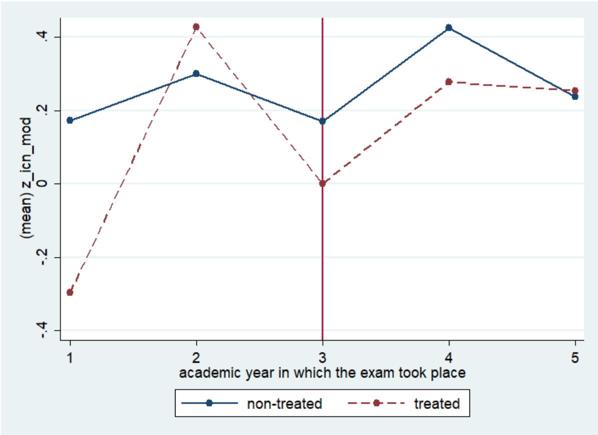


(a) Unmatched sample

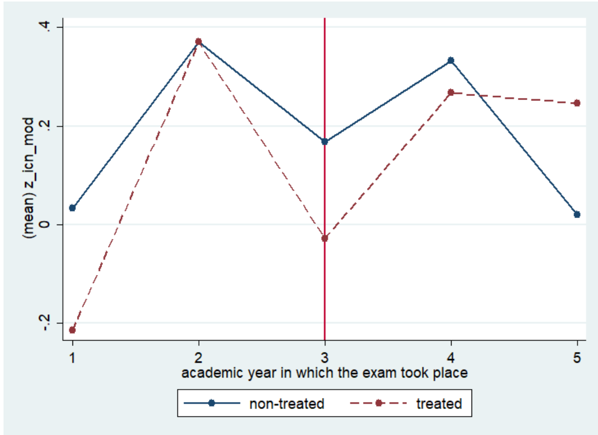


(b) Matched sample (PSM)

Figure 15: SB Exam Natural Sciences Scores of Private Schools 2014-2019

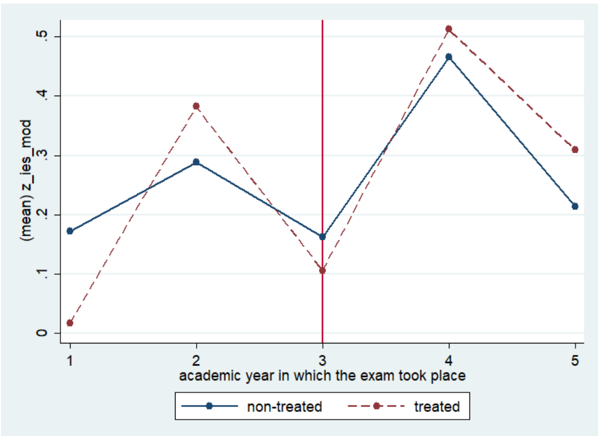


(a) Unmatched sample

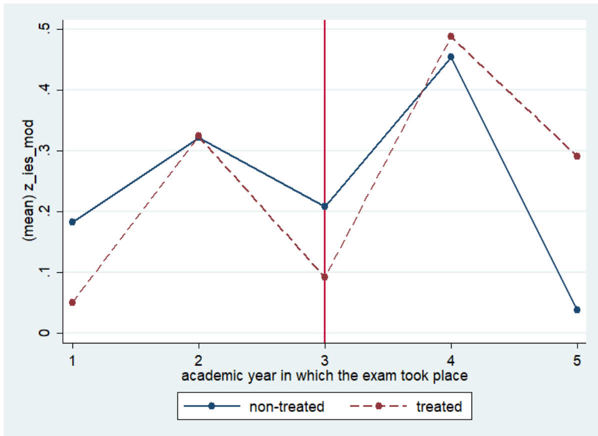


(b) Matched sample (PSM)

Figure 16: SB Exam Social Sciences Scores of Private Schools 2014-2019

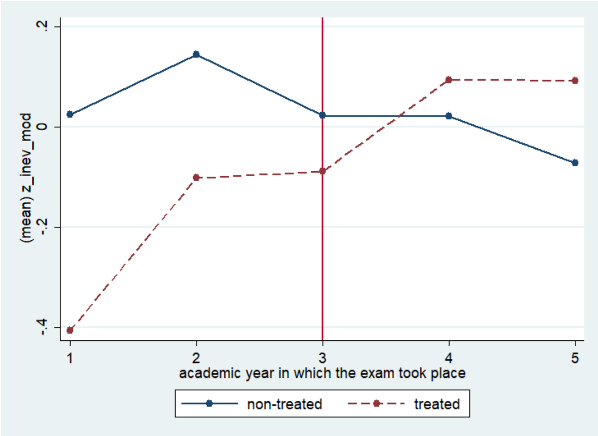


(a) Unmatched sample

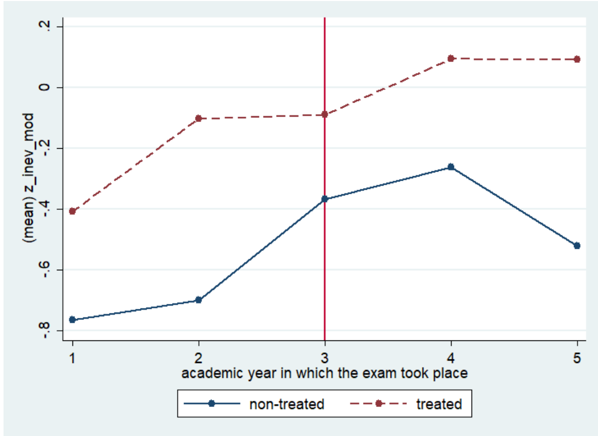


(b) Matched sample (PSM)

Figure 17: SB Exam Global Scores of Mixed Schools 2014-2019

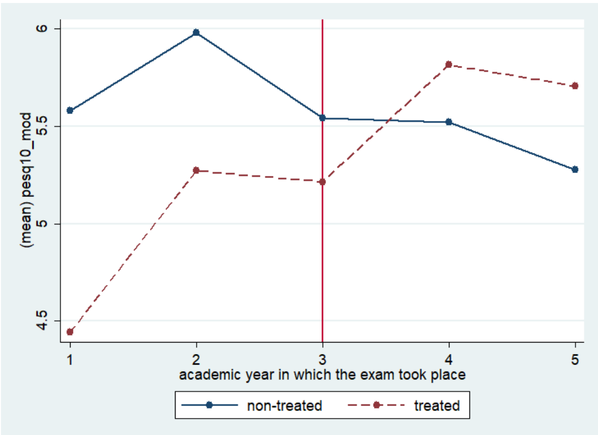


(a) Unmatched sample

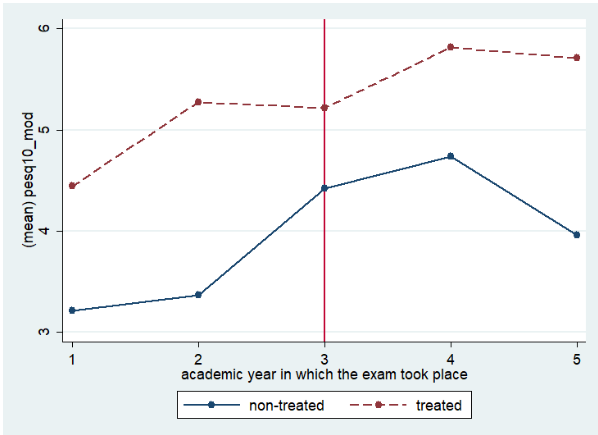


(b) Matched sample (PSM)

Figure 18: Students' SB Exam Performance Decile of Mixed Schools 2014-2019

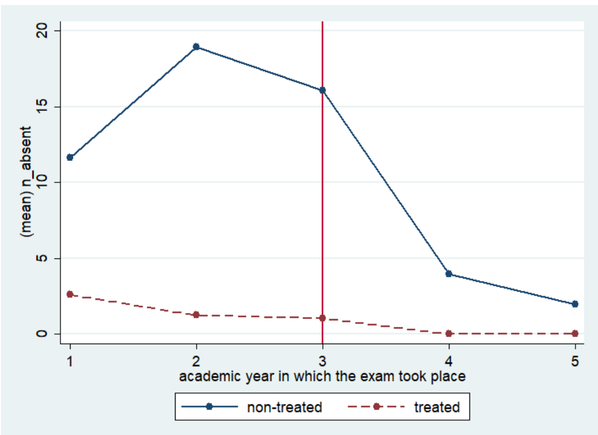


(a) Unmatched sample

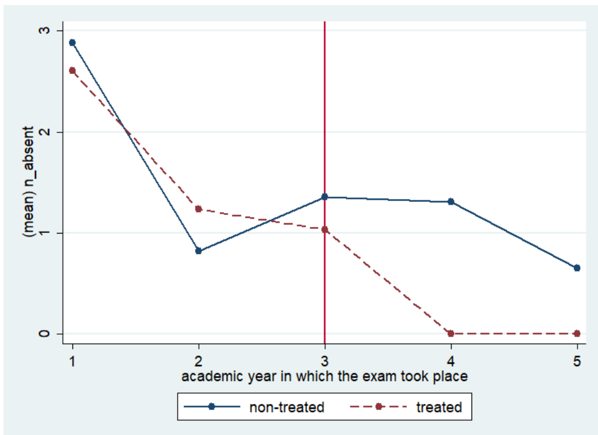


(b) Matched sample (PSM)

Figure 19: SB Exam Average Number of Absent Students of Mixed Schools 2014-2019

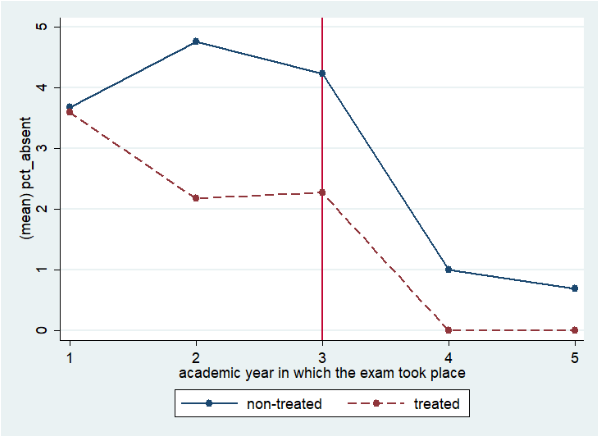


(a) Unmatched sample

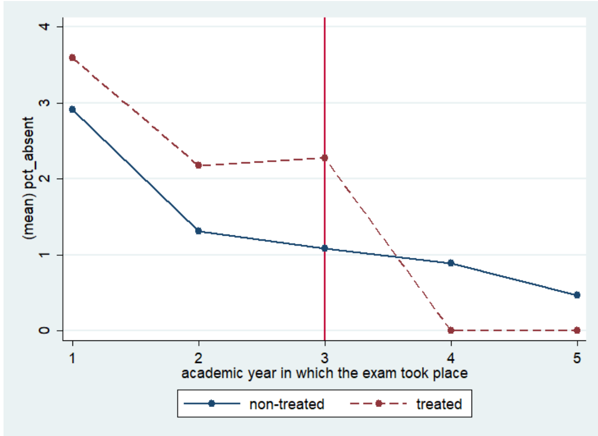


(b) Matched sample (PSM)

Figure 20: SB Exam Percentage of Absent Students of Mixed Schools 2014-2019

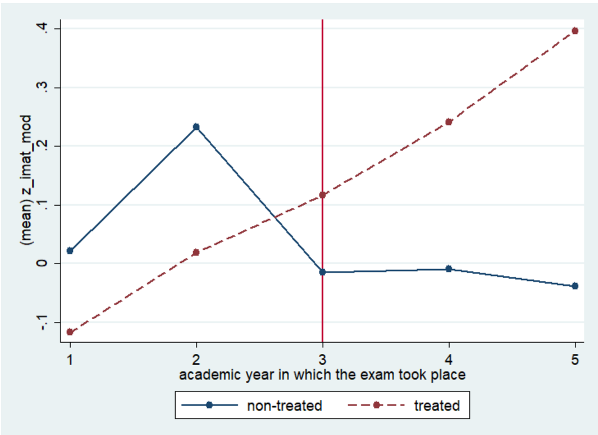


(a) Unmatched sample

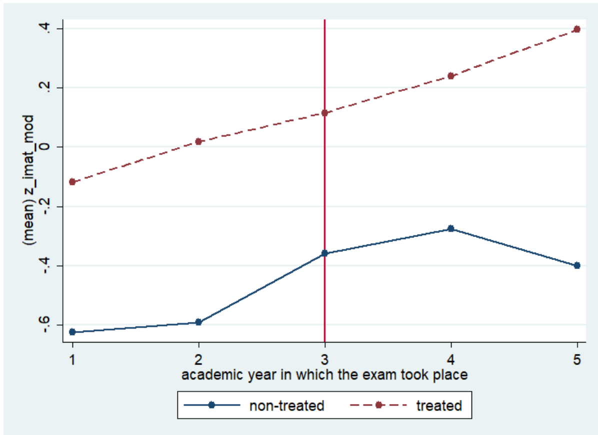


(b) Matched sample (PSM)

Figure 21: SB Exam Mathematics Scores of Mixed Schools 2014-2019

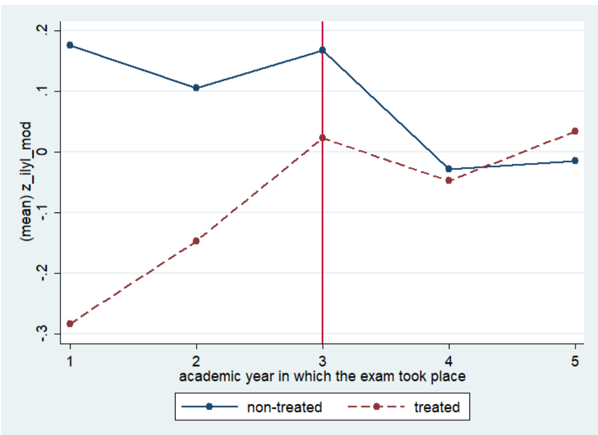


(a) Unmatched sample

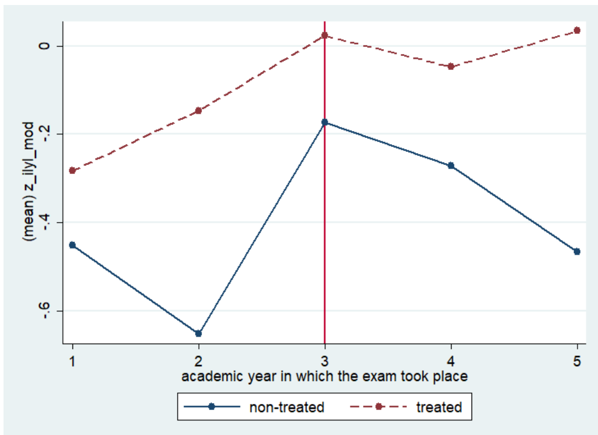


(b) Matched sample (PSM)

Figure 22: SB Exam Language Scores of Mixed Schools 2014-2019

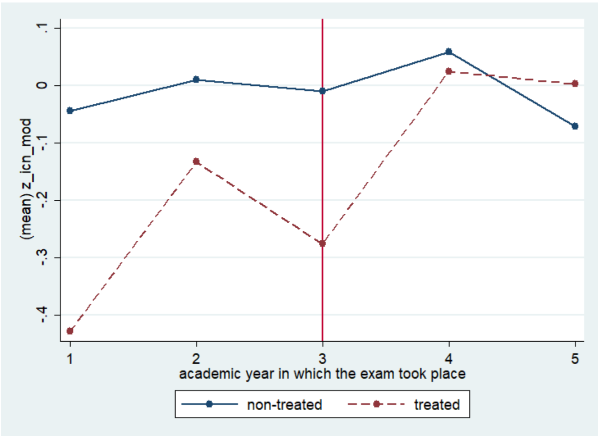


(a) Unmatched sample

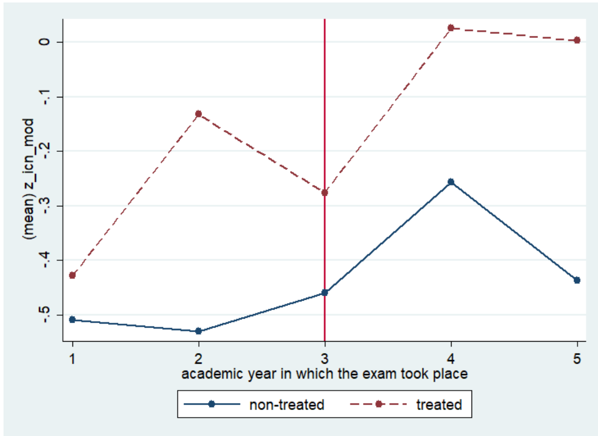


(b) Matched sample (PSM)

Figure 23: SB Exam Natural Sciences Scores of Mixed Schools 2014-2019

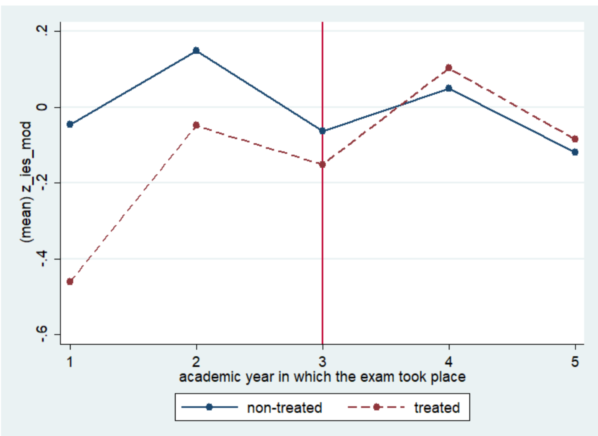


(a) Unmatched sample

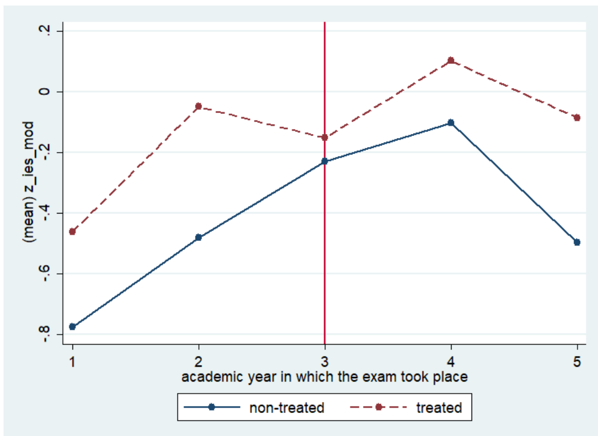


(b) Matched sample (PSM)

Figure 24: SB Exam Social Sciences Scores of Mixed Schools 2014-2019



(a) Unmatched sample



(b) Matched sample (PSM)

11 Annex B: Tables

Table 1: Summary Statistics of Outcomes

	Unmatched Sample				*Matched Sample*			
Outcomes	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
SB Global Exam Average Scores	-0.1266498	0.9851602	-4.364957	3.088182	-0.1914606	1.034703	-4.110741	3.088182
Mathematics Scores	-0.1213183	0.9821585	-5.0625	2.804308	-0.1496264	1.017642	-5.0625	2.804308
Language Scores	-0.0414754	1.014208	-6.936484	2.334071	-0.116416	1.073488	-6.936484	2.334071
Natural Sciences Scores	-0.1231448	0.9632344	-7.3991	2.707589	-0.1816128	1.000271	-6.369675	2.707589
Social Sciences Scores	-0.1353438	1.013566	-7.665333	2.529353	-0.1735704	1.083059	-6.231511	2.529353
SB Exam Performance Percentile	461.3026	287.0944	1	1000	442.0559	298.2933	1	1000
SB Exam Performance Decile	5.115872	2.859975	1	10	4.92438	2.965261	1	10
SB Exam Number of Absent Students	9.6273	26.03701	0	475	5.900929	16.44053	0	156
SB Exam Percentage of Absent Students	3.273155	5.926292	0	98	3.315118	6.426938	0	50.54945
Observations	*663,105*				*51,468*			

Table 2: Summary Statistics of Controls

	Unmatched Sample				*Matched Sample*			
Controls	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
SB Global Exam Average Scores	14.83574	15.42994	0	100	22.01658	17.86306	0	100
*% of Female Students per School*Exam Year*	52.00621	16.10233	0	100	51.26023	13.00971	0	100
*% of Mother's Level of Education per School*Exam Year*	12.85302	13.5087	0	100	11.74647	14.59168	0	75
*% of Schools Without Water Taps per School*Exam Year*	15.99497	16.98069	0	100	31.67908	21.24038	0	100
*% of Schools Without Sewage per School*Exam Year*	34.98888	24.02978	0	100	54.88544	23.77378	0	100
*% of Schools With No Electricity per Schools*Exam Year*	1.550493	2.042196	0	56.25	2.394192	3.17402	0	40
*% of Schools With No Washing Machines per Schools*Exam Year*	33.87818	17.10692	0	100	37.96791	15.53775	0	100
*% of Internet per School*Exam Year*	52.7412	23.59426	0	100	35.75165	22.61113	0	100
*% of Class Friends per School*Exam Year*	87.13321	11.6188	14.28572	100	88.40869	11.30458	14.28572	100
*% of Making Friends per School*Exam Year*	77.85275	9.134146	0	100	80.24246	10.05601	30	100
*% of Motivated Students per School*Exam Year*	89.34517	7.488882	7.142858	100	91.94961	6.329783	7.142858	100
*% of Child Labour 2 per School*Exam Year*	9.674082	8.500781	0	100	12.21581	9.887111	0	100
*% of Child Labour 3 per School*Exam Year*	26.64754	16.98664	0	100	29.48826	16.62096	0	100
*% of One Child per School*Exam Year*	13.47551	15.79974	0	100	12.38322	13.80265	0	83.33333
Observations	*663,105*				*51,468*			

Table 3: Summary Statistics of Outcomes Before and After the Earthquake

	Unmatched Sample								**Matched Sample**							
	Before				*After*				*Before*				*After*			
Outcomes	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
SB Global Exam Average Scores	-0.1291462	0.9831048	-4.364957	3.088182	-0.0475295	1.045159	-3.31341	3.088182	-0.2835195	1.015636	-4.110741	2.94533	-0.0375893	1.047935	-3.31341	3.088182
Mathematics Scores	-0.1238913	0.9795915	-5.0625	2.804308	-0.0397689	1.057088	-3.535956	2.804308	-0.22094	0.9849598	-5.0625	2.678697	-0.0304299	1.059405	-3.535956	2.804308
Language Scores	-0.0430727	1.011423	-6.936484	2.334071	0.0091492	1.097653	-3.855806	2.334071	-0.1993026	1.049929	-6.936484	2.334071	0.0221243	1.097896	-3.855806	2.334071
Natural Sciences Scores	-0.1245888	0.9606646	-7.3991	2.707589	-0.0773802	1.04039	-3.507032	2.707589	-0.2484268	0.9670881	-6.369675	2.707589	-0.0699372	1.043923	-3.507032	2.707589
Social Sciences Scores	-0.138096	1.010895	-7.665333	2.529353	-0.0481146	1.0913	-3.587458	2.529353	-0.2517487	1.068835	-6.231511	2.529353	-0.0428999	1.094051	-3.587458	2.529353
SB Exam Performance Percentile	460.5568	286.5966	1	1000	484.9406	301.4984	1	1000	414.8691	292.7426	1	1000	487.4971	301.9379	1	1000
SB Exam Performance Decile	5.108458	2.85513	1	10	5.350853	3.000085	1	10	4.654245	2.908084	1	10	5.375895	3.004778	1	10
SB Exam Number of Absent Students	9.841025	26.38826	0	475	2.853466	6.853998	0	57	7.698839	19.85091	0	156	2.895827	6.999729	0	57
SB Exam Percentage of Absent Students	3.317114	5.958915	0	98	1.87989	4.564078	0	45.6	4.212141	7.188144	0	50.54945	1.815795	4.515704	0	45.6
Observations	*642,823*				*20,282*				*32,202*				*19,266*			

Table 4: Summary Statistics of Controls Before and After the Earthquake

	Unmatched Sample								Matched Sample							
	Before				*After*				*Before*				*After*			
Controls	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
*% of Ethnic Minorities per School*Exam Year*	14.69618	15.37373	0	100	19.25903	16.51644	0	100	23.70615	18.51477	0	100	19.19256	16.33191	0	100
*% of Female Students per School*Exam Year*	52.03203	16.26729	0	100	51.18777	9.452828	0	93.75	51.19779	14.72526	0	100	51.3646	9.471752	12.5	93.75
*% of Mother's Level of Education per School*Exam Year*	12.90966	13.55983	0	100	11.05796	11.63167	0	63.63636	11.98341	16.13189	0	75	11.35044	11.55778	0	63.63636
*% of Schools Without Water Taps per School*Exam Year*	15.40685	16.49705	0	100	34.63485	21.05051	0	100	31.03867	22.39781	0	100	32.74948	19.10295	0	100
*% of Schools Without Sewage per School*Exam Year*	34.19063	23.64859	0	100	60.28867	22.20826	0	100	52.29742	24.48907	0	100	59.21117	21.85432	0	100
*% of Schools With No Electricity per Schools*Exam Year*	1.514089	1.975242	0	56.25	2.704298	3.364976	0	33.33334	2.352102	3.608206	0	40	2.464544	2.268245	0	33.33334
*% of Schools With No Washing Machines per Schools*Exam Year*	33.74754	17.19107	0	100	38.01862	13.54599	0	100	38.28849	16.80084	0	100	37.43208	13.14158	0	100
*% of Internet per School*Exam Year*	53.33841	23.44018	0	100	33.81307	20.4162	0	100	36.32733	24.04513	0	100	34.78942	19.94943	0	100
*% of Class Friends per School*Exam Year*	86.95048	11.72347	14.28572	100	92.92458	4.792093	14.28572	100	85.74866	13.10077	37.77778	100	92.85477	4.788787	14.28572	100
*% of Making Friends per School*Exam Year*	77.65161	9.110625	0	100	84.22768	7.423927	37.5	100	77.96245	10.77516	30	100	84.05336	7.271581	37.5	100
*% of Motivated Students per School*Exam Year*	89.21655	7.516797	19.04762	100	93.4216	5.066221	7.142858	100	91.13986	6.839377	62.22223	100	93.30307	5.091476	7.142858	100
*% of Child Labour 2 per School*Exam Year*	9.697529	8.481325	0	100	8.930957	9.064747	0	100	14.57446	11.08826	0	100	8.273447	5.550305	0	75
*% of Child Labour 3 per School*Exam Year*	26.4549	16.97832	0	100	32.75321	16.09547	0	100	27.50905	16.67165	0	100	32.79638	15.99867	0	84.61539
*% of One Child per School*Exam Year*	13.45371	15.82848	0	100	14.16674	14.84392	0	77.27273	11.36081	12.97322	0	83.33333	14.09211	14.9324	0	77.27273
Observations	*642,823*				*20,282*				*32,202*				*19,266*			

Table 5: Results of SB Exam Average Scores, Performance Results and Absence

	(1)	(2)	(3)	(4)
	SB Exam Average	**SB Exam Performance Decile**	**SB Exam Number of Absent Students**	**SB Exam Percentage of Absent Students**
Variables	*z_inev_mod*	*pesq10_mod*	*n_absent*	*pct_absent*
A) Specification #1				
*Treated_ci*AfterEarthquake*	0.225	0.597	-0.068	1.153
	(0.200)	(0.572)	(15.665)	(3.858)
Observations	51,468	51,468	51,468	51,468
R-squared	0.413	0.407	0.544	0.715
B) Specification #2				
*Treated_ci*After_2014/2015*	-0.173	-0.470	0.180	-1.203
	(0.145)	(0.432)	(3.787)	(1.555)
*Treated_ci*After_2015/2016*	-0.203	-0.540	-0.512	-1.636
	(0.150)	(0.437)	(10.043)	(2.510)
*Treated_ci*After_2017/2018*	0.062	0.230	-1.162	-1.448
	(0.124)	(0.365)	(3.973)	(1.481)
*Treated_ci*After_2018/2019*	0.090	0.266	-0.223	-0.988
	(0.140)	(0.420)	(3.739)	(1.384)
Observations	50,630	50,630	50,630	50,630
R-squared	0.333	0.323	0.354	0.487
C) Specification #3				
*Treated*After*	0.336	0.958	3.002	1.155
	(0.294)	(0.840)	(22.294)	(5.392)
*Treated*After*Private_s*	-0.824**	-2.438**	3.886	3.866
	(0.338)	(0.936)	(22.603)	(5.959)
*Treated*After*Mixed_s*	-0.929	-2.853*	-3.576	0.159
	(0.560)	(1.522)	(22.293)	(5.540)
Observations	51,468	51,468	51,468	51,468
R-squared	0.422	0.416	0.558	0.729

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 6: Results of SB Exam Scores Per Subject

	(5)	(6)	(7)	(8)
	Mathematics Scores	**Language Scores**	**Natural Sciences Scores**	**Social Sciences Scores**
Variables	*z_imat_mod*	*z_ilyl_mod*	*z_icn_mod*	*z_ies_mod*
A) Specification #1				
*Treated_ci*AfterEarthquake*	0.182	0.125	0.240	0.155
	(0.169)	(0.158)	(0.175)	(0.208)
Observations	51,468	51,468	51,468	51,468
R-squared	0.354	0.312	0.306	0.285
B) Specification #2				
*Treated_ci*After_2014/2015*	-0.096	-0.110	-0.214*	-0.138
	(0.119)	(0.143)	(0.116)	(0.145)
*Treated_ci*After_2015/2016*	-0.143	-0.126	-0.225*	-0.143
	(0.114)	(0.137)	(0.127)	(0.158)
*Treated_ci*After_2017/2018*	0.143	0.071	0.013	0.005
	(0.095)	(0.137)	(0.116)	(0.106)
*Treated_ci*After_2018/2019*	0.117	0.120	0.042	0.056
	(0.120)	(0.138)	(0.123)	(0.127)
Observations	50,360	50,360	50,360	50,360
R-squared	0.280	0.251	0.237	0.219
C) Specification #3				
*Treated*After*	0.259	0.236	0.342	0.245
	(0.234)	(0.230)	(0.241)	(0.309)
*Treated*After*Private_s*	-0.711**	-0.564**	-0.877***	-0.582
	(0.303)	(0.255)	(0.311)	(0.373)
*Treated*After*Mixed_s*	-0.391	-0.877	-0.912**	-0.872*
	(0.735)	(0.570)	(0.391)	(0.434)
Observations	51,468	51,468	51,468	51,468
R-squared	0.363	0.319	0.313	0.288
Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1				

Table 7: Potential Mechanisms

	(1)	(2)	(3)
	Ethnic Minority Students	**Female Students**	**Mother's Level of Education**
Variables	*min_ethnic*	*stu_female*	*edmother_3levplu*
Mechanisms - Specification #3			
*Treated*After*	-0.061	-0.012	0.026*
	(0.043)	(0.030)	(0.013)
*Treated*After*Private_s*	0.095	0.012	-0.099**
	(0.082)	(0.058)	(0.045)
*Treated*After*Mixed_s*	0.039	0.106*	-0.038
	(0.206)	(0.061)	(0.047)
Observations	50,508	51,468	50,645
R-squared	0.148	0.062	0.201

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1