



Shaken up or still studying? Student performance after the Central Italy earthquake

Davide Di Marcoberardino & Marco Cucculelli

To cite this article: Davide Di Marcoberardino & Marco Cucculelli (2026) Shaken up or still studying? Student performance after the Central Italy earthquake, *Regional Studies, Regional Science*, 13:1, 2615501, DOI: [10.1080/21681376.2026.2615501](https://doi.org/10.1080/21681376.2026.2615501)

To link to this article: <https://doi.org/10.1080/21681376.2026.2615501>



© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



[View supplementary material](#)



Published online: 02 Feb 2026.



[Submit your article to this journal](#)



[View related articles](#)



[View Crossmark data](#)

Shaken up or still studying? Student performance after the Central Italy earthquake

Davide Di Marcoberardino  and Marco Cucculelli 

Department of Economics and Social Sciences, Marche Polytechnic University, Ancona, Italy

ABSTRACT

Natural hazards and disasters have diverse impacts on populations worldwide in different ways, including significant effects on students and educational systems. While the effects of COVID-19 on students have been extensively explored, less attention has been given to the impacts of disasters at the NUTS (nomenclature of territorial units for statistics)-3 level, particularly in Western European countries. This study investigates the effects of the 2016 Central Italy earthquake on the learning outcomes of primary school students using standardised test scores at the NUTS-3 level provided by INVALSI (Istituto Nazionale per la Valutazione del Sistema Educativo di Istruzione e di Formazione). Using a quasi-experimental design, we analyse the data through a dual methodological approach that combines synthetic difference-in-differences (SDID) and event study methodologies. The findings reveal a significant negative impact of the earthquake on the test scores of second-year primary school students, while effects on fifth-year students are not statistically significant. Notably, the negative impact persists for approximately two years, highlighting the enduring educational consequences of disasters. This case study offers policy implications for educational systems in the aftermath of an earthquake, as well as a quantitative background for comparative research on education in Europe.

ARTICLE HISTORY

Received 24 April 2025
Accepted 5 January 2026

KEYWORDS

Disasters; natural disasters;
earthquake; education;
educational outcomes

JEL

Q54; I21; H75


1. Introduction

Natural hazards and disasters have a profound impact on populations worldwide, with their frequency and severity increasing due to the combined forces of climate change and urbanisation (Botzen et al., 2019; Frieters et al., 2023; Wang et al., 2021). While the economic and social consequences are often localised and rarely escalate to the national level (Barone & Mocetti, 2014; Bănică et al., 2020; Bui et al., 2014; Cohen & Werker, 2008; Deryugina, 2022; Escaleras & Register, 2012; Kukeli, 2025; Marin & Modica, 2017; Meltzer et al., 2021), their impact extends far beyond physical infrastructure damage and loss of life, profoundly affecting individuals' emotional, behavioural and psychological well-being (Bonanno et al., 2010; Caruso et al., 2024; Park et al., 2020; Perdana & Vall Castelló, 2025; Vogel & Vernberg, 1993).

A critical yet often overlooked consequence of disasters is the disruption of education. This disruption can manifest through temporary school closures and the relocation of students, significantly impeding access to education and undermining both the quality and quantity of learning (Caruso et al., 2024; Esnard et al., 2018; Gibbs et al., 2019; Hussain & Mukhopadhyay, 2024; Kousky, 2016; Lai et al., 2019; Lassa et al., 2023; Schady et al., 2023). While much research has focused on the detrimental effects of the COVID-19 pandemic, the broader impacts of disasters on education remain underexplored in the literature (Brummet, 2014; Carlana et al., 2023; Dagorn & Moulin, 2025; Gillitzer & Prasad, 2024; Grewenig et al., 2021; Schady et al., 2023).

Children are particularly vulnerable in such scenarios (Kousky, 2016; Peek, 2008), with an estimated 75 million affected annually by educational disruptions due to conflicts and disasters (Venegas Marin et al., 2024). This has significant implications for educational inequalities and human capital development (Hyde et al., 2021).

CONTACT Davide Di Marcoberardino  d.dimarcoberdino@staff.univpm.it

 Supplemental data for this article can be accessed online at <https://doi.org/10.1080/21681376.2026.2615501>

© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group
This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

Most existing research has examined educational outcomes using indicators such as years of schooling and enrolment rates, showing that disasters reduce learning performance among students who remain in school and shorten overall schooling duration (Oppen et al., 2023). For instance, studies have examined the impact of the L'Aquila earthquake on local university enrolment (Cerqua & Di Pietro, 2017) and the effect of earthquakes on schooling years in Indonesia (Shidiqi et al., 2023). Much of this literature focuses on low- and middle-income countries (Cadag et al., 2017; David et al., 2018; Deuchert & Felfe, 2015; Hussain & Mukhopadhyay, 2024; Nguyen & Minh Pham, 2018; Paudel & Ryu, 2018; Raeburn, 2025; Tian et al., 2022) or specific disasters, such as hurricanes in the United States (Harris & Larsen, 2023; Imberman et al., 2012; Lai et al., 2019; Sacerdote, 2012). However, the impact of disasters on education in high-income countries outside the United States has been insufficiently investigated (Cerqua & Di Pietro, 2017; Lassa et al., 2023) and mainly, at the individual level.

Specifically, few studies have examined the broader, area-level impacts of disasters on educational outcomes. Cerqua and Di Pietro (2017) investigated individual university enrolment decisions following the 2009 L'Aquila earthquake, while Lassa et al. (2023) assessed the effects of flooding on individual learning quality in Indonesia, a lower-income context. Segarra-Almística et al. (2022) analysed multiple hazard types – hurricanes and earthquakes – in Puerto Rico. However, existing research exhibits two main limitations. First, prior analyses predominantly adopt the individual as the unit of observation, often within low-income or US settings. Second, they tend to consider multiple hazards simultaneously, complicating causal inference. In contrast, our study isolates the effects of a single disaster and shifts the analytical focus from individual- to area-level impacts, offering new evidence on how a major hazard shapes learning performance across NUTS (nomenclature of territorial units for statistics)-3 regions.

This study aims to address this gap by examining the impact of the 2016 earthquake in central Italy on education, focusing on student performance at the NUTS-3 level in Italy.¹ The earthquake involved three major shocks and affected a large area covering six provinces across four regions: Abruzzo, Lazio, Marche and Umbria. The first shocks in August, with a magnitude of 6.0 on the Richter scale, had their epicentre between Accumoli (province of Rieti, Lazio region) and Arquata del Tronto (province of Ascoli Piceno, Marche region). In October, two additional earthquakes occurred: one near Ussita, Visso and Castelsantangelo sul Nera (province of Macerata, Marche region), and the strongest – 6.5 on the Richter scale – between Norcia and Preci (province of Perugia, Umbria region) on 30 October. This magnitude was surpassed only three times in Italy during the past century (1920, 1930 and 1980). The earthquake caused over 300 fatalities, displaced approximately 41,000 people, and inflicted extensive damage on buildings and cultural heritage (Dottori, 2024).

This study evaluates whether the 2016 earthquake affected student performance in standardised assessments and examines the persistence of these effects in the years following the event. The analysis draws on data from the National Evaluation Institute for the School System (INVALSI – Istituto Nazionale per la Valutazione del Sistema Educativo di Istruzione e di Formazione), which annually assesses student achievement in core subjects such as Italian and Mathematics. Administered by INVALSI under the authority of Italy's Ministry of Education, these standardised tests provide a robust empirical foundation for evaluating the educational impact of the earthquake. The data, collected annually at the individual level near the end of the academic year, are aggregated by INVALSI at the NUTS-3 level.²

The empirical analysis employs two different methodological approaches. First, the synthetic difference-in-differences (SDID) method (Abadie et al., 2010; Arkhangelsky et al., 2021) combines the strengths of difference-in-differences and synthetic control methods to estimate causal effects. This approach compares the treated group with synthetic units constructed *ad hoc* to provide robust estimations. Second, the event study methodology (Clarke & Tapia-Schythe, 2021; Freyaldenhoven et al., 2019) is applied to capture the temporal dynamics of the effects, analysing variations before and after the event. Both methods utilise the same set of covariates to ensure the reliability and consistency of the results.

The findings reveal a decline in INVALSI assessment performance in both Italian and Mathematics among second-year primary students, with reductions ranging from approximately 0.7% to 2.2% of their scores. Notably, these effects persist for approximately two years. The consistency of the results across both methodologies underscores their robustness. In contrast, no significant trends were observed among fifth-year students, as the results in both subjects were statistically not significant. To validate these findings further, robustness and sensitivity checks have been conducted, including placebo tests,

modifications to the donor pool, adjustments to the analysis time windows and changes in the treatment group. Although this study focuses on a single event, its contribution is valuable because of the scarcity of similar research in subnational European areas. As such, it is a meaningful basis for future comparative studies across different European countries.

The remainder of the paper is organised as follows: Section 2 reviews the relevant literature; Section 3 details the empirical strategy and data; Section 4 presents the results and sensitivity and robustness checks; Section 5 discusses the findings; and Section 6 concludes the study.

2. Literature review

Disasters have a profound and multifaced impact on education systems, disrupting the learning experiences of students from different grade levels and socio-economic backgrounds. These events often affect children's access to educational opportunities (Gibbs et al., 2019; Lassa et al., 2023; Paudel, 2023) and trigger a cascade of challenges. For example, disasters often lead to class suspensions, school closures and transportation difficulties, while also affecting the physical and social environment of schools (Cadag et al., 2017; Montero et al., 2024; Morrill & Westall, 2023; Opper et al., 2023; Venegas Marin et al., 2024). Even when school buildings remain structurally undamaged, they can face operational challenges if they are repurposed as evacuation centres, leading to extended closures and potential structural damage (Cadag et al., 2017; David et al., 2018; Rawls & Turnquist, 2012; Venegas Marin et al., 2024).

These educational disruptions are often compounded by communication breakdowns, unstable housing conditions and the emotional and financial strain on families (Venegas Marin et al., 2024). Reported consequences range from attendance difficulties to adjustments to course schedules, fluctuations in academic performance and increased educational disparities (Breen & Meyer, 2021; Hyde et al., 2021; Opper et al., 2023; Venegas Marin et al., 2024). These impacts disproportionately affect vulnerable groups, including children with disabilities, children from low-income families and students with lower academic achievement (Segarra-Alméstica et al., 2022). The severity of these impacts is influenced by factors such as the socio-economic vulnerability of families and the physical resilience of school infrastructure (Esnard et al., 2018; Gravel et al., 2021; Marin et al., 2021).

The consequences for students are substantial and extend to the psychological domain. Disasters frequently give rise to symptoms of post-traumatic stress (Barkin et al., 2021; La Greca et al., 2010; Opper et al., 2023). Even in the absence of direct exposure, students may suffer indirectly as school closures limit access to essential health and social services, thereby increasing their overall vulnerability (Segarra-Alméstica et al., 2022).

The literature has extensively examined the impact of disasters on school enrolment. Disruptions such as infrastructure damage, student displacement and financial hardship negatively impact enrolment rates at all levels of education, from enrolment to graduation (Wang, 2024). For example, Cerqua and Di Pietro (2017) found no statistically significant effect on university enrolment in the three years following the 2009 L'Aquila earthquake. However, disaggregated data showed negative effects on younger students and students in engineering programmes that suffered major infrastructure damage. Similarly, Raeburn (2025) observed stable overall enrolment but noted a decline in school attendance among girls in rural areas. Jiménez-Martínez and Jiménez-Martínez (2025) found a decline in attendance following an earthquake for both primary and secondary school students, while no significant effects were observed among university students.

Severe disasters often lead to a greater decline in school enrolment. Opper et al. (2023) reported significant reductions in higher education enrolment following highly destructive events, while Crespo Cuaresma (2010) and Deuchert and Felfe (2015) found declines in secondary school enrolment and long-term declines in overall schooling levels, respectively. Paudel (2023) linked forest fires to decreased middle school graduation rates, while Gibbs et al. (2019) found that bushfires negatively affected reading and numeracy outcomes.

Disasters also increase the likelihood of school dropout, especially among students in affected areas (Segarra-Alméstica et al., 2022; Venegas Marin et al., 2024; Wang, 2024). Nguyen and Minh Pham (2018), who compared different hazards in four countries (Ethiopia, India, Peru and Vietnam), found significant negative effects of floods on the number of grades completed in all countries, although these varied in severity. These challenges often have broader economic implications, including reduced rental income and decreased demand for local goods and services (Cerqua & Di Pietro, 2017).

Academic performance is another critical area of concern. Several studies have documented the decline in test scores following disasters. Morrill and Westall (2023) and Segarra-Alméstica et al. (2022) reported slight declines in test scores after Hurricanes Florence and María, respectively. Deuchert and Felfe (2015) found that disasters often lead to lower test scores and an increased grade gap, while Venegas Marin et al. (2024) confirmed long-term negative effects on educational attainment. Hussain and Mukhopadhyay (2024) observed a negative relationship between the intensity of disasters and educational outcomes in India, and Tian et al. (2022) found lower educational attainment in adulthood among individuals exposed in utero to the 1976 Tangshan earthquake, while Caruso and Miller (2015) found lower years of schooling among individuals exposed in utero to the 1970 Ancash earthquake.

Conversely, some studies suggest that the impact of disasters on school performance need not always be negative. Smilde-van den Doel et al. (2006) reported that children's academic performance was similar to that of unaffected peers within three years after a disaster, with affected students even outperforming their peers shortly after the event. Beaglehole et al. (2017) also found no evidence of a sustained decline in academic performance after earthquakes. Sacerdote (2012) argued that disasters can have positive effects when students are moved from low-performing schools to better facilities. Academic achievement tends to improve when students are placed alongside high-achieving peers but worsens when they are surrounded by lower-performing students (Imberman et al., 2012).

In summary, while disasters often have detrimental effects on educational systems, outcomes vary depending on factors such as the severity of the disaster, socio-economic conditions, and the nature of post-disaster interventions. This complexity highlights the importance of further research to examine the nuanced impact of disasters on student achievement and to develop targeted policy responses.

3. Data and methods

3.1. Data

The National Evaluation Institute for the School System (INVALSI) conducts annual large-scale assessments across Italy to monitor student achievement in Italian (including reading comprehension and grammatical knowledge), Mathematics and, more recently, English Language (Costanzo & Desimoni, 2017; Montanaro & Sestito, 2014; Sacco & Falzetti, 2021). This study draws on INVALSI data at the NUTS-3 level for the period from 2013 (the earliest available year) through 2019. Specifically, the analysis focuses on standardised tests in Italian and Mathematics administered for the students in primary school at the end of 2nd and the 5th grades, covering the academic years from 2012–2013 to 2018–2019. The primary measure of interest is the weighted likelihood estimate (WLE) score,³ an ability estimate derived from the Rasch model (Costanzo & Desimoni, 2017; Montanaro & Sestito, 2014; Sacco & Falzetti, 2021). INVALSI provides WLE scores while incorporating potential adjustments for instances of cheating and differences in items difficulties, thereby ensuring the reliability of the assessment outcomes⁴ (INVALSI, 2024).

The choice of this level of analysis (NUTS-3 regions) is driven by data limitations, as municipal-level data are only available for municipalities with at least three primary schools. Consequently, a significant number of severely affected smaller municipalities are excluded from the sample.⁵ The NUTS-3 level of aggregation is likely to attenuate the effects, implying that the true impact in the most severely affected areas may be both larger and more enduring.⁶

Specifically, the analysis focuses on INVALSI scores for grades 2 and 5, corresponding to the second and fifth year of primary school. Four Sardinian NUTS-3 regions (Olbia-Tempio, Ogliastra, Medio Campidano and Carbonia-Iglesias) are excluded from the analysis, as these regions changed in 2017 and the data after that year are not available. Additionally, the provinces of Trento and Bolzano are also excluded due to missing values in certain covariates for some years.

3.2. Sample

In this study, we define 'treated' NUTS-3 regions as those with at least 10 municipalities designated as affected areas by the national government and Civil Protection Agency under Decree-Law 189 of 2016.

These NUTS-3 regions include Ascoli Piceno, Fermo, Macerata (in the Marche region), Perugia (in the Umbria region), Teramo (in the Abruzzo region), and Rieti (in the Lazio region).

To ensure robustness, we excluded marginally affected NUTS-3 such as Ancona (2 affected municipalities), L'Aquila (6 affected municipalities), and Terni (4 affected municipalities). Additionally, NUTS-3 regions impacted by other major disasters – such as the 2012 Emilia earthquake (Modena, Reggio Emilia, Rovigo, Mantua, Ferrara) and Livorno (severely flooded in 2017) – were excluded from the donor pool.

Sensitivity checks are conducted to assess the robustness of the decision to exclude marginally affected NUTS-3 regions. To this end, the analysis is also performed including the regions of Ancona, L'Aquila, and Terni.

3.3. Empirical strategy

Our methodological approach employs the synthetic difference-in-differences (SDID) method (Abadie et al., 2010; Arkhangelsky et al., 2021), which integrates the strengths of the synthetic control approach with those of the traditional difference-in-differences (DiD) methodology. This technique enhances causal inference by constructing a weighted combination of control units that closely replicates the pre-treatment trajectory of the treated units. The weights are optimised to minimise pre-treatment discrepancies between the treated unit and the synthetic control. By combining the robust identification strategy of DiD with the precision of the synthetic control method, SDID is particularly well-suited for comparative case studies. Indeed, the SDID estimator constructs a synthetic control by simultaneously optimising unit weights w_j and time weights v_t , allowing for a close approximation of the treated units' pre-treatment trajectory. This enables the identification of the average treatment effect as follows:

$$\hat{\delta} = \frac{1}{|T|} \sum_{i \in T} \left(Y_{it} - \sum_{j \notin T} w_j Y_{jt} \right) \quad (1)$$

where Y_{it} denotes the outcome of interest for unit i at time t , and T indicates the set of treated units. The model can also be expressed as follows:

$$Y_{it} = \delta_{it} D_{it} + X_{it} \beta + \alpha_i + \gamma_t + \varepsilon_{it} \quad (2)$$

where D_{it} is the treatment indicator, δ_{it} the treatment effect, and X_{it} the vector of covariates, while α_i and γ_t are represent unit and fixed effects, respectively, and ε_{it} is the error term.

To gain deeper insights into the temporal dynamics of the treatment effects and assess robustness, we apply an event study methodology (Clarke & Tapia-Schythe, 2021; Freyaldenhoven et al., 2019). While SDID primarily estimates the average treatment effects on the treated (ATT), it does not explicitly account for variation in effects over time. The event study approach addresses this limitation by examining the evolving impact of a treatment or event over time, estimating effects at various intervals. By modelling outcomes as a function of relative time, this method captures trends before and after the event, offering valuable insights into the timing, magnitude and persistence of effects. Furthermore, it offers a more rigorous verification of the parallel trend assumption through the analysis of pre-treatment coefficients. The panel event study is estimated as follows (Clarke & Tapia-Schythe, 2021):

$$Y_{it} = \alpha + \sum_{j=2}^J \beta_j (\text{Lead}_j) + \sum_{k=0}^K \gamma_k (\text{Lag}_k)_{it} + u_i + \lambda_t + X'_{it} + \varepsilon_{it} \quad (3)$$

where Y_{it} denotes the outcome of interest for unit i at time t , u_i and γ_t represent unit and fixed effects respectively, and X'_{it} refers to the covariates. Lags and leads are indicators representing periods before and after the occurrence of the event.

The combination of these two methodologies enhances the accuracy and the interpretative depth of causal analyses, leading to a more comprehensive understanding of treatment effects.

The treatment period is defined as beginning in 2017, with the vertical bar in the graphs marking 2016. This delineation aligns with the timeline of the 2016 earthquakes (August and October) and the administration of standardised tests at the end of the academic year (April–May). Consequently, the 2016 scores are unaffected by the earthquakes, making 2017 the first year influenced by the treatment.

The SDID approach was computed using the bootstrap strategy with 500 replications. Robustness was further assessed using a placebo strategy, also implemented with 500 replications. For the event study methodology, we employed fixed effects and included an interaction term between the dummy of central regions (Abruzzo, Lazio, Marche, Tuscany, Umbria) and the year to control for region-specific time trends, as the treated provinces are mostly located in central Italy, and only one in the south (Teramo); L'Aquila is also considered in the sensitivity analysis. This adjustment accounts for structural characteristics of different areas, which are unrelated to the earthquake. Apart from this additional term, both analyses utilised the same set of covariates. Finally, the sample is the same in both the methodological frameworks.

3.4. Variables

To control for potential confounding factors, the analysis incorporates a range of covariates, selected based on insights from the literature. These include the corruption index (Nifo & Vecchione, 2014), school characteristics such as class size and repeating students' percentage (ISTAT), per capita gross domestic product (GDP) (Eurostat), and INVALSI's scores in Italian and Mathematics from the preceding academic year.

The selection of covariates aligns with evidence in the literature highlighting their relevance to educational outcomes. For instance, class size is a key determinant of student achievement (Brunello & Checchi, 2005; Figueroa et al., 2016; Krueger & Whitmore, 2001), while economic conditions, proxied by GDP per capita, play a significant role (Filmer & Pritchett, 1999; Huang, 2013). The descriptive statistics of all the variables, with a breakdown for treated and not treated, are shown in Table 1.

4. Results

In this section, we present the findings of our analysis on student performance, as measured by test scores, to evaluate their effects on academic achievement. The first sub-section will present the results of the double methodological approach, while the second sub-section will present the robustness checks.

4.1 Effects on students' performance

Our analysis identifies a significant and negative impact of the earthquake on test scores of Italian language and Mathematics for Grade 2 (second year of primary school). Starting from the outcomes of the SDID

Table 1. Descriptive statistics.

Variable	Not treated									
	Pre-treatment					Post-treatment				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
ItaGrade2	264	201.9	5.258	183.1	212.9	264	205.3	4.491	189.7	215.4
MathGrade2	264	202.5	5.024	182.5	213.5	264	207.1	4.347	194.0	221.1
ItaGrade5	264	200.7	5.753	182.4	211.3	264	202.3	5.373	182.7	211.8
MathGrade5	264	201.6	6.342	176.4	217.4	264	204.8	5.021	185.9	215.6
Gdppc (x 1000)	264	247.1	68.42	145.0	533.0	264	263.8	74.47	152.0	558.0
Corruption	264	0.775	0.196	0	0.971	264	0.775	0.186	0	0.982
Studentsperclass	264	18.73	1.770	12.03	22.65	264	18.32	1.924	12.47	22.82
Repeatingstudents	264	0.004	0.002	0.001	0.010	264	0.003	0.002	0	0.009
Variable	Treated									
	Pre-treatment					Post-treatment				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
ItaGrade2	18	207.5	3.345	201.3	213.1	18	208.6	4.153	201.5	216.1
MathGrade2	18	208.2	3.666	198.5	213.3	18	210.3	4.055	204.5	217.5
ItaGrade5	18	205.7	3.425	200.5	211.4	18	207.7	3.961	200.6	214.5
MathGrade5	18	205.4	4.399	196.0	211.2	18	209.1	3.922	201.8	213.1
Gdppc (x 1000)	18	230.9	23.14	181.0	253.0	18	245.8	25.91	186.0	217.0
Corruption	18	0.857	0.079	0.721	0.958	18	0.874	0.105	0.681	0.965
Studentsperclass	18	18.35	0.975	16.07	19.40	18	17.66	1.185	14.67	19.00
Repeatingstudents	18	0.003	0.001	0.001	0.005	18	0.003	0.002	0.001	0.006

Source: Our elaboration on INVALSI, Nifo and Vecchione (2014) and ISTAT data.

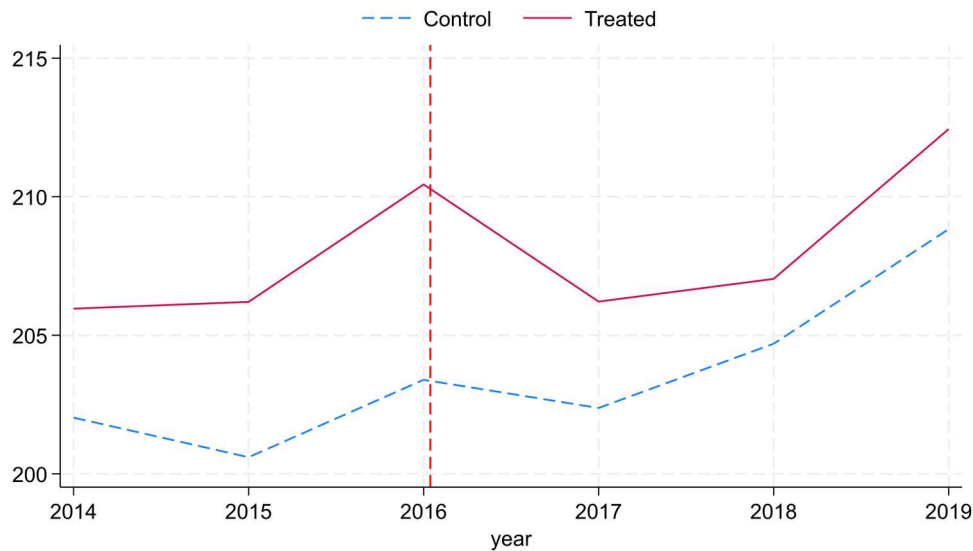


Figure 1. Parallel trend outcome for SDID for Italian Grade 2.

Note: The treatment period is defined as beginning in 2017, with the vertical bar in the graphs marking 2016. This delineation aligns with the timeline of the 2016 earthquakes (August and October) and the administration of standardised tests at the end of the academic year (April–May). Consequently, the 2016 scores are unaffected by the earthquakes, making 2017 the first year influenced by the treatment. Source: Our elaboration on INVALSI data.

methodology,⁷ Figures 1 and 2 illustrate that this adverse effect, even if not so big, persisted for approximately two years. Notably, students tested one year after the earthquake were in their first year of primary school during the event, whereas those tested two years later had not yet started primary school at the time of the earthquake. This timeline distinction may help explain the observed persistence of the negative effects over the two-year period.

Table 2 presents the average performance drops after the earthquake, highlighting the negative impact of the disaster on Grade 2 test scores. Italian scores decreased by approximately 2.7 points, while Mathematics scores declined by about 1.5 points. Relative to the treated group's average scores, these reductions correspond to a decline of approximately 1.3% for Italian and 0.7% for Mathematics.

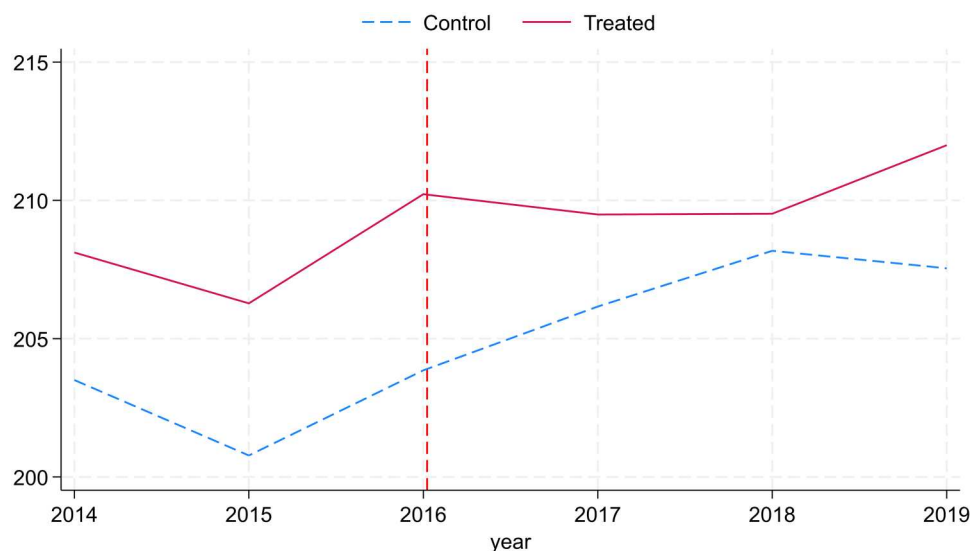


Figure 2. Parallel trend outcome for SDID for mathematics Grade 2.

Note: The treatment period is defined as beginning in 2017, with the vertical bar in the graphs marking 2016. This delineation aligns with the timeline of the 2016 earthquakes (August and October) and the administration of standardised tests at the end of the academic year (April–May). Consequently, the 2016 scores are unaffected by the earthquakes, making 2017 the first year influenced by the treatment. Source: Our elaboration on INVALSI data.

Table 2. SDID outcomes of Italian Grade 2 and mathematics Grade 2.

VARIABLES	(1) ItalianGrade2	(2) MathsGrade2
EQ2016	-2.716*** (0.589)	-1.533** (0.703)
Observations	564	564

Note. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source: Our elaboration on INVALSI data.

Interestingly, no significant effects were observed for Grade 5 (fifth year of primary school) in both Italian and Mathematics, underscoring the earthquake's differential impact across age groups of students. These findings remain consistent when the analysis is replicated using the event study methodology. As illustrated in Figures 3 and 4, the event study approach similarly identifies a persistent and significant negative effect for both subjects. This effect is evident in the tests administered during the second class and persists for students who were affected by the earthquake during their first year of primary school. Additionally, in the case of Italian language, the decline is also apparent in the third year following the earthquake, for students that were affected in their year prior to primary school. In contrast, the negative effect is not statistically significant for Mathematics. Additionally, the parallel trends assumption is maintained, as shown by the graphs and the non-significant coefficients of the three leads.

The event study methodology highlights some differences compared to the SDID method. For Italian language, the event study approach suggests that the negative effect lasted for three years, with little variations in magnitude, as detailed in Table 3.

The event study approach reveals a negative impact of the earthquake on attainments, with a decline of approximately 3.2 points in Italian and 3 points for Mathematics during the first year following the disaster, a percent decreases of about 1.6% and 1.4%, respectively. In the second year, the effects increased to 3.9 points for Italian and 4.6 points for Mathematics, equivalent to reductions of 1.9% and 2.2%, respectively. By the third year, a negative effect persisted only for Italian language, with an estimated decline of about 2.2 points (about 1.1%).

For Grade 5, both the SDID and the event study methodologies consistently indicate no significant earthquake-related impact on test scores in Italian and Mathematics. These results, detailed in the Appendix⁸ in the online supplemental file and in Tables 4 and 5, highlight the resilience or lower exposure of older students to the disruptions caused by the earthquake.

4.2 Sensitivity analysis

In the methodology section, we explained that the analysis focused on the most affected NUTS-3 regions, identified based on the number of impacted municipalities. To further assess the reliability and robustness of our results, we extended the analysis to include NUTS-3 regions that were minimally affected by the earthquake (Ancona, L'Aquila, and Terni). The results are reported in Tables 6 and 7.

The findings indicate that the effects remain statistically significant and negative for both Italian and Mathematics in Grade 2, across both model specifications. However, the magnitude of the coefficients is smaller, suggesting the robustness of the original results and reflecting the lower level of impact experienced by these additional regions. For Grade 5, the effects continue to be statistically insignificant.

4.3 Robustness analysis

To validate the robustness and reliability of the analysis, we replicated the SDID method using a placebo strategy with 500 replications. This approach assesses the validity of the counterfactual and ensures that the estimated effects are not driven by randomness. As presented in Table 8, the results remain consistent across the different analyses.

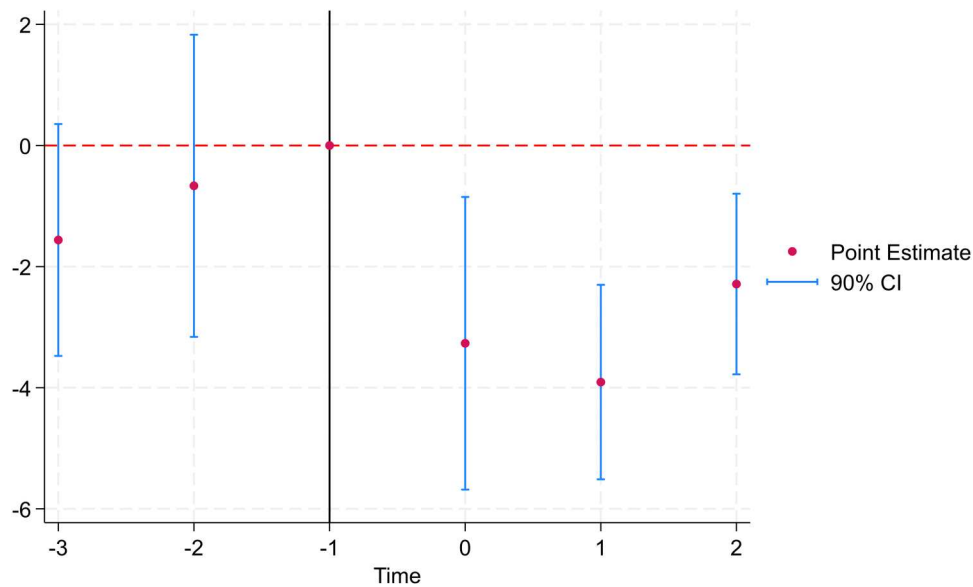


Figure 3. Event study graph for Italian Grade 2.

Note: The treatment period is defined as beginning in 2017, with the vertical bar in the graphs marking 2016. This delineation aligns with the timeline of the 2016 earthquakes (August and October) and the administration of standardised tests at the end of the academic year (April–May). Consequently, the 2016 scores are unaffected by the earthquakes, making 2017 the first year influenced by the treatment. Source: Our elaboration on INVALSI data.

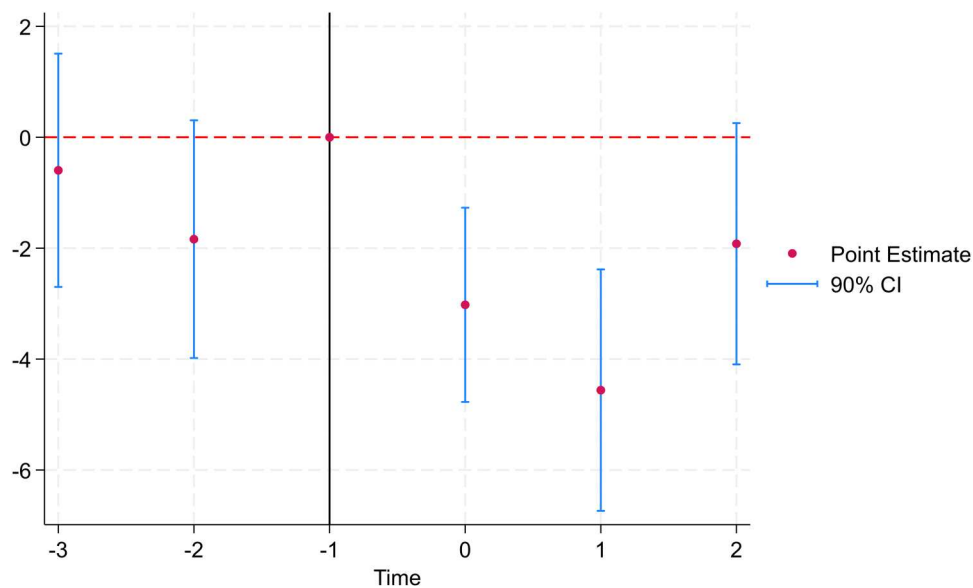


Figure 4. Event study graph for mathematics Grade 2.

Note: The treatment period is defined as beginning in 2017, with the vertical bar in the graphs marking 2016. This delineation aligns with the timeline of the 2016 earthquakes (August and October) and the administration of standardised tests at the end of the academic year (April–May). Consequently, the 2016 scores are unaffected by the earthquakes, making 2017 the first year influenced by the treatment. Source: Our elaboration on INVALSI data.

To further validate the results, we expanded the donor pool to include NUTS-3 regions affected by the 2012 Emilia earthquake, which were previously excluded. This replication yielded consistent results with negligible changes in the coefficients and standard errors. The analysis was also repeated to include Livorno and other moderately-affected provinces (Ancona, Terni and L'Aquila) to further confirm the soundness of the results. Finally, we retest the finding excluding the lag of the dependent variables from the covariates. As shown in Table 9, the results remain consistent.

Table 3. Event study outcomes of Italian Grade 2 and mathematics Grade 2.

VARIABLES	(1) ItalianGrade2	(2) MathsGrade2
lead3	-1.560 (1.152)	-0.596 (1.266)
lead2	-0.666 (1.501)	-1.838 (1.290)
lag0	-3.266** (1.501)	-3.022*** (1.054)
lag1	-3.907*** (0.966)	-4.560*** (1.310)
lag2	-2.288** (0.897)	-1.920 (1.309)
L.ItalianGrade2	0.115** (0.0574)	
L.MathsGrade2		-0.0124 (0.0401)
gdppc	-0.00107*** (0.000286)	-0.000899*** (0.000323)
Corruption	-7.693 (4.794)	-12.60* (7.258)
studentsperclass	-1.539*** (0.411)	-1.583*** (0.621)
repeatingstudents	-169.0 (194.7)	-136.2 (200.0)
Constant	242.5*** (16.30)	269.8*** (21.85)
Observations	564	564
R-squared	0.597	0.487
Number of id	94	94

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Our elaboration on INVALSI data.

Table 4. SDID outcomes of Italian Grade 5 and mathematics Grade 5.

VARIABLES	(1) ItalianGrade5	(2) MathsGrade5
EQ2016	0.387 (0.462)	0.624 (0.976)
Observations	564	564

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Our elaboration on INVALSI data.

In accordance with the event study methodology, we tested the joint significance of the lead variables to assess the parallel trends assumption. As reported in Table 10, we fail to reject the null hypothesis, supporting the validity of the parallel trends assumption.⁹

Subsequently, we tested the robustness of our results by varying the time windows for lags and leads, and by including the NUTS-3 regions affected by the 2012 Emilia earthquake. Finally, we re-estimated the model after removing the lag of the dependent variable from the set of covariates. As shown in the Appendix¹⁰ in the online supplemental file, the results remain consistent across these different specifications, confirming the robustness of our findings.

5. Discussion and policy implications

This study identifies a decline in standardised test performance among second-year primary school students in NUTS-3 regions affected by the 2016 earthquake. However, although the estimated effect appears modest, it is likely a conservative lower bound of the true impact. This is because the NUTS-3 level analysis includes both affected and unaffected schools and municipalities, with only 127 out of 307 municipalities directly impacted by the earthquake. Consequently, the inclusion of unaffected areas may dilute the estimated impact, suggesting that the actual effect of the earthquake could be more substantial and persistent than indicated by the findings.

Table 5. Event study outcomes of Italian Grade 5 and mathematics Grade 5.

VARIABLES	(1) ItalianGrade5	(1) MathsGrade5
lead3	0.0940 (1.139)	-0.221 (1.839)
lead2	-1.486 (1.273)	-0.461 (1.473)
lag0	-0.804 (1.163)	0.580 (1.820)
lag1	-0.173 (0.803)	-1.446 (1.310)
lag2	0.580 (0.836)	0.250 (1.647)
L.MathsGrade5		0.157*** (0.0570)
L.ItalianGrade5	0.0209 (0.0420)	
gdppc	-0.000469** (0.000227)	-0.000796** (0.000347)
Corruption	-10.38*** (3.509)	-19.19*** (5.731)
studentsperclass	-1.194*** (0.432)	-1.721*** (0.556)
repeatingstudents	65.58 (175.2)	70.36 (251.6)
Constant	238.6*** (13.26)	238.1*** (23.06)
Observations	564	564
R-squared	0.427	0.468
Number of id	94	94

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Our elaboration on INVALSI data.

Table 6. Sensitivity analysis – SDID outcomes with inclusion of Ancona, L'Aquila and Terni as treated.

VARIABLES	(1) ItalianGrade2	(2) MathsGrade2	(3) ItalianGrade5	(4) MathsGrade5
EQ2016	-2.156*** (0.549)	-1.218** (0.528)	0.0717 (0.403)	0.506 (0.648)
Observations	582	582	582	582

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Our elaboration on INVALSI data.

Estimated results indicate that the negative impact is concentrated primarily in the early years of education, with Grade 2 students experiencing statistically significant declines in performance. In contrast, the effect on Grade 5 students appears to be statistically not significant. This pattern aligns with existing literature, which highlight the heightened vulnerability of younger children and lower level of educations to disruptions caused by disasters (Jiménez-Martínez & Jiménez-Martínez, 2025; Kousky, 2016). Younger students are particularly vulnerable to environmental and emotional disruptions, which can adversely affect their cognitive and educational development during their formative years. Indeed, the literature has shown that exposure to traumatic events, such as the major earthquake experienced by the students, can impair concentration and cognitive performance (Lau et al., 2010; Pistoia et al., 2018; Yilancioğlu & Özbaran, 2023).

The absence of a significant effect on Grade 5 performance warrants further exploration. While the inclusion of unaffected municipalities within the NUTS-3 regions might obscure the full extent of the earthquake's impact, post-disaster recovery efforts may also play a mitigating role. For instance, Belmonte et al. (2020) demonstrated that post-disaster investments in school infrastructure can lead to significant improvements in test scores, particularly in Mathematics and among lower-achieving students. Similarly, Beaglehole et al. (2017) emphasised the importance of robust disaster response efforts in reducing adverse effects on young populations. Harris and Larsen (2023) further argued that significant reforms in school system design following disasters can yield positive effects on student outcomes while Kourtit et al. (2023) found that the

Table 7. Sensitivity analysis – event study outcomes with inclusion of Ancona, L’Aquila and Terni as treated.

VARIABLES	(1) ItalianGrade2	(2) MathsGrade2	(3) ItalianGrade5	(4) MathsGrade5
lead3	-0.972 (1.097)	-0.912 (1.016)	-0.639 (1.206)	0.270 (1.332)
lead2	0.410 (1.542)	-1.450 (1.006)	-1.777 (1.094)	-0.231 (1.319)
lag0	-2.403** (1.128)	-1.931* (1.155)	-1.759 (1.102)	0.257 (1.283)
lag1	-2.529** (1.041)	-3.686*** (1.170)	-0.242 (0.757)	-0.747 (1.017)
lag2	-1.735** (0.841)	-1.543 (1.026)	-0.146 (0.806)	0.219 (1.215)
L.ItalianGrade2	0.117** (0.0563)			
L.MathsGrade2		-0.0120 (0.0397)		
L.ItalianGrade5			0.0164 (0.0414)	
L.MathsGrade5				0.156*** (0.0563)
gdppc	-0.00102*** (0.000281)	-0.000866*** (0.000319)	-0.000490** (0.000227)	-0.000810** (0.000345)
Corruption	-6.852 (4.682)	-13.15* (7.090)	-10.07*** (3.444)	-19.22*** (5.602)
studentsperclass	-1.604*** (0.413)	-1.604** (0.610)	-1.125*** (0.424)	-1.696*** (0.624)
repeatingstudents	-174.9 (191.1)	-127.3 (213.2)	52.06 (173.7)	64.33 (247.9)
Constant	241.8*** (15.98)	269.8*** (21.78)	237.6*** (13.08)	237.5*** (24.07)
Observations	582	582	582	582
R-squared	0.594	0.489	0.426	0.470
Number of codice_provincia	97	97	97	97

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Our elaboration on INVALSI data.

Table 8. Robustness placebo strategy for SDID of performance test outcomes Italian and mathematics Grade 2 and 5.

VARIABLES	(1) ItalianGrade2	(2) MathsGrade2	(3) ItalianGrade5	(4) MathsGrade5
EQ2016	-2.716*** (0.894)	-1.533* (0.870)	0.387 (0.610)	0.624 (0.892)
Observations	564	564	564	564

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

Source: Our elaboration on INVALSI data.

Table 9. Robustness for SDID of performance test outcomes Italian and mathematics Grade 2 and 5 without the lag of the dependent variables.

VARIABLES	(1) ItalianGrade2	(2) MathsGrade2	(3) ItalianGrade5	(4) MathsGrade5
EQ2016	-2.556*** (0.882)	-2.540** (1.098)	0.432 (0.536)	0.529 (0.658)
Observations	564	564	564	564

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

Source: Our elaboration on INVALSI data.

recovery process after a disaster can correspond to an increase in their education index, especially in the long run.

Additionally, in the case of 2016 earthquake, many individuals, including children, were forced to relocate to larger cities due to the difficult conditions in their hometowns (Dottori, 2024). Save the Children reported that approximately 30% of primary school students in the affected municipalities were directly impacted by the earthquake, with the total number of children under the age of 11 involved exceeding

Table 10. Joint significance test for leads – Event study.

Joint significance test for leads		
Italian2Grade	F-stat	1.3408
	P-Value	0.2666
	Degrees of freedom	(2,93)
Maths2Grade	F-stat	1.1107
	P-Value	0.3337
	Degrees of freedom	(2,93)

84,000.¹¹ Furthermore, Save the Children noted that approximately 10% of the inspected schools were declared completely unusable, while a further 25% were considered partially or temporarily unusable. In response, Commissario Straordinario Ricostruzione Sisma (2016, 2022) reported a national government investment of approximately €1.3 billion for around 450 interventions both within and beyond the affected areas.

Sacerdote (2012) found that relocation to higher-performing schools can improve educational outcomes, potentially explaining the limited persistence of negative effects and the lack of significant impact on Grade 5 performance. Conversely, Özek (2023) highlighted that a substantial influx of migrant students can adversely affect the performance of existing students in host schools. These contrasting dynamics may help contextualise the findings, suggesting that the interplay of relocation, school quality and disaster response measures could have shaped the observed educational outcomes.

In our case, although this aspect was not formally included in the analysis due to data limitations, we observed a significant relocation of students within NUTS-3 regions from the areas affected by the event. Specifically, using data from the Italian Ministry of Education spanning the 2015–2016 to 2018–2019 academic years, we identified a significant decline in student enrolment in the affected municipalities (Table 11).¹²

However, this trend was not statistically significant at the broader NUTS-3 level (Table 12).

This pattern suggests a relocation dynamic in which many students moved from the affected municipalities to other municipalities within the same NUTS-3 region. As a result, the overall sample may not have been substantially impacted by the relocation phenomenon.

It is therefore essential to consider which institutional measures can be implemented to mitigate the issues identified in the analysis. The concentration of performance decline among younger students highlights the need for increased attention to early-age cohorts, who appear to possess fewer emotional resources to cope with such disruptions. A potential policy response should include the implementation of targeted remedial programs for affected children, potentially supplemented by psycho-pedagogical support. Indeed, beyond interruptions to schooling, children also lost access to their usual social environments for peer interaction, as well as opportunities to engage in sports and recreational activities.

Moreover, although the evidence is descriptive, it suggests that student displacement occurred within the NUTS-3 regions. In such cases, psychological support may be crucial to help relocated students manage the challenges associated with displacement. To facilitate such interventions, the collection of detailed, individual-level data – accessible to researchers – would be essential in addressing the complexities of disaster recovery at the student level.

Table 11. Regression on relocation effects for municipalities.

VARIABLES	(1) Students2/5	(2) %Students2/5
EQ2016_dummy	−3.567** (1.421)	−0.0364*** (0.00848)
L.students1/4	0.829*** (0.00465)	−0.000156*** (2.87e-05)
Constant	54.62*** (1.497)	1.046*** (0.00924)
NUTS-3 Fixed Effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	19,239	19,197
R-squared	0.721	0.004
Number of id_prov	6413	6413

Source: Our elaboration on Ministry of Education data.

Table 12. Regression on relocation effects for NUTS-3 regions.

VARIABLES	(1) Students2/5	(2) %Students2/5
EQ2016_dummy	-13.17 (46.00)	-0.000624 (0.00321)
L.students1/4	0.961*** (0.0223)	-7.83e-07 (1.56e-06)
Constant	749.4* (442.2)	1.015*** (0.0309)
NUTS-3 Fixed Effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	312	312
R-squared	0.933	0.112
Number of id_prov	104	104

Source: Our elaboration on Ministry of Education data.

Policymakers should also prioritise restoring pre-earthquake conditions through increased investment in disaster preparedness. Enabling students to return to normalcy as quickly as possible can mitigate the long-term educational and emotional consequences of such events. When school attendance is temporarily disrupted, online learning provides an effective measure of mitigating adverse educational effects on children (Laprairie & Hinson, 2006; Wang, 2024). This approach enables affected students to continue their education and maintain learning progress. These potential strategies are consistent with those pointed out by Reimers (2021) for UNESCO and the International Academy of Education during the COVID-19 period.

6. Conclusion

This study investigates the impact of the 2016 Central Italy Earthquake on standardised test performance in six NUTS-3 regions affected: Fermo, Macerata and Ascoli Piceno (Marche region); Rieti (Lazio region); Perugia (Umbria region); and Teramo (Abruzzo region). The findings indicate a significant negative effect on test scores among second-year primary school students with declines ranging from approximately 1% to 2% and a persistence of about two years. In contrast, no significant impact was observed for fifth-year primary school students.

The analysis employed a dual methodological approach, combining the SDID strategy and the event study methodology. The consistency of results across these methods underscores the robustness and reliability of the findings, providing strong evidence of the earthquake's adverse effects on early primary education outcomes.

This paper is not free from limitations. The analysis would benefit from more granular data as the aggregation at the NUTS-3 level includes both affected and unaffected municipalities (within the provinces) not impacted by the earthquake. Specifically, only 127 out of 307 municipalities in the affected regions were directly impacted by the earthquake. This aggregation is likely to dilute the observed effects, suggesting that the true impact on the most severely affected areas may be greater and more persistent. Unfortunately, municipal-level data are only available for municipalities with at least three primary schools, excluding a significant number of heavily-affected small municipalities from the sample. Given that the earthquake predominantly impacted small municipalities, this limitation is particularly severe and restricts the completeness of the findings. Other potential limitations of using this level of aggregation include measurement error and the risk of ecological fallacy when interpreting the results. Furthermore, the unavailability of data prior to 2013 limited the depth of the pre-treatment period in both analyses.

Future research should aim to overcome these limitations by utilising more granular municipal- or school-level data to better differentiate between affected and unaffected students. Such data would enable a more accurate estimation of the earthquake's impact, particularly in the most severely affected areas. Additionally, having this data can enable the capture of the heterogeneity of the impact within the NUTS-3 regions, capturing also differences in socio-economic level and in peak ground acceleration (PGA) suffered by the municipalities (Jiménez Martínez et al., 2020; Jiménez-Martínez & Jiménez-Martínez, 2025). Finally, incorporating information on the individual relocation of students could provide deeper insights into the long-term educational consequences of disasters, offering valuable guidance for policymakers and educators in designing effective recovery strategies.

Notes

1. The NUTS-3 regions are the smallest geographical units within the European Union's (EU) nomenclature of territorial units for statistics (NUTS) classification system. Typically, a NUTS-3 region range between 150,000 and 800,000 inhabitants (REGULATION (EC) No 1059/2003 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 26 May 2003). For example, in Italy they are called provinces, while in Germany are generally districts known as Kreise or as 'kreisfreie Städte' or in France as 'départments'.
2. While aggregated data may be subject to measurement error, the use of INVALSI as a data source helps ensure the reliability and accuracy of the information. Finally, we acknowledge the potential risk of ecological fallacy in drawing conclusions; however, we take care to avoid this bias by not interpreting the results as directly applicable to each individual within the sample.
3. The rationale for this choice is grounded in the existing literature that utilises INVALSI data (Costanzo & Desimoni, 2017; Falzetti, 2024; Sacco & Falzetti, 2021; Sacco & Le Rose, 2022), as well as in several working papers published by the institution itself (Donno et al., 2020; Leggi et al., 2020).
4. The WLE scores are calculated by INVALSI using the Rasch model (Rasch, 1980) through a two-stage procedure: first, item parameters are calibrated on a representative sample; then, those calibrated parameters are applied to derive scores for the entire population (Desimoni et al., 2019). For a detailed description of the methodology, see the INVALSI technical report https://invalsi-areaprove.cineca.it/docs/2024/Rilevazioni_Nazionali/Rapporto/Rapporto%20Prove%20INVALSI%202024.pdf.
5. For the six affected provinces, data are available only for municipalities with at least three primary schools. Consequently, the sample includes 3 out of 16 affected municipalities in Teramo, 2 out of 15 in Rieti, 2 out of 15 in Ascoli Piceno, 4 out of 45 in Macerata, 1 out of 17 in Fermo, and 1 out of 11 in Perugia (source: Italian Ministry of Education – <https://dati.istruzione.it/opendata/>).
6. Notably, only 127 of the 307 municipalities within the affected regions experienced direct exposure to the earthquake.
7. The weights from the SDID analysis are reported in the Appendix in the online supplemental file for cases with significant effects (Tables A.1, A.2 and A.3). Weights for the remaining cases are available upon request.
8. Figures A.1, A.2, A.3 and A.4 in the online supplemental file.
9. We conducted the test only for the analyses with significant effects, specifically for Grade 2 in Italian and Mathematics.
10. Tables A.4 and A.5 in the online supplemental file.
11. https://www.savethechildren.it/press/terremoto-centro-italia-sei-mesi-dal-terremoto-le-conseguenze-sulla-vita-di-piu-di-84000?utm_.
12. The analysis is based on a panel fixed effects regression. Two separate models are estimated: the first at the municipal level, and the second at the NUTS-3 regional level. The variables included in the models are as follows:
 - *Students2/5*: The number of students enrolled in grades two through five in a given year.
 - *Students1/4*: The number of students enrolled in grades one through four in the previous year.
 - *EQ2016_dummy*: A binary variable equal to 1 if the municipality (or NUTS-3 region) was affected by the 2016 earthquake in the 2017 school year, and 0 otherwise.
 - *%Students2/5*: The ratio of students in grades two through five in a given year to the number of students in grades one through four in the previous year.

These variables allow us to capture potential shifts in student enrolment patterns resulting from the earthquake, distinguishing between local (municipal) and broader (NUTS-3) impacts.

Acknowledgements

We are grateful to Silvia Mattiozzi (Università Politecnica delle Marche) and Riccardo Persio (Università dell'Aquila) for their helpful suggestions about the empirical framework. We also wish to thank the participants of the IAERE Conference session held in February 2025 in Rome, Italy, for their insightful comments.

Disclosure statement

No potential conflict of interest was reported by the author(s).

AI statement

During the preparation of this work the author(s) used CHATGPT in order to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Data availability statement

The datasets used in this research are publicly accessible from previously published sources, as cited in the text. The authors did not generate or distribute any new data.

ORCID

Davide Di Marcoberardino  <http://orcid.org/0000-0002-8328-8825>

Marco Cucculelli  <https://orcid.org/0000-0003-0035-9454>

References

- Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105(490), 493–505. <https://doi.org/10.1198/jasa.2009.ap08746>
- Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, 111(12), 4088–4118. <https://doi.org/10.1257/aer.20190159>
- Bănică, A., Kourtit, K., & Nijkamp, P. (2020). Natural disasters as a development opportunity: A spatial economic resilience interpretation. *Review of Regional Research*, 40(2), 223–249. <https://doi.org/10.1007/s10037-020-00141-8>
- Barkin, J. L., Buoli, M., Curry, C. L., von Esenwein, S. A., Upadhyay, S., Kearney, M. B., & Mach, K. (2021). Effects of extreme weather events on child mood and behavior. *Developmental Medicine & Child Neurology*, 63(7), 785–790. <https://doi.org/10.1111/dmcn.14856>
- Barone, G., & Mocetti, S. (2014). Natural disasters, growth and institutions: A tale of two earthquakes. *Journal of Urban Economics*, 84, 52–66. <https://doi.org/10.1016/j.jue.2014.09.002>
- 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. <https://doi.org/10.1111/1753-6405.12625>
- Belmonte, A., Bove, V., D'Inverno, G., & Modica, M. (2020). School infrastructure spending and educational outcomes: Evidence from the 2012 earthquake in Northern Italy. *Economics of Education Review*, 75, 101951. <https://doi.org/10.1016/j.econedurev.2019.101951>
- Bonanno, G. A., Brewin, C. R., Kaniasty, K., & Greca, A. M. L. (2010). Weighing the costs of disaster. *Psychological Science in the Public Interest*, 11(1), 1–49. <https://doi.org/10.1177/1529100610387086>
- Botzen, W. J. W., Deschenes, O., & Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, 13(2), 167–188. <https://doi.org/10.1093/reep/rez004>
- Breen, K., & Meyer, M. A. (2021). Staying above water: Educational outcomes of college students during the 2016 Louisiana flood. *International Journal of Mass Emergencies & Disasters*, 39(2), 199–226. <https://doi.org/10.1177/028072702103900201>
- Brummet, Q. (2014). The effect of school closings on student achievement. *Journal of Public Economics*, 119, 108–124. <https://doi.org/10.1016/j.jpubeco.2014.06.010>
- Brunello, G., & Checchi, D. (2005). School quality and family background in Italy. *Economics of Education Review*, 24(5), 563–577. <https://doi.org/10.1016/j.econedurev.2004.09.001>
- Bui, A. T., Dungey, M., Nguyen, C. V., & Pham, T. P. (2014). The impact of natural disasters on household income, expenditure, poverty and inequality: Evidence from Vietnam. *Applied Economics*, 46(15), 1751–1766. <https://doi.org/10.1080/00036846.2014.884706>
- Cadag, J. R. D., Petal, M., Luna, E., Gaillard, J. C., Pambid, L., & Santos, G. V. (2017). Hidden disasters: Recurrent flooding impacts on educational continuity in the Philippines. *International Journal of Disaster Risk Reduction*, 25, 72–81. <https://doi.org/10.1016/j.ijdrr.2017.07.016>
- Carlana, M., La Ferrara, E., & Lopez, C. (2023). Exacerbated inequalities: The learning loss from COVID-19 in Italy. *AEA Papers and Proceedings*, 113, 489–493. <https://doi.org/10.1257/pandp.20231010>
- Caruso, G., de Marcos, I., & Noy, I. (2024). Climate changes affect human capital. *Economics of Disasters and Climate Change*, 8(1), 157–196. <https://doi.org/10.1007/s41885-023-00140-2>
- Caruso, G., & Miller, S. (2015). Long run effects and intergenerational transmission of natural disasters: A case study on the 1970 Ancash earthquake. *Journal of Development Economics*, 117, 134–150. <https://doi.org/10.1016/j.jdeveco.2015.07.012>
- Cerqua, A., & Di Pietro, G. (2017). Natural disasters and university enrolment: Evidence from L'Aquila earthquake. *Applied Economics*, 49(14), 1440–1457. <https://doi.org/10.1080/00036846.2016.1218431>
- Clarke, D., & Tapia-Schythe, K. (2021). Implementing the panel event study. *The Stata Journal: Promoting Communications on Statistics and Stata*, 21(4), 853–884. <https://doi.org/10.1177/1536867X211063144>
- Cohen, C., & Werker, E. D. (2008). The political economy of “natural” disasters. *Journal of Conflict Resolution*, 52(6), 795–819. <https://doi.org/10.1177/0022002708322157>

- Commissario Straordinario Ricostruzione Sisma 2016. (2022). *Ricostruzione e adeguamento sismico di tutte le scuole danneggiate dal sisma 2016*.
- Costanzo, A., & Desimoni, M. (2017). Beyond the mean estimate: A quantile regression analysis of inequalities in educational outcomes using INVALSI survey data. *Large-scale Assessments in Education*, 5(1), 14. <https://doi.org/10.1186/s40536-017-0048-4>
- Crespo Cuaresma, J. (2010). Natural disasters and human capital accumulation. *The World Bank Economic Review*, 24(2), 280–302. <https://doi.org/10.1093/wber/lhq008>
- Dagorn, E., & Moulin, L. (2025). Dropping out of university in response to the COVID-19 pandemic. *Economics of Education Review*, 104, 102604. <https://doi.org/10.1016/j.econedurev.2024.102604>
- David, C. C., Monterola, S. L. C., Paguirigan, A., Legara, E. F. T., Tarun, A. B., Batac, R. C., & Osorio, J. P. (2018). School hazard vulnerability and student learning. *International Journal of Educational Research*, 92, 20–29. <https://doi.org/10.1016/j.ijer.2018.07.005>
- Deryugina, T. (2022). *Economic effects of natural disasters*. IZA World of Labor. <https://doi.org/10.15185/izawol.493>
- Desimoni, M., Lasorsa, C., Papa, D., & Ceravolo, R. (2019). *Le prove computer based per la rilevazione nazionale degli apprendimenti INVALSI 2018: aspetti metodologici*.
- Deuchert, E., & Felfe, C. (2015). The tempest: Short- and long-term consequences of a natural disaster for children's development. *European Economic Review*, 80, 280–294. <https://doi.org/10.1016/j.euroecorev.2015.09.004>
- Donno, S., Bagnarol, C., & Marsili, M. (2020). *Analisi spaziale degli apprendimenti scolastici negli istituti del Sud Italia* (46/2020; Working Papers INVALSI).
- Dottori, D. (2024). The effect of the earthquake in Central Italy on the depopulation of the affected territories. *Regional Science and Urban Economics*, 105, 103985. <https://doi.org/10.1016/j.regsciurbeco.2024.103985>
- Escaleras, M., & Register, C. A. (2012). Fiscal decentralization and natural hazard risks. *Public Choice*, 151(1-2), 165–183. <https://doi.org/10.1007/s11127-010-9740-4>
- Esnard, A.-M., Lai, B. S., Wyczalkowski, C., Malmin, N., & Shah, H. J. (2018). School vulnerability to disaster: examination of school closure, demographic, and exposure factors in Hurricane Ike's wind swath. *Natural Hazards*, 90(2), 513–535. <https://doi.org/10.1007/s11069-017-3057-2>
- Falzetti, P. (2024). *Survey on students: INVALSI national and international tests: VI seminar INVALSI data: A tool for teaching and scientific research* (P. Falzetti, Ed.). Franco Angeli. <https://digital.casalini.it/9788835164302>
- Figueroa, L. L., Lim, S., & Lee, J. (2016). Spatial analysis to identify disparities in Philippine public school facilities. *Regional Studies, Regional Science*, 3(1), 1–27. <https://doi.org/10.1080/21681376.2015.1099465>
- Filmer, D., & Pritchett, L. (1999). The effect of household wealth on educational attainment: Evidence from 35 countries. *Population and Development Review*, 25(1), 85–120. <https://doi.org/10.1111/j.1728-4457.1999.00085.x>
- Freyaldenhoven, S., Hansen, C., & Shapiro, J. M. (2019). Pre-event trends in the panel event-study design. *American Economic Review*, 109(9), 3307–3338. <https://doi.org/10.1257/aer.20180609>
- Frijters, P., Johnston, D. W., Knott, R. J., & Torgler, B. (2023). Resilience to disaster: Evidence from American wellbeing data. *Global Environmental Change*, 79, 102639. <https://doi.org/10.1016/j.gloenvcha.2023.102639>
- Gibbs, L., Nurse, J., Cook, J., Ireton, G., Alkemade, N., Roberts, M., Gallagher, H. C., Bryant, R., Block, K., Molyneaux, R., & Forbes, D. (2019). Delayed disaster impacts on academic performance of primary school children. *Child Development*, 90(4), 1402–1412. <https://doi.org/10.1111/cdev.13200>
- Gillitzer, C., & Prasad, N. (2024). The effect of school closures on standardized test scores: Evidence under zero-COVID policies. *Economics of Education Review*, 102, 102577. <https://doi.org/10.1016/j.econedurev.2024.102577>
- Gravel, N., Levasseur, E., & Moyes, P. (2021). Evaluating education systems. *Applied Economics*, 53(45), 5177–5207. <https://doi.org/10.1080/00036846.2021.1922586>
- Grewenig, E., Lergetporer, P., Werner, K., Woessmann, L., & Zierow, L. (2021). COVID-19 and educational inequality: How school closures affect low- and high-achieving students. *European Economic Review*, 140, 103920. <https://doi.org/10.1016/j.euroecorev.2021.103920>
- Harris, D. N., & Larsen, M. F. (2023). Taken by storm. *Journal of Human Resources*, 58(5), 1608–1643. <https://doi.org/10.3368/jhr.58.5.0819-10367R2>
- Huang, J. (2013). Intergenerational transmission of educational attainment: The role of household assets. *Economics of Education Review*, 33, 112–123. <https://doi.org/10.1016/j.econedurev.2012.09.013>
- Hussain, Y. R., & Mukhopadhyay, P. (2024). Impact of natural disasters on educational attainment in India: A panel data analysis. *Discover Sustainability*, 5(1), 279. <https://doi.org/10.1007/s43621-024-00498-7>
- Hyde, A., Li, A., & Maltbie, A. (2021). *Bringing inequalities to the fore: The effects of the coronavirus pandemic and other disasters on educational inequalities in the United States* (pp. 381–400). https://doi.org/10.1007/978-3-030-65417-7_20
- 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. <https://doi.org/10.1257/aer.102.5.2048>
- INVALSI. (2024). *RAPPORTO INVALSI 2024*. <https://series.francoangeli.it/index.php/oa/catalog/view/445/252/2146>
- Jiménez-Martínez, M., & Jiménez-Martínez, M. (2025). Education system response to an extreme shock analyzing the short, medium and long-term impact of the stronger earthquake in Chile. *International Journal of Disaster Risk Reduction*, 119, 105327. <https://doi.org/10.1016/j.ijdrr.2025.105327>

- Jiménez Martínez, M., Jiménez Martínez, M., & Romero-Jarén, R. (2020). How resilient is the labour market against natural disaster? Evaluating the effects from the 2010 earthquake in Chile. *Natural Hazards*, 104(2), 1481–1533. <https://doi.org/10.1007/s11069-020-04229-9>
- Kourtit, K., Nijkamp, P., & Banica, A. (2023). An analysis of natural disasters' effects – A global comparative study of 'blessing in disguise.'. *Socio-economic Planning Sciences*, 88, 101599. <https://doi.org/10.1016/j.seps.2023.101599>
- Kousky, C. (2016). Impacts of natural disasters on children. *The Future of Children*, 26(1), 73–92. <https://doi.org/10.1353/foc.2016.0004>
- Krueger, A. B., & Whitmore, D. M. (2001). The effect of attending a small class in the early grades on college-test taking and middle school test results: Evidence from project star. *The Economic Journal*, 111(468), 1–28. <https://doi.org/10.1111/1468-0297.00586>
- Kukeli, A. (2025). The effects and the macroeconomic dynamics of natural disaster damages: Investigation of local evidence. *Regional Studies, Regional Science*, 12(1), 5–22. <https://doi.org/10.1080/21681376.2025.2452524>
- La Greca, A. M., Silverman, W. K., Lai, B., & Jaccard, J. (2010). Hurricane-related exposure experiences and stressors, other life events, and social support: Concurrent and prospective impact on children's persistent posttraumatic stress symptoms. *Journal of Consulting and Clinical Psychology*, 78(6), 794–805. <https://doi.org/10.1037/a0020775>
- Lai, B. S., Esnard, A., Wyczalkowski, C., Savage, R., & Shah, H. (2019). Trajectories of school recovery after a natural disaster: Risk and protective factors. *Risk, Hazards & Crisis in Public Policy*, 10(1), 32–51. <https://doi.org/10.1002/rhc3.12158>
- Laprairie, K. N., & Hinson, J. M. (2006). When disaster strikes, move your school online. *Journal of Educational Technology Systems*, 35(2), 209–214. <https://doi.org/10.2190/D154-XK20-7264-5013>
- Lassa, J., Petal, M., & Surjan, A. (2023). Understanding the impacts of floods on learning quality, school facilities, and educational recovery in Indonesia. *Disasters*, 47(2), 412–436. <https://doi.org/10.1111/disa.12543>
- Lau, J. T. F., Yu, X., Zhang, J., Mak, W. W. S., Choi, K. C., Lui, W. W. S., Zhang, J., & Chan, E. Y. Y. (2010). Psychological distress among adolescents in Chengdu, sichuan at 1 month after the 2008 Sichuan earthquake. *Journal of Urban Health*, 87(3), 504–523. <https://doi.org/10.1007/s11524-010-9447-3>
- Leggi, F., Pastori, V., & Russo, M. C. (2020). *Nativi e stranieri di seconda generazione: un'analisi longitudinale* (47/2020; Working Papers INVALSI).
- Marin, G., & Modica, M. (2017). Socio-economic exposure to natural disasters. *Environmental Impact Assessment Review*, 64, 57–66. <https://doi.org/10.1016/j.eiar.2017.03.002>
- Marin, G., Modica, M., Paleari, S., & Zoboli, R. (2021). Assessing disaster risk by integrating natural and socio-economic dimensions: A decision-support tool. *Socio-economic Planning Sciences*, 77, 101032. <https://doi.org/10.1016/j.seps.2021.101032>
- Meltzer, R., Ellen, I. G., & Li, X. (2021). Localized commercial effects from natural disasters: The case of Hurricane Sandy and New York city. *Regional Science and Urban Economics*, 86, 103608. <https://doi.org/10.1016/j.regsciurbeco.2020.103608>
- Montanaro, P., & Sestito, P. (2014). *La qualità dell'istruzione italiana: un confronto tra PISA e le rilevazioni nazionali dell'Invalsi* (218; Questioni Di Economia e Finanza).
- Montero, J.-M., Naimy, V., Farraj, N. A., & El Khoury, R. (2024). Natural disasters, stock price volatility in the property-liability insurance market and sustainability: An unexplored link. *Socio-economic Planning Sciences*, 91, 101791. <https://doi.org/10.1016/j.seps.2023.101791>
- Morrill, M., & Westall, J. (2023). Heterogeneity in the educational impacts of natural disasters: Evidence from Hurricane Florence. *Economics of Education Review*, 94, 102373. <https://doi.org/10.1016/j.econedurev.2023.102373>
- Nguyen, C. V., & Minh Pham, N. (2018). The impact of natural disasters on children's education: Comparative evidence from Ethiopia, India, Peru, and Vietnam. *Review of Development Economics*, 22(4), 1561–1589. <https://doi.org/10.1111/rode.12406>
- Nifo, A., & Vecchione, G. (2014). Do institutions play a role in skilled migration? The case of Italy. *Regional Studies*, 48(10), 1628–1649. <https://doi.org/10.1080/00343404.2013.835799>
- Opper, I. M., Park, R. J., & Husted, L. (2023). The effect of natural disasters on human capital in the United States. *Nature Human Behaviour*, 7(9), 1442–1453. <https://doi.org/10.1038/s41562-023-01610-z>
- Özek, U. (2023). Examining the educational spillover effects of severe natural disasters. *Journal of Human Resources*, 58(2), 421–451. <https://doi.org/10.3368/jhr.58.4.0520-10893R2>
- Park, R. J., Goodman, J., Hurwitz, M., & Smith, J. (2020). Heat and learning. *American Economic Journal: Economic Policy*, 12(2), 306–339. <https://doi.org/10.1257/pol.20180612>
- Paudel, J. (2023). Do environmental disasters affect human capital? The threat of forest fires. *Economics of Education Review*, 97, 102463. <https://doi.org/10.1016/j.econedurev.2023.102463>
- Paudel, J., & Ryu, H. (2018). Natural disasters and human capital: The case of Nepal's earthquake. *World Development*, 111, 1–12. <https://doi.org/10.1016/j.worlddev.2018.06.019>
- Peek, L. (2008). Children and disasters: Understanding vulnerability, developing capacities, and promoting resilience – An introduction. *Children, Youth and Environments*, 18(1), 1–29. <https://doi.org/10.1353/cye.2008.0052>
- Perdana, A. R. A., & Vall Castelló, J. (2025). Shattered ground, shaken minds: Mental health consequences of earthquakes. *Economics & Human Biology*, 56, 101448. <https://doi.org/10.1016/j.ehb.2024.101448>

- Pistoia, F., Conson, M., Carolei, A., Dema, M. G., Splendiani, A., Curcio, G., & Sacco, S. (2018). Post-earthquake distress and development of emotional expertise in young adults. *Frontiers in Behavioral Neuroscience*, 12, 91. <https://doi.org/10.3389/fnbeh.2018.00091>
- Raeburn, K. (2025). The effect of school damages on educational outcomes in post-Hurricane Jamaica. *Education Economics*, 33(1), 138–160. <https://doi.org/10.1080/09645292.2023.2289345>
- Rasch, G. (1980). *Probabilistic models for some intelligence and attainment tests* (Copenhagen, Danish institute for educational research) (Expanded edition). The University of Chicago Press.
- Rawls, C. G., & Turnquist, M. A. (2012). Pre-positioning and dynamic delivery planning for short-term response following a natural disaster. *Socio-Economic Planning Sciences*, 46(1), 46–54. <https://doi.org/10.1016/j.seps.2011.10.002>
- Reimers, F. (2021). *Learning to build back better futures for education: Lessons from educational innovation during the COVID-19 pandemic*.
- Sacco, C., & Falzetti, P. (2021). Spatial variations of school-level determinants of Reading achievement in Italy. *Large-scale Assessments in Education*, 9(1), 12. <https://doi.org/10.1186/s40536-021-00105-5>
- Sacco, C., & Le Rose, G. (2022). Network analysis of early school dropouts' risk factors in Italy. *Social Psychology of Education*, 25(6), 1459–1479. <https://doi.org/10.1007/s11218-021-09680-5>
- Sacerdote, B. (2012). When the saints go marching out: Long-term outcomes for student Evacuees from Hurricanes Katrina and Rita. *American Economic Journal: Applied Economics*, 4(1), 109–135. <https://doi.org/10.1257/app.4.1.109>
- Schady, N., Holla, A., Sabarwal, S., Silva, J., & Yi Chang, A. (2023). *Collapse and recovery: How the COVID-19 pandemic eroded human capital and what to do about it*. World Bank. <http://hdl.handle.net/10986/39403>
- Segarra-Alméstica, E., Caraballo-Cueto, J., Cordero, Y., & Cordero, H. (2022). The effect of consecutive disasters on educational outcomes. *International Journal of Disaster Risk Reduction*, 83, 103398. <https://doi.org/10.1016/j.ijdr.2022.103398>
- Shidiqi, K.-A., Di Paolo, A., & Choi, Á. (2023). Earthquake exposure and schooling: Impacts and mechanisms. *Economics of Education Review*, 94, 102397. <https://doi.org/10.1016/j.econedurev.2023.102397>
- 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. <https://doi.org/10.1542/peds.2005-2781>
- Tian, X., Gong, J., & Zhai, Z. (2022). Natural disasters and human capital accumulation: Evidence from the 1976 Tangshan earthquake. *Economics of Education Review*, 90, 102304. <https://doi.org/10.1016/j.econedurev.2022.102304>
- Venegas Marin, S., Schwarz, L., & Sabarwal, S. (2024). Impacts of extreme weather events on education outcomes: A review of evidence. *The World Bank Research Observer*, 39(2), 177–226. <https://doi.org/10.1093/wbro/lkae001>
- Vogel, J. M., & Vernberg, E. M. (1993). Part 1: Children's psychological responses to disasters. *Journal of Clinical Child Psychology*, 22(4), 464–484. https://doi.org/10.1207/s15374424jccp2204_7
- Wang, J. (2024). Impact of natural disasters on student enrollment in higher education programs: A systematic review. *Heliyon*, 10(6), e27705. <https://doi.org/10.1016/j.heliyon.2024.e27705>
- Wang, P., Zhang, H., & Wood, J. (2021). Chapter 7 - Foreign direct investment, natural disasters, and economic growth of host countries. In T. Chaiechi (Ed.), *Academic Press Economic Effects of Natural Disasters* (pp. 97–117). Elsevier. <https://doi.org/10.1016/B978-0-12-817465-4.00007-8>.
- Yılancıoğlu, H. Y., & Özbaran, B. (2023). Psychiatric effects of earthquakes on children and adolescents. *The Journal of Pediatric Research*, 10(4), 249–254. <https://doi.org/10.4274/jpr.galenos.2023.70456>