Heterogeneous Peer Effects and Rank Concerns in the Classroom

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Abstract

I examine how disruptions to students' ability to study spill over to their classmates to understand the mechanisms behind social interactions in the classroom. I combine administrative and survey information on students with detailed information on damages to their homes caused by the sixth most-violent earthquake ever recorded, which occurred in Chile in 2010. I find that damages to a student's own home increased the self-reported cost of study effort, that schools mitigated detrimental effects from average damages among classmates, and that the dispersion in damages among a student's classmates affected students' achievement and GPA heterogeneously across the initial performance distribution, but without changing students' initial ranks. I show that a game of status model in which students strategically interact to compete for grades can rationalize these findings. The result suggests that, beyond the much-studied desire to conform, a desire to compete could be a reason why the ability to study of peers matters for learning in many contexts.

1 Introduction

Childhood and early adulthood are fundamental years for cognitive development (Cunha, Heckman, Lochner, and Masterov (2006)). The academic ability of school peers can affect cognitive achievement during these crucial years[1], but the mechanisms

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[1]See Ammermueller and Pischke (2009); Arcidiacono, Foster, Goodpaster, and Kinsler (2012); Booij, Leuven, and Oosterbeek (2017); Carrell, Sacerdote, and West (2013); Duflo, Dupas, and Kremer (2011); Garlick (2018); Hanushek, Kain, Markman, and Rivkin (2003); Hoxby (2000); Imberman, Kugler, and Sacerdote (2012); Lyle (2009); Sacerdote (2001).

are not fully understood, limiting our ability to design policies that can be effective across contexts.

This paper studies why the ability to study of peers can shape the academic achievement of schoolchildren. It introduces a new dataset that links students' academic outcomes and self-reported study ability to newly constructed measures of disruptions to their environment stemming from one of the most violent earthquakes ever recorded. The dataset allows me to examine how disruptions to students' ability to study spill over to their classmates. Identification relies on variation in the disruptions to peers, keeping their characteristics constant. It does not rely on variation in peers' lagged test scores, avoiding the usual confounding influences that have been the focus of much of the empirical literature on ability peer effects in education.[2] This approach allows me to draw on the empirical evidence to understand what drives students' effort choices in the classroom, and propose a new theory of peer influence in cognitive development. While formulated within the context of an environmental shock, the theory can be extrapolated to understand why the ability of peers matters for learning in many contexts.

The empirical context is the 2010 Maule mega-earthquake, the sixth strongest ever instrumentally recorded (USGS, 2023). I combine administrative and survey data with information on damage propagation among over 150,000 students. I start by building a measure of each student's home's vulnerability to the earthquake using information on housing quality. From the last pre-earthquake census I obtain information on the construction materials of the homes of the nearly one million Chilean households with at least one school-aged child. I employ an unsupervised learning algorithm to stochastically assign their homes to seismic resistance classes (Massone et al. (2010)). Armed with this housing quality measure, I develop a model that can accurately predict housing quality from a household's characteristics, and apply it to administrative data on Chilean students to predict the quality of their homes. Drawing upon the structural engineering literature, I then combine this newly developed measure of housing quality with geocoded information on ground-shaking intensity in each student's hometown to construct a measure of home damages for each student.[3] This variable measures the shock to each student's environment.

[2] Examples of studies using naturally occurring exogenous variation in peer characteristics to account for such confounding effects are Hoxby (2000); Angrist and Lang (2004); Hoxby and Weingarth (2005); Lavy, Paserman, and Schlosser (2012); Imberman, Kugler, and Sacerdote (2012).

[3] I gratefully acknowledge Prof. Sergio Ruiz of the Geology Department at the University of Chile, a leading expert on the seismic vulnerability of Chilean buildings, for feedback on the damage measure. The measure falls within Deterministic Earthquake Loss Estimation, which aims to estimate losses from a specific seismic event. It stands in contrast to Probabilistic Earthquake Loss Estimation, which aims to predict potential losses from many possible seismic events (McGuire (2004)).

I link the damage measure to administrative and survey data from the Chilean Ministry of Education. Data on students include standardized test scores at two points in time (in fourth and eighth grade), GPA, GPA rank in the classroom, family background, type of school attended, and survey information on self-reported ability to study and to engage with course content. Data on teachers include the fraction of the curriculum they were able to cover. All observations can be assigned to classrooms and schools through unique student, teacher, classroom, and school identifiers.

Using this newly constructed dataset, I first document a new fact about socioeconomic segregation among Chilean children. Poorer students were more likely to live in the rural localities experiencing more ground shaking, and conditional on locality, their homes were built according to worse construction standards. As a result, compared with students whose parents have more than 14 years of education (who likely attended some college), those whose parents have at most 14 incurred twice the amount of home damages (USD 1,607 vs. USD 798, or 49% vs. 25% of annual income).

I then estimate the causal impacts on students' outcomes of damages to their own homes and to the homes of their classmates, focusing on the mean and standard deviation of damages among classmates. The identification strategy relies on a difference-in-differences framework leveraging the different correlation between seismic vulnerability and outcomes across two cohorts of students, one whose outcomes were measured in 2009, before the earthquake struck, and one whose outcomes were measured in 2011, after the earthquake struck. This strategy eliminates confounding effects that could arise if the measures of earthquake vulnerability correlated with unobserved outcome determinants. The identifying assumption is that the relationship between outcomes and earthquake vulnerability would be the same across cohorts absent the earthquake. I provide evidence supporting this assumption using data from the regions that were never affected by the earthquake, showing that the seismic vulnerability of the students' homes and of their peers' homes are not differently correlated with outcomes across cohorts in these regions. Finally, to gauge how schools responded to the earthquake, I estimate two models: one with and one without school-by-cohort fixed effects. As the fixed effects absorb the (assumed constant) effect of school-level responses to the earthquake, comparing the estimates from the two models informs us on schools' mitigation efforts.

Using this strategy, I find that the damage incurred by a student's own home had a negative and non-negligible effect on test scores 22 months post-earthquake. A 1 standard deviation increase in damages lowered test scores by 0.033-0.036 standard deviations. Using survey data, I provide evidence that damages at the students' own homes decreased students' reported ability to study and engage with course content, suggesting a diminished ability to study could have mediated the detrimental impacts on achievement.

Regarding the spillover effect of damages to peers' homes keeping fixed a student's own exposure to the earthquake, I find that increasing the average damages suffered by classroom peers increases own test scores, and the effects are not significantly different across students with different initial performance. This appears to be the result of schools overcompensating any potential negative impacts, as in the model with school-by-cohort fixed effects the estimated effect of increasing average damages is (imprecisely) null. In contrast, schools do not appear to react to the standard deviation of damages in their classrooms, which lowered the achievement of students with high initial performance and increased the achievement of those with low initial performance, regardless of fixed effect inclusion. A possible reason for the asymmetry in the schools' response is that emergency funds were granted depending on the overall damage severity, not its dispersion (Gobierno de Chile (2010)).

Next, I analyze potential mediators of the damage spillover effects. I do not find evidence that the mean and standard deviation of damage among peers influenced the percentage of the curriculum teachers were able to cover. This suggests that teachers adapting their pace of instruction is not a mechanism behind schools' mitigation efforts in response to mean damages. It also suggests that teachers did not slow their pace of instruction to focus on lower-ability students in response to an increase in damage dispersion, which could have rationalized why these students' outcomes benefit from damage dispersion, while those of higher-ability students suffer. Teachers did not adapt their grading either, as the impacts on GPA, graded by teachers, traced those on the centrally-graded test scores.

To better understand the mechanisms behind the spillover effects, I analyze impacts on GPA rank in the classroom. Since average damages had similar impacts across the baseline performance distribution, we do not expect them to affect students' GPA rank, and this is what the evidence shows. In contrast, the heterogeneous impacts of damage dispersion on GPA could have triggered changes to students' GPA rank in the classroom. But surprisingly, I find that this is not the case. Students with higher initial performance experienced drops in GPA in classrooms with more dispersed damages, without an accompanying drop in their GPA rank. A possible reason for this is that students care about their GPA rank. Faced with a changed ability to study among their peers, students adjust their effort and learning (a peer effect), but not at the expense of their classroom standing.

Drawing on this empirical insight and the empirical findings, I formulate a new theory of interactions in the classroom. I formalize the simple intuition that students care about their classroom standing through a game-of-status model of simultaneous effort choices in the classroom. In the model, students are characterized by an effort cost type, which is affected by the damages to their home. They produce GPA by exerting costly effort, and derive utility from GPA and GPA rank. To account for the evidence on the schools' reactions to the earthquake, in the model schools can mitigate the impacts of average damages. I show that the model, which admits a unique symmetric Bayesian Nash equilibrium, can rationalize the empirical findings. Specifically, a school's mitigating efforts lead to positiv, Ludovica, e effects of average damages, which would be null or negative absent the school's response. The competition motive behind students' effort choices causes the damage dispersion to have heterogeneous impacts on GPA, and null effects on GPA rank, along the baseline test score distribution. By changing the density of nearby competitors differently for different students, damage dispersion has heterogeneous effects on the returns to effort, generating exactly the heterogeneous effects on GPA observed in the data: positive impacts for students with low initial performance and negative impacts for those with medium initial performance, who face, respectively, more and less competition from similarly able students, and negative impacts for those with high initial performance, who now face less competition from below.

The central theoretical insight can be applied more broadly outside the realm of environmental shocks: when competitive motives drive study effort, changing the dispersion of peers' ability to study, be it through a shock or through a compositional change from classroom assignment policies, affects learning, and does so differently for different students depending on how the change affects the number of nearby competitors and the effort of all competitors. This has important and so far mostly unexplored implications for policy, as I discuss in this article's concluding section.

Methodologically, this study relates to the small literature that examines peer interactions relying on random shocks to students that keep group composition constant (see the survey in Bramoullé, Djebbari, and Fortin (2020)). One of the closest studies is Fruehwirth (2013), who exploits the introduction of a student accountability policy in North Carolina targeted at low-achievers. The policy serves as a shock to the effort of some but not all students in the classroom; the fraction of affected peers is used to estimate the impact of peers' achievement on own achievement within a linear-in-means framework.[4] The estimates are interpreted as best-response functions through the lens of a model of effort choices in a strategic environment where students desire to conform to each other. In contrast, this paper considers a continuous shock,

[4] Berlinski, Busso, and Giannola (2023) have applied a similar strategy to data from a literacy remediation program in Colombia, and Dieye, Djebbari, and Barrera-Osorio (2014) to data from a randomized experiment on a scholarship program in Colombia. See also Fruehwirth (2014) for an in-depth analysis of the identification of the effect of contemporaneous peer outcomes on own outcomes when outcomes are partly determined by unobserved factors.

the extent of damages that each student's home incurred. Rather than identifying best-response functions, an 'endogenous peer effect' in the terminology of Manski (1993), this paper examines the reduced-form impact of changing the distribution of the shocks within the classroom, an 'exogenous peer effect' in this terminology. It interprets the estimates as comparative statics on the equilibrium outcomes of classrooms characterized by different distributions of shocks to students' ability to study, through the lens of a model where students desire to compete with each other.[5] The impacts of the mean and of the dispersion of this continuous shock among peers are shown to be helpful to inform a new theory of peer influence.[6]

Within the vast literature on peer effects in education, relatively few studies have developed theories of peer influence. Existing theories commonly assume that students have a desire to conform to their peers, or that there are complementarities between peers in the achievement production technology (e.g. Brock and Durlauf (2001a, 2006); Calvó-Armengol, Patacchini, and Zenou (2009); Fruehwirth (2013); Conley, Mehta, Stinebrickner, and Stinebrickner (2023)). Both assumptions rationalize the workhorse linear-in-means model of peer effects with continuous outcomes (Blume, Brock, Durlauf, and Jayaraman (2015)). In contrast, I present a new theory that rationalizes why moments beyond the mean may matter. It offers a simple insight: when students derive utility from rank, changing the ability of peers affects own effort, because it changes the ability of competitors. Empirically, this generates a peer effect where moments beyond the mean matter. Such a mechanism has been largely ignored despite its intuitive appeal.[7]

There are several reasons for students to care about their achievement rank in school. It provides future benefits (Elsner and Isphording (2017); Murphy and Weinhardt (2020)). Often teachers grade on a curve (Calsamiglia and Loviglio (2019)). And increasingly, higher education systems assign college seats based partly (Grau (2018)) or entirely (Horn, Flores, and Orfield (2003)) on within-school rank. Moreover, recent experimental evidence from Chilean schools confirms that study effort responds to rank incentives (Tincani, Kosse, and Miglino (2023)).[8] These implicit

[5]The choice of estimating an exogenous rather than endogenous social effect to inform the theory is driven by the fact that game-of-status models do not typically deliver best-response functions as functions of peers' choices. Instead, the model delivers an equilibrium effort function, that is, effort as a function of a student's own ability, which varies with the distribution of the ability to study of peers, which I assume to be affected by the earthquake shocks. The parameters I estimate, therefore, are the empirical counterparts of the theory-derived comparative statics.

[6]De Giorgi and Pellizzari (2013) also test theories of peer influence. They use evidence on the effects of changing peer composition, which is deliberately kept constant here.

[7]In line with the theory first introduced in this paper (as detailed in e.g. Tincani (2017)), Rosenzweig and Xu (2023) recently provided evidence supporting this mode of interaction within the context of Southeast Asian refugee students in the US.

[8]A small strand of the literature on college admissions has developed models capturing how rank incentives affect student effort in high school (Bodoh-Creed and Hickman (2017); Grau (2018);

and explicit reward structures, therefore, could plausibly be one of the reasons why peer ability matters for learning in many contexts.

This paper also relates to the empirical literature using natural disasters to identify peer effects in education, such as Cipollone and Rosolia (2007), Imberman, Kugler, and Sacerdote (2012), and Sacerdote (2008). In contrast to previous studies, this paper does not use forced relocations of students for identification.[9] Finally, the paper relates to the empirical literature on ability peer effects studying the impacts of moments beyond the mean (Lyle (2009); Booij, Leuven, and Oosterbeek (2017); Ding and Lehrer (2007); Vigdor and Nechyba (2007); Hoxby and Weingarth (2005)) and of partitioning the support of ability, which varies first and higher-order moments simultaneously (Carrell, Sacerdote, and West (2013); Duflo, Dupas, and Kremer (2011)). These studies tend to find that moments beyond the mean matter for learning.

The article is structured as follows. Section 2 details the data, damage measure, and describes damage propagation among students. Section 3 delves into the empirical analysis of damage effects on achievement, and assesses the identifying assumption and robustness. Section 4 presents evidence on mediating factors using administrative and survey data. Section 5 introduces the theory of peer influence based on rank concerns, rationalizing the evidence. Section 6 concludes, discussing policy implications and suggesting future research avenues.

2 Data and Measurements

This section describes the data sources and measurements and performs a descriptive data analysis.

2.1 Data

I construct a dataset on two cohorts of students combining information from the SIMCE dataset (*Sistema de Medición de la Calidad de la Educación*) and enrollment and grade registries (*Rendimiento*). I refer to the two cohorts as pre- and post-earthquake cohorts, depending on whether their outcomes were measured before or

Tincani, Kosse, and Miglino (2023)). The most relevant to this paper is Tincani, Kosse, and Miglino (2023). After showing experimentally that rank incentives affect study effort, they develop and structurally estimate a tournament model of simultaneous effort choices using data from Chilean high schools, in which college seats are assigned according to the within-school GPA rank. The goal of these papers, however, is not to study ability peer effects given rank incentives, but to explore the impacts of changing the rank incentives, keeping fixed peer ability.

[9] This distinguishes this paper also from the experimental and quasi-experimental literature that use variation in assignment to peer groups, such as dorms (Sacerdote (2001); Zimmerman (2003); Stinebrickner and Stinebrickner (2006); Kremer and Levy (2008); Garlick (2018)) or classrooms (Duflo, Dupas, and Kremer (2011); Whitmore (2005); Kang (2007)).

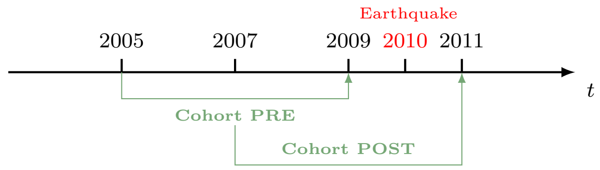


Figure 1: Data time-line.

after the earthquake. The 8^{th} grade outcome for the pre-earthquake cohort is observed in 2009, before the 2010 earthquake, the 8^{th} grade outcome for the post-earthquake cohort is observed in 2011, 20 to 22 months after the 2010 earthquake (Figure 1). The sample includes students in public and private subsidized schools.[10] I obtained from the Ministry of Education the list of schools that closed as a consequence of the earthquake, and used registry data to identify the schools where the evacuated students relocated to. I dropped from the sample both sets of schools, from both cohorts, to ensure the absence of earthquake-induced relocations in my sample.[11] Such relocations could directly affect the outcomes of evacuated students and indirectly those of incumbent students in receiving schools through changes in peer composition. Such effects could confound the effects of interest in this paper. I dropped observations with missing classroom identifiers,[12] and classrooms with five or fewer students.[13] The final sample consists of $354,108$ students in $13,267$ classrooms and in $4,798$ schools. As explained in the next section, to mitigate measurement error on the damage measure, the main analyses exclude around a quarter of observations, corresponding to schools located in coastal towns. The sizes of the pre- and post-earthquake samples, with and without such restriction, can be seen in Table 1.

For both cohorts I observe administrative records on 8^{th} grade and 4^{th} grade Mathematics and Language standardized test scores and school grades, gender, town of residence and unique student, classroom and school identifiers. I complement these data with linked survey data on students' perceptions, on the household socioeconomic background, and on teachers' instruction. Administrative school-level information includes rurality and public or private status. Finally, I match students to classrooms, teachers and schools through unique pseudo-identifiers.

[10] I exclude students from the elite private unsubsidized schools. They represent approximately 7% of the student population and they come from the most well-off families in the country.

[11] I dropped $36,941$ observations from the post-earthquake cohort and $38,784$ from the pre-earthquake cohort, corresponding to 16% of the sample.

[12] These are $17,969$ observations in the post-earthquake cohort and $21,194$ observations in the pre-earthquake cohort. The school and student identifiers are never missing.

[13] These correspond to $2,484$ student-level observations, or 0.7 percent of the sample.

2.2 Measuring damages to homes

Earthquake. On February 27^{th} 2010, at 3.34 local time, Chile was struck by a magnitude 8.8 earthquake, the sixth-largest ever instrumentally recorded and technically referred to as a mega-earthquake (Astroza, Ruiz, and Astroza (2012), USGS (2023)). Figure 2 shows its position in the global earthquake distribution since 1900. Shaking was felt strongly throughout 500 km along the country, covering six regions that together make up approximately 80% of the country's population. Damage was widespread, with costs estimated at 18 percent of GDP (WHO (2010)). The Government implemented a national plan to rebuild or repair housing units for low- and middle-income families. The mega-earthquake had continued impact on people's lives during the period covered by my sample. The post-earthquake cohort, whose outcomes were collected when they were in the 8^{th} grade in 2011, was about to start the 7^{th} grade when the earthquake struck. By the time the 2011 outcome data were collected, 20-22 months had passed since the earthquake struck. Yet, only 24 percent of home reconstructions and repairs had been completed (Comerio (2013)), leading to frustration in the population (Appendix Figure A1).

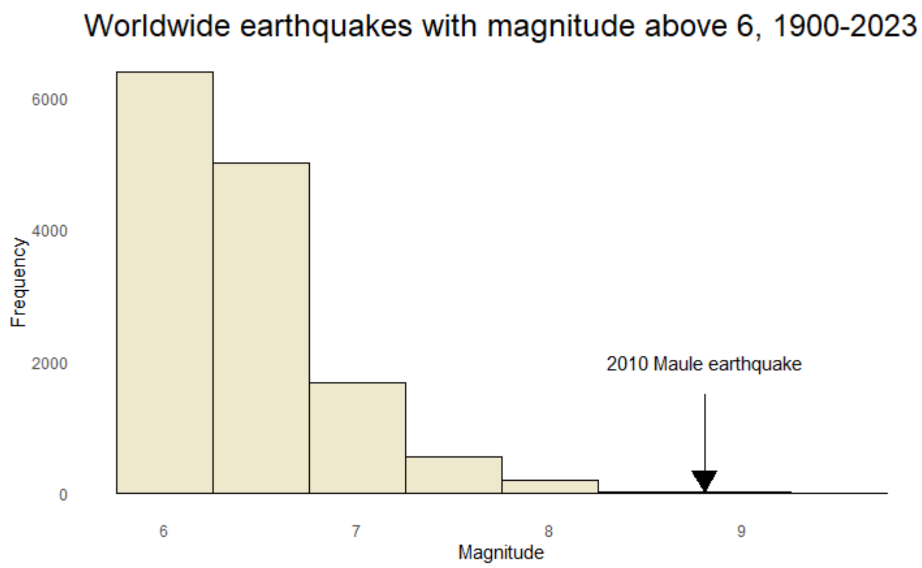


Figure 2: *Source*: Global Earthquake Catalog maintained by the United States Geological Survey (USGS (2023)).

Measuring earthquake damage to a student's home. The damage to a student's home depends on the level of ground shaking and on the construction materials. I proceed in three steps. First, I construct a measure of the shaking that each student's home was subject to. Second, I build a measure of the seismic vulnerability of each student's home, which depends on the construction materials. Third, I combine these two measures to calculate home damages. I now describe each step.

Step one: ground shaking. For students who reside in earthquake-afflicted regions, I build a measure of distance between each student's town of residence and the asperity centroid as $\Delta_A = \sqrt{R^2 + h^2}$, where R is the distance between the town's center and the point on the earth's surface vertically above the asperity centroid, whose coordinates are (34.8^{o}S, 72.6^{o}W), and $h = 20$km is the depth of the latter. I then apply the intensity attenuation formula derived by Astroza, Ruiz, and Astroza (2012) for the 2010 Chilean earthquake that gives for each distance Δ_A a level of severity of ground shaking, I, measured on the Medvedev-Sponheuer-Karnik (MSK) scale: $I = 19.781 - 5.927 \log_{10}(\Delta_A) + 0.00089\Delta_A$ ($R^2 = 0.9894$).[14]

Step two: seismic vulnerability. A building's seismic vulnerability depends on its construction materials. The construction materials of students' homes are not included in the education dataset, but they are included in census data. Therefore, I use census data to develop a model that can accurately predict the seismic vulnerability of a household's home from a set of observable household characteristics that are available in the education dataset, and I apply this model to the education dataset to build a measure of the seismic vulnerability of the homes of the students in my sample. The procedure comprises three steps. In the first, using census data I build a measure of seismic vulnerability of a building based on its construction materials. In the second, using census data I develop the prediction model and assess its ability to correctly predict housing quality from household characteristics. Finally, I apply the prediction model to the students in my sample (the education data). I now describe the first two steps in more detail (the third step is trivial).

The first step consists in building a measure of seismic vulnerability of a home from information on its building materials as per census data. I obtained the 2002 census data, the last one before the earthquake struck, from the Chilean National Institute for Statistics. I restricted the data to the nearly one million households with at least one school-aged child, and extracted information on the construction materials of their homes: for the exterior walls, roof and floor. Table A4 in the Appendix shows the distribution of building materials in this population.

I then mapped the vector of building materials into a predicted seismic vulnerability class (Grünthal (1998), Table 1). To do so, I estimated a logistic latent-class-analysis (LCA) model that assigns to each home the predicted probabilities of belonging to each of three classes, an unsupervised learning algorithm.[15] Post-estimation, I predicted the distribution of building materials by class. As an unsupervised algo-

[14] Δ_A is non-negative because it measures a distance, and it is never equal to zero because no town was directly above the asperity, which was in the ocean.

[15] The estimation of the LCA model is performed on a randomly selected sample of 100,000 households from this population, for computational reasons.

rithm, LCA does not label the classes, a step requiring human input. Therefore, I attached a label to each class (low, medium or high seismic vulnerability) depending on the similarity between the predominant construction materials within each class generated by the LCA model and the predominant construction materials used in Chile within each seismic vulnerability class (Massone et al., 2010). In this step of the data construction, I obtained feedback from a leading expert on the seismic vulnerability of Chilean buildings.[16,17] Figure 3 shows the predicted class proportions in the population of households with at least one school-aged child in the census and the within-class distributions of construction materials.

The second step consists in building a model that can accurately predict the seismic vulnerability of a household's home based on household characteristics, in the population of families with school-aged children. The dependent variable is seismic vulnerability as obtained from the LCA model, that is, a vector containing the probabilities that a home belongs to the low-, medium- or high-vulnerability class. For the independent variables, I restrict attention to the characteristics that are available in both the census and the education data. These are: the age of the household head, the average years of education of mothers and fathers, and the region of residence, to capture any differences in construction standards across regions.[18]

Predicting seismic vulnerability from household characteristics is remarkably easy in Chile, as I find striking socioeconomic stratification in housing quality among Chilean families with school-aged children. As shown in Figure 4, students from high socioeconomic status (SES) households are those most likely to live in homes with low seismic vulnerability, students from middle SES households in homes with medium seismic vulnerability, and students from low SES households in homes with high seismic vulnerability. Such socioeconomic segregation is not built into the seismic vulnerability measure, which is constructed only from construction materials. Therefore, the fact that the distribution of seismic vulnerability varies as expected with SES informally validates the procedure I developed to construct seismic vulnerability. To my knowledge, this is the first direct evidence that housing quality, in terms of

[16]I thank Professor Sergio Ruiz of the Geology Department at the University of Chile for his expert feedback on this step of the data construction, confirming that the distribution of building materials within the classes generated by the algorithm correspond to that found within the seismic vulnerability classes in Chile.

[17]Astroza, Ruiz, and Astroza (2012) identify four seismic vulnerability classes in Chile, but two of them (confined masonry and confined masonry designed according to the NCh2123 Chilean Code) are indistinguishable from each other using census information. Therefore, I group them into one class. These two types of constructions have the best earthquake resistance profiles (see Table 2 in Astroza, Ruiz, and Astroza (2012)), so they are assigned to the low vulnerability class. But in calculating damages, I acknowledge that this class contains two different kinds of constructions: I assume that half of these homes are built according to the NCh2123 Chilean Code, and half are not.

[18]I assume that the parent who fills out the education questionnaire is the household head.

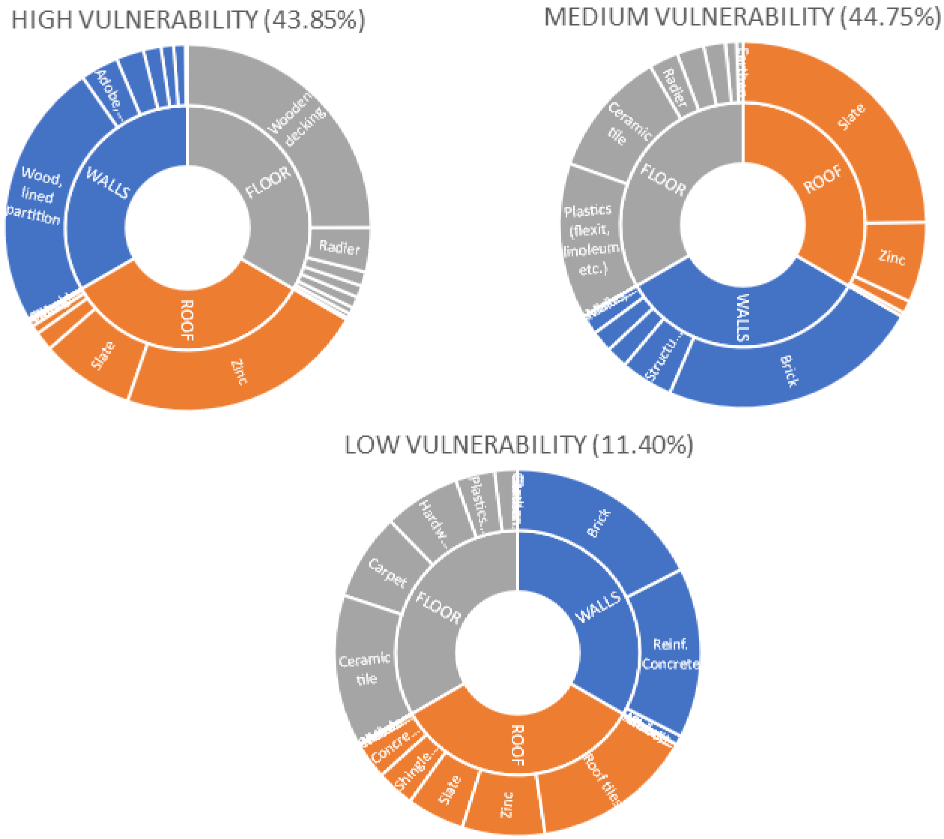


Figure 3: Results of the latent-class-analysis model estimated on census data: distribution of seismic vulnerability classes and of building materials within each class. *Notes*: The percentages next to each class label represent the proportion of homes in that class in the population of households with at least one school-aged child according to the 2002 census.

earthquake resistance, is highly segregated along socioeconomic lines among Chilean students.

I build the prediction model by estimating a LASSO regression on census data. The model can be used to predict the seismic vulnerability of the homes of students in the education dataset because it uses household characteristics available in both the census and the education dataset. Appendix A.1 describes the model. For each household, the model predicts the probabilities that the home belongs to each of the three seismic vulnerability classes. Figure 5 shows that its fit is excellent: the housing quality predicted using the estimated LASSO model traces very closely the actual housing quality built from information on building materials. The fit worsens slightly only among very old or very highly educated parents, who are very few in the education dataset. This gives me confidence that the model can accurately predict seismic vulnerability for nearly all students in the education dataset.

Step three: combining ground shaking and seismic vulnerability to build a measure of damages. For each student in the sample I now have measures of the

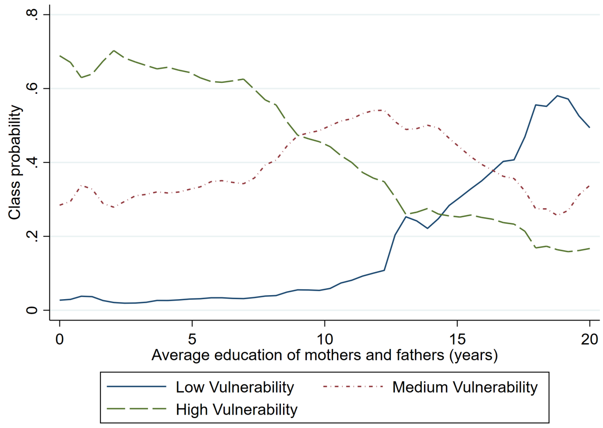


Figure 4: Evidence of socioeconomic segregation in housing quality among Chilean families with school-aged children. This graph plots the probability that the home of a school-aged child belongs to each of three seismic vulnerability classes (low-, medium- and high-vulnerability) by the education of the parents. *Sources:* census 2002 data, restricted to households with at least one school-aged child. Class probabilities stem from latent-class-analysis using census information on the construction materials of the families' homes.

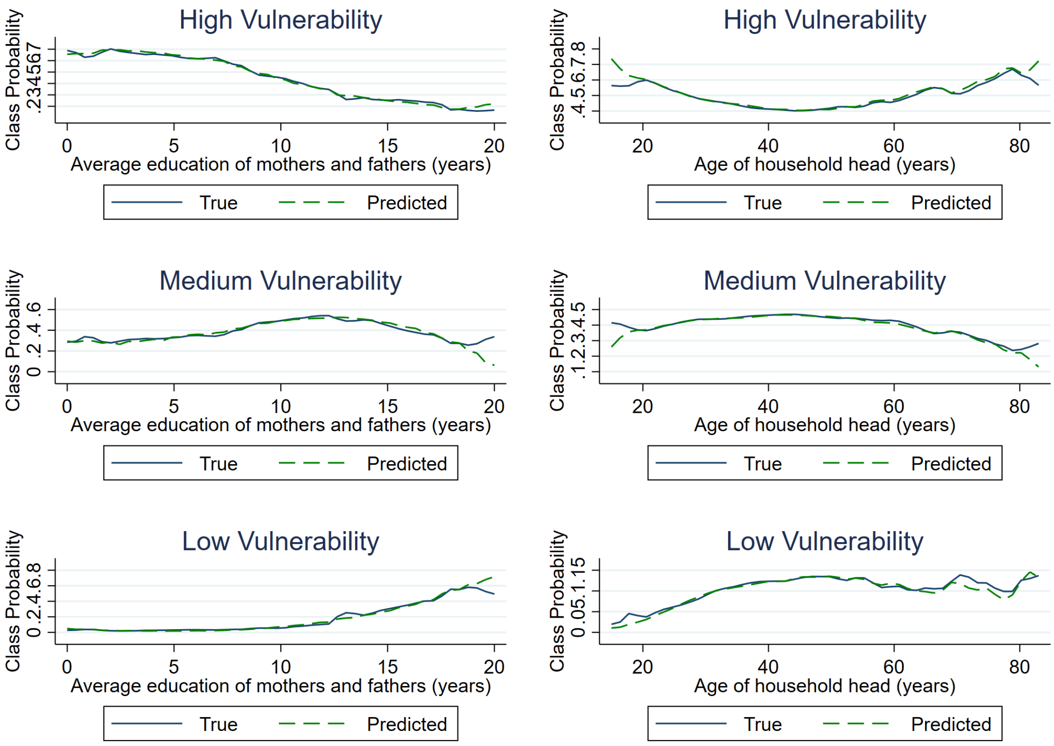


Figure 5: Goodness of fit of predicted seismic-vulnerability-class probability by parental education and by age of household head. *Notes:* census 2002, families with school-aged children.

intensity of ground shaking and of the seismic vulnerability of her home. I combine these two pieces of information to build a measure of expected damage, defined as the fraction of the home that needs to be rebuilt. The procedure is as follows.

For each vulnerability class and ground shaking level, Astroza, Ruiz, and Astroza (2012) provide the distribution of damage grades, which are divided into six categories, ranging from no damage ($DG_m = 0$) to complete collapse: ($DG_m = 5$). Following Bommer et al. (2002), I assign to each category DG_m a numerical damage measure $d \in [0, 1]$, called "damage ratio," which measures damages as a fraction of complete collapse, where $d = 1$ represents complete collapse. If the vulnerability class was observed, we could obtain the expected damage ratio of household i given its vulnerability class vc_i and ground shaking intensity level I_i as $E[d_i|vc_i, I_i] = \sum_{m=0}^{5} d(DG = m)p^m(vc_i, I_i)$, where $p^m(vc_i, I_i)$ is the probability that a house of vulnerability class vc_i subject to ground shaking I_i suffers a damage grade $DG = m$, which carries a level of damage ratio equal to $d(DG = m)$. But the vulnerability class is not observed. Instead, for each student in the data I observe a vector of predicted probabilities that her house belongs to one of each vulnerability class. Therefore, for each household with characteristics x_i I use the predicted likelihood that it belongs to each vulnerability class $j = 1, 2, 3$ ($\hat{p}^j(x_i)$ in Appendix A.1) to build a measure of the expected damage ratio:

$$d_i = E[d|x_i, I_i] = \sum_{j=1}^{3} \hat{p}^j(x_i) \cdot \left(\sum_{m=0}^{5} d(DG = m)p^m(vc = j, I_i) \right) \quad (1)$$

I standardize this measure in the sample so that it has mean zero and unit variance. This is the measure of home damage used throughout the analysis.

Tsunami. The damage ratio is not designed to measure damage stemming from the accompanying tsunami that afflicted coastal towns. In coastal areas it may suffer from larger measurement error, which would lead to attenuation bias. To avoid this, I restrict the sample to non-coastal towns, defined as those located more than 0.5 km from the coast, verifying the robustness of the results to different geographical restrictions. This sample restriction excludes approximately 25% of the observations from the analysis.

2.3 Descriptive analysis

I use the student-level measure of earthquake damage to document new facts about the propagation of damages from the 2010 Maule earthquake among students.

Among students of the post-earthquake cohort who live in earthquake regions (i.e., the students affected by the earthquake), the fraction of the home that collapsed ranged from 0% to 57%, and on average was 1.8%. The distribution was right-skewed, with most students suffering damage ratios below 10%. Average reconstruction costs amounted to USD $1,498$, i.e., around 46% of the average annual earnings of households who incurred the damages.[19] Lower earners incurred disproportionately higher damages; a 1% increase in earnings is associated with USD 91 fewer damages.

We have already seen that students from lower SES live in homes with larger seismic vulnerability (Figure 4). Figure 6 shows that also the level of home damage, which depends on both seismic vulnerability and ground shaking, decreased with students' SES, as measured by parental education. On average, the homes of students whose parents have at least some college education incurred 809 fewer USD of damages, or half the amount, than those of students whose parents do not have any college education. The Figure also shows that at all levels of parental education, students in public schools suffered more home damage than those in private schools, and those in rural schools more than those in urban schools. The evidence therefore suggests that the homes of the more disadvantaged students (i.e., those with less educated parents, those in public schools, those in rural schools) suffered the largest earthquake damages. Appendix Tables A2 and A3 show how all student and school characteristics correlate with home damages and building quality.

Why did homes of disadvantaged students incur greater damage? Figure 7 visually displays this disparity across two panels, each featuring a map of how damage propagated geographically. The left panel is based on lower-SES students — those without college-educated parents — while the right is based on higher-SES students — those with college educated parents. The circle size indicates the proportion of the respective SES populations living in a particular town. The color intensity indicates the average damage severity for students in that town and SES group, with darker colors indicating worse damage.

The maps reveal that lower-SES students were more likely to live in the (mostly rural) areas most affected by the earthquake than higher-SES students. But even conditional on residing in the same town, the homes of lower-SES students were more damaged, because of lower-quality housing. Damage propagation, therefore, was unequal across socioeconomic lines in Chile because of differences in residential choice and housing quality. While such socioeconomic inequality may appear unsurprising, this is one of the first times it was documented.

[19] These back of the envelope calculations use the 2010 USD to CLP exchange rate, and depend on the assumed cost of reconstructing a completely collapsed home. I assume the cost is equal to the average market price of a $50m^2$ home in Chile in 2010, which was USD $84,175$ (see https://www.globalpropertyguide.com/Latin-America/Chile/square-meter-prices and https://cchc.cl/centro-de-informacion/indicadores/indice-real-de-precios-de-vivienda). If a home suffered an unstandardized damage ratio of $x\%$, then the damage in dollars is measured as $x\% \cdot 84,175$. In the remainder of the paper I use the standardized damage ratio d_i, defined in equation (1), as the measure of damages, because its value does not depend on assumptions on home reconstruction costs.

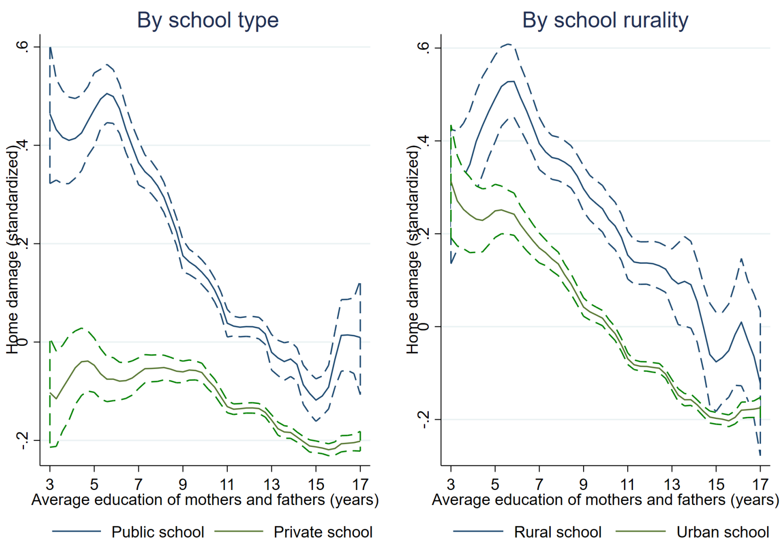


Figure 6: Relationship between home damage and parental education by school characteristics. *Notes:* sample of students in earthquake-affected regions in the post-earthquake cohort and residing more than 0.5 km from the coast. The figures present local polynomial regression estimates with 95% confidence intervals. Home damage is measured by the standardized damage ratio d_i, defined in equation (1). The top and bottom 1% of observations in terms of parental education were trimmed.

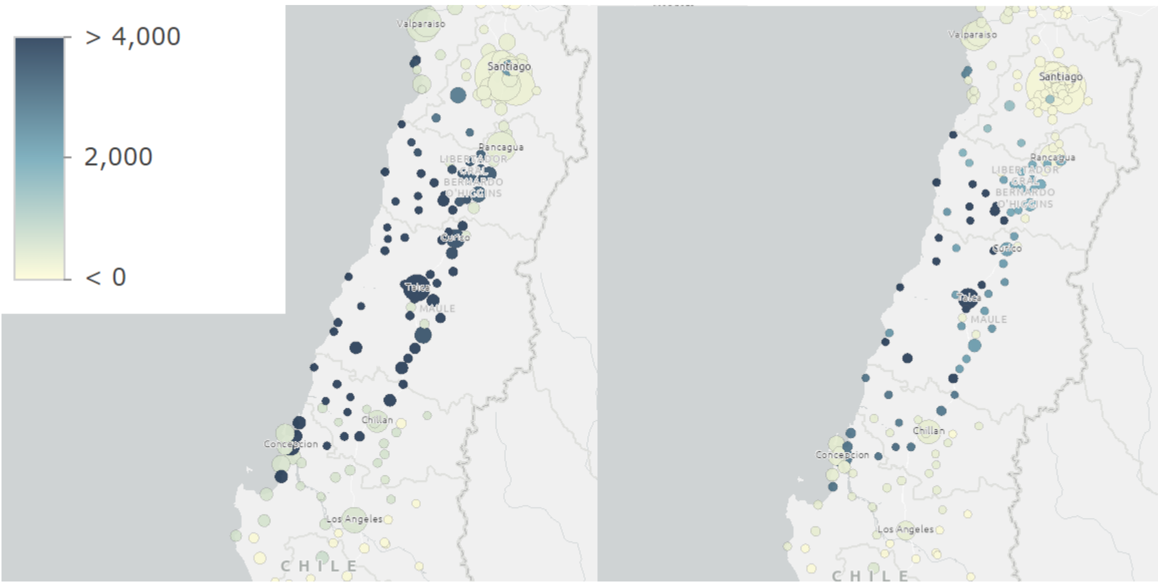


Figure 7: Damage propagation among students by socioeconomic demographics. *Notes:* The left panel shows damage propagation among students whose parents do not have college education, the right panel among students whose parents have college education. Each circle represents a town. Its size represents the percentage of the sample of college-educated parents (left panel) or of non-college-educated parents (right panel) living in that town. The shade reflects the average level of damages to the homes of the students without (left panel) or with (right panel) college educated parents in that town, measured in USD. For reference, the average annual wage in the entire sample is USD 8,378. College education is defined as having more than 14 years of education, as most vocational higher-education degrees require at most 14 years of education.

There is variation in how students in the same classroom were affected by the earthquake: 98% of students from the post-earthquake cohort going to school in affected regions were enrolled in classrooms where not all students suffered equal damages. This fraction is the same across public and private schools, and slightly larger among urban (99%) than rural (97%) schools. Students in these classrooms were exposed to a standard deviation in non-standardized damage ratios of 0.5% on average, or USD 422 at 2010 reconstruction costs (over half the average monthly household income), but in some classrooms the standard deviation in damages reached staggering levels, such as 6.2% at the 99^{th} percentile, or USD $5,146$, over seven months worth of income. Therefore, while students attending the same classroom tended to live in nearby towns and belong to similar socioeconomic classes, there was variation within classrooms in how students were affected by the earthquake, driven by differences in ground shaking and housing quality. This provides rich within-classroom variation in individual-level shocks.

Finally, Table 1 presents country-wide descriptive statistics of the pre- and post-earthquake cohorts of students, which display similar characteristics.

Table 1: Summary statistics of student and school characteristics in all regions of Chile.

	Pre-earthquake cohort			Post-earthquake cohort		
	Mean	St.dev.	N	Mean	St.dev.	N
	(1)	(2)	(3)	(4)	(5)	(6)
A. All students						
Baseline test score	.175	.822	155958	.159	.82	150791
Parental education (years)	10.9	3.11	175511	11	3.06	167565
Female student	.504	.5	180244	.504	.5	173864
Rural school	.113	.317	180244	.106	.307	173864
Public school	.478	.5	180244	.466	.499	173864
Earthquake-affected region	.754	.431	180244	.739	.439	173864
B. Excluding coastal towns						
Baseline test score	.174	.823	117446	.153	.822	110577
Parental education (years)	10.8	3.11	132564	10.9	3.06	122867
Female student	.504	.5	135950	.505	.5	127583
Rural school	.12	.325	135950	.115	.319	127583
Public school	.471	.499	135950	.463	.499	127583
Earthquake-affected region	.826	.379	135950	.806	.395	127583

Notes: Baseline test scores are the average of Mathematics and language SIMCE test scores in fourth grade, standardized in the population of test takers. A town is defined as coastal if it lies within 0.5 km of the coast.

3 Empirical Analysis of Earthquake Effects

3.1 Main findings

Damages to students' homes varied based on the quality of their homes and the distance of their hometown from the earthquake's asperity. This suggests that we can estimate the causal impact of earthquake damages on student outcomes by using data from a cohort of students with measurable pre-existing vulnerability to the earthquake but whose outcomes were measured before the earthquake struck. A difference-in-differences estimator exploits the differential correlation between vulnerability and outcomes across cohorts to tease out causal impacts.[20]

Equation (2) presents the regression model I estimate. I use the damage ratios defined in equation (1) to measure pre-existing earthquake vulnerability, which reflects actual home damages for the cohort exposed to the earthquake. The vector D_{ic} of vulnerability variables comprises the student's damage ratio and the (leave-one-out) mean and standard deviation of damage ratios in the classroom. The dummy variable $post_i$ takes on value 1 if a student belongs to the post-earthquake cohort, the one exposed to the earthquake, and 0 otherwise. The vector x_i of student characteristics includes a lagged achievement measure (the standardized test score in grade 4), making this a value-added model. The vector w_{cs} of school and classroom characteristics includes the school building's vulnerability.[21] Results from different specifications are reported in Appendix Table A7. The Table notes contain the full list of regressors.

$$y_{ics} = \alpha_0 + \alpha_1 \cdot w_{cs} + \alpha_2 \cdot x_i + \beta' \cdot D_{ic} + post_i \cdot \Big[\gamma + \delta' \cdot D_{ic}\Big] + \epsilon_{ics}. \tag{2}$$

For the pre-earthquake cohort, the parameter β captures the spurious relationship between vector D_{ic} and outcomes: the location and quality of a student's and her classmates' homes could correlate with unobserved outcome determinants. If such spurious relationship is constant across cohorts, an assumption I assess in section 3.2, the δ parameters reveal the effects of earthquake damages on test scores, keeping school building damages fixed. This is the parameter vector of interest.

The impacts estimated from equation (2) could be mediated by the school's response to the earthquake. For example, schools suffering more extensive average

[20] In this section, "vulnerability" refers to overall vulnerability, measured in damage ratios, which considers both construction quality and distance from the asperity.

[21] I do not observe the construction materials of the school building, but I observe the shaking intensity in the school's town. To allow for different shaking-resistance levels depending on construction materials, I include as regressors the shaking in the school's town, the shaking interacted with whether the school is public or private (to account for building quality differences across public and private schools), the latter interacted with the cohort dummy, and the cohort dummy interacted with whether a school is public or private.

damages in their classrooms might have received more emergency funds. The impacts estimated by δ thus capture the net effect of the disruptions and any remedial actions by schools. To account for school responses, I introduce a modified model that includes school-by-cohort fixed effects:

$$y_{ics} = \tilde{\alpha}_0 + \tilde{\alpha}_1 \cdot w_{cs} + \tilde{\alpha}_2 \cdot x_i + \tilde{\beta}' \cdot D_{ic} + post_i \cdot \tilde{\delta}' \cdot D_{ic} + \eta_{sp} + \nu_{ics} \qquad (2')$$

The model in equation (2') draws on comparisons across classrooms within the same school and cohort. The fixed effects absorb school-wide reactions to the earthquake, such that the $\tilde{\delta}$ parameters capture the damage impacts not mediated by school responses. These include the direct impacts on students' ability to learn, and any indirect ones such as teachers' reactions.

Table 2 presents the results. The outcome is the average between the Mathematics and Language SIMCE standardized test scores. Appendix Table A6 shows that considering the two subjects separately yields similar patterns. A one standard deviation increase in a student's damage ratio, corresponding to increasing the collapsed portion of the home by 4.4 percentage points, lowers test scores by 0.033-0.036 standard deviations (std). The effect does not vary substantially with the inclusion of the school-by-cohort fixed effects. To put the magnitude into perspective, this impact is a quarter of that of a one-standard-deviation improvement in teacher value added (Chetty, Friedman, and Rockoff (2014)).[22]

The average damages to the homes of classmates have positive effects on own test scores when the school-by-cohort fixed effects are not included, but the effect becomes null and insignificant once they are included. This suggests that schools counteracted any potential adverse learning conditions caused by average damages. Overcompensation in response to the earthquake was evidenced also in post-earthquake crime prevention in Chilean municipalities (Hombrados (2020)). The inclusion of the fixed effects, however, renders the estimate more imprecise, suggesting, unsurprisingly, that there is limited variation in mean damages across classrooms within schools. In contrast, the damage dispersion effect can be estimated with similar precision regardless of the inclusion of fixed effects. The damage dispersion had a negative but insignificant effect on test scores.

To summarize, damages affected the learning of the student living in the damaged home. The detrimental impacts occurred at a critical time in the educational path of students (the year before transferring to secondary education) and were disproportionately borne by students of lower socioeconomic status due to their greater

[22] Teachers are one of the most important school inputs into the production of achievement, but school inputs are generally not as impactful as home interventions (e.g. Heckman, Liu, Lu, and Zhou (2022), Heckman (2006)).

Table 2: Impacts of earthquake damages on standardized eighth-grade test score

	(1)	(2)
Effect of damage to own home	-0.033**	-0.036***
	(0.013)	(0.014)
Effect of average damage among classmates	0.052***	-0.000
	(0.019)	(0.128)
Effect of standard deviation of damage among classmates	-0.049	-0.020
	(0.045)	(0.052)
Observations	154900	154900
R^2	0.581	0.505
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\bar{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variable is the average between Mathematics and Language SIMCE scores, standardized to have mean 0 and variance 1. The treatment variables are measured in standard deviations of the damage distribution; Table A5 shows estimates where each treatment variable is measured in standard deviations of the treatment variable itself. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors are clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

exposure (Figures 4 and 7). While schools could not mitigate the impact of such individual-level shocks, they appear to have successfully mitigated the effect of the average level of damage in the classrooms. Damage dispersion in the classroom had insignificant effects, on average.

3.2 Identifying assumption

The identifying assumption underlying the estimator is that the relationship between achievement and the earthquake vulnerability variables would be the same in the pre- and post-earthquake cohorts in the absence of the earthquake. A concern is that the estimates may capture changes in this relationship across cohorts, rather than true damage impacts. For example, the estimate of the impact of mean damages in the classroom would be biased if the government introduced a policy between 2009 and 2011, the period between the outcomes for the two cohorts were measured, that changed the student composition across schools, such as changes to the vouchers for disadvantaged students to attend private schools.[23] If such a policy were introduced, it could alter how a school's socioeconomic composition, on which the mean damage measure is based, correlates with its unobserved quality across cohorts. This would violate the identifying assumption. To address such concerns, all specifications include

[23]Chile has a voucher policy in place, but it did not undergo any changes at this time (Neilson (2021)).

a set of controls for socioeconomic composition. By the same logic, they include controls for individual characteristics.[24]

But bias could still arise if unmeasured components of socioeconomic composition or of individual characteristics correlate with earthquake vulnerability variables differently across cohorts. To address this concern, I assess the validity of the identifying assumption using data from regions of Chile not affected by the earthquake. As Table 1 showed, around a quarter of students in the sample lived in regions so far from the asperity that no damage to buildings occurred.

The ideal test would be to re-estimate equations (2) and (2') on the sample of students living in non-affected regions. Failing to reject the null hypotheses that $\delta = 0$ and $\tilde{\delta} = 0$ provides evidence in favor of the identifying assumption: we would not be able to reject the notion that, in the absence of an earthquake, the measures of earthquake vulnerability I built (own vulnerability, and mean and standard deviation of vulnerability among classmates) correlate with outcomes identically across cohorts (under the assumption that the evolution of such correlation across cohorts in the regions unaffected by the earthquake equals that in the regions affected).[25]

I cannot run the ideal test because damage ratios are equal to zero by construction in regions where the ground did not shake ($d(DG = m)$ in equation (1) is zero). As a result, I focus on variation in students' home quality, which can be constructed for any student nationwide. When holding the town of residence constant, this metric becomes a proxy for earthquake vulnerability. This is because within a town, differences in damage ratios are determined solely by differences in housing quality.

Therefore, I use the sample of classrooms where every students resides in the same town (the school's town). I then re-estimate regressions (2) and (2'), using earthquake vulnerability measures based on housing quality in vector D_{ic}. For each student, we have a vector of probabilities indicating the likelihood their home falls into one of three seismic vulnerability classes. From this vector I construct an index. A value of 1 indicates that a student certainly lives in a high-vulnerability home, a value of 0 that she certainly lives in a low-vulnerability home.[26] I standardize this index across the entire sample, so that a one-unit increase corresponds to an increase in earthquake vulnerability by one standard deviation. I also generate the leave-one-out classroom mean and standard deviation of this vulnerability index.

[24]Appendix Table A7 shows that results are similar in specifications without such individual and group controls, retaining only the three individual characteristics used to build the damage measure.

[25]More formally, letting y_0 be the potential outcome in the absence of treatment $D = d$, and $E = 1$ for regions affected by the earthquake and $E = 0$ for regions not affected, the assumption is $\frac{\partial E[y_0|post,D=d,E=1]}{\partial d} - \frac{\partial E[y_0|pre,D=d,E=1]}{\partial d} = \frac{\partial E[y_0|post,D=d,E=0]}{\partial d} - \frac{\partial E[y_0|pre,D=d,E=0]}{\partial d}$, $\forall d$.

[26]The index is $1 \cdot \hat{p}_i^{HV} + 0.5 \cdot \hat{p}_i^{MV} + 0 \cdot \hat{p}_i^{LV}$.

Table 3 shows the results. As a plausibility check on the measure of earthquake vulnerability only based on housing quality, the first two columns are based on the sample of students from earthquake-affected regions. The patterns align with the main findings presented in Table 2, suggesting that the measure of damages based on housing quality and keeping location fixed is a good proxy for the measure based on damage ratios used in the main analysis.[27]

Table 3: Validity of the identifying assumption

	(1)	(2)	(3)	(4)
Effect of own home vulnerability	-0.038***	-0.040***	-0.006	-0.012
	(0.012)	(0.012)	(0.021)	(0.021)
Effect of average home vulnerability among classmates	0.071***	-0.194	-0.034	-0.220
	(0.027)	(0.161)	(0.028)	(0.252)
Effect of standard deviation of home vulnerability among classmates	0.276**	0.134	-0.202	0.281
	(0.132)	(0.194)	(0.160)	(0.331)
Observations	46670	46670	31502	31502
R^2	0.575	0.530	0.589	0.516
School-by-cohort fixed effects	No	Yes	No	Yes

Notes: Sample of classrooms where all students reside in the school's town. Columns 1 and 2 restrict the sample to earthquake-affected regions and towns more than 0.5km from the coast. Columns 3 and 4 restrict the sample to earthquake-unaffected regions. Home vulnerability is measured as an index ranging from 0 (for sure living in low-vulnerability home) to 1 (for sure living in high-vulnerability home), standardized to have mean zero and variance one in the entire sample. The average and standard deviation of home vulnerability among classmates are leave-one-out moments of this standardized index. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variable is the average between Mathematics and Language SIMCE eighth-grade test scores. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females; classroom average and standard deviation of lagged test scores and of parental education. The regressions with school-by-cohort fixed effects omit school-level controls and the cohort dummy. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Columns (3) and (4) assess the validity of the identifying assumption, presenting estimates of δ from equation (2) and δ' from equation (2') using data from regions *not* affected by the earthquake. We cannot reject the hypotheses that $\delta = 0$ and $\delta' = 0$ at any conventional significance level. This suggests that any potential spurious correlation between pre-existing vulnerability to the earthquake and outcomes — attributable to correlations between housing quality and unobserved determinants of student achievement — is constant across cohorts. This gives us more confidence in interpreting the main findings from Table 2 as causal.

3.3 Heterogeneity by baseline test scores

The impacts of damages to students' homes can vary depending on the students' prior preparation or ability. To explore this, I estimate models (3) and (3'), where ability a_i is measured through a standardized test in fourth grade:

[27]The main difference is the significant positive impact of the standard deviation when excluding school-by-cohort fixed effects. This can be explained by the fact that damage dispersion has heterogeneous effects by ability (positive for low-ability and negative for high-ability students, as per section 3.3), and the sample underlying Table 3 is selected (those attending schools that do not attract students from other towns tend to be lower-ability students).

$$y_{ics} = \alpha_0 + \alpha_1 \cdot w_{cs} + \alpha_2 \cdot x_i + \beta_1^{'} \cdot D_{ic} + \beta_2^{'} \cdot D_{ic} \cdot a_i + post_i \cdot \left[\gamma_1 + \gamma_2 \cdot a_i + \delta_1^{'} \cdot D_{ic} + \delta_2^{'} \cdot D_{ic} \cdot a_i\right] + \epsilon_{ics}, \tag{3}$$

$$y_{ics} = \tilde{\alpha}_0 + \tilde{\alpha}_1 \cdot w_{cs} + \tilde{\alpha}_2 \cdot x_i + \tilde{\beta}_1^{'} \cdot D_{ic} + \tilde{\beta}_2^{'} \cdot D_{ic} \cdot a_i + post_i \cdot \left[\tilde{\gamma}_2 \cdot a_i + \tilde{\delta}_1^{'} \cdot D_{ic} + \tilde{\delta}_2^{'} \cdot D_{ic} \cdot a_i\right] + \eta_{sp} + \nu_{ics}. \tag{3'}$$

The difference between these two models is whether the school-by-cohort fixed effects are included or excluded. The parameters of interest are $\delta_1, \tilde{\delta}_1$, which capture the effects of D_{ic} for a student with mean ability (i.e., $a_i = 0$), and $\delta_2, \tilde{\delta}_2$, the coefficients on the interaction terms. These inform us about the variation in the effects across students of different ability.

The results are presented in Table 4 and Figure 8. The detrimental impacts of damages to a student's own home did not substantially vary with a student's ability, as seen in the second row of Table 4 and top-left panel of Figure 8. In the model without fixed effects, the average damage among classmates had (insignificantly) stronger positive impacts on higher-ability students, as seen in the fourth row and first column of Table 4. For higher-ability students, the impacts were positive and statistically significant, as seen in the top-right panel of Figure 8. This suggests that remedial measures undertaken by schools may have benefited higher-ability students more, although the difference in impacts between students of different ability is imprecisely estimated. Estimates of the impact of average damages become imprecise with the inclusion of the fixed effects, as seen in the top-right panel Appendix Figure A2.

While the dispersion in damages in the classroom showed insignificant average effects (Table 2), the effects varied substantially and significantly across students (last row of Table 4). A rise in such dispersion raised the achievement of lower-ability students and lowered that of higher-ability students, as can be seen in the bottom-left panel of Figure 8. Including school-by-cohort fixed effects does not meaningfully change these findings, as seen by comparing Figure 8 to Appendix Figure A2, suggesting that school reactions to damage dispersion were minimal. For some students, the dispersion in damages had a similar or even larger effect than that of the damages at their own home.[28]

[28] Magnitude comparisons rely on the unit of measurement. In Table 4, all treatment variables are measured in terms of standard deviations of the distribution of damages. In Table A11, each treatment variable is measured in terms of standard deviations of the distribution of the treatment variable itself. For example, we consider the impact of increasing the damage standard deviation by one standard deviation of the distribution of damage standard deviations across classrooms. Regardless of the unit of measurement, for students near the tail of the ability distribution, the impacts of the standard deviation of damages are similar or larger than the impact of the damage to the student's own home.

Table 4: Heterogeneous impacts of earthquake damages on standardized eighth-grade test score

	(1)	(2)
Effect of damage to own home	-0.033**	-0.039***
	(0.013)	(0.014)
Interacted with baseline test score	-0.008	-0.009
	(0.017)	(0.016)
Effect of average damage among classmates	0.051***	-0.013
	(0.019)	(0.128)
Interacted with baseline test score	0.028	0.020
	(0.019)	(0.019)
Effect of standard deviation of damage among classmates	-0.041	-0.017
	(0.045)	(0.051)
Interacted with baseline test score	-0.096***	-0.081***
	(0.037)	(0.029)
Observations	154900	154900
R^2	0.581	0.505
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (3) and (3'). The outcome variable is the average between Mathematics and Language SIMCE scores. The treatment variables are measured in standard deviations of the damage distribution; Table A11 shows estimates where each treatment variable is measured in standard deviations of the treatment variable itself. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

These findings hold regardless of the interaction term or specification used. Eliminating individual, classroom and school controls does not change the results (Appendix Table A14). Relaxing the linearity assumption using an interaction with deciles of the ability distribution or including interactions with other student socioeconomic characteristics result in less precise estimates but confirm the patterns (Appendix Tables A12 and A13).[29]

In summary, the negative effects of damages to a student's own home were similar across the ability distribution. The positive effects of classroom mean damages, which likely reflect school remedial actions, were (insignificantly) stronger for higher-ability students. Relatively substantial earthquake impacts arose from damage dispersion in classrooms, especially lowering the achievement of high-ability students.

[29] In principle, more flexible non-parametric approaches could be used to model the bias arising from unobserved correlates within the difference-in-differences framework, as demonstrated in the seminal conditional difference-in-differences method developed in Heckman, Ichimura, Smith, and Todd (1998). In the context of social effects, this could be achieved by relaxing parametric restrictions of control function approaches (see Brock and Durlauf (2001b, 2006), who, by bringing the insights from Heckman (1979) and Heckman and Robb (1986) into the study of social effects, demonstrated that control functions can aide in their identification.). The treatment effects could be modelled as non-parametric functions of student characteristics to examine heterogeneity more flexibly. However, such non-parametric methods deliver impractically large estimator variances in this empirical setting.

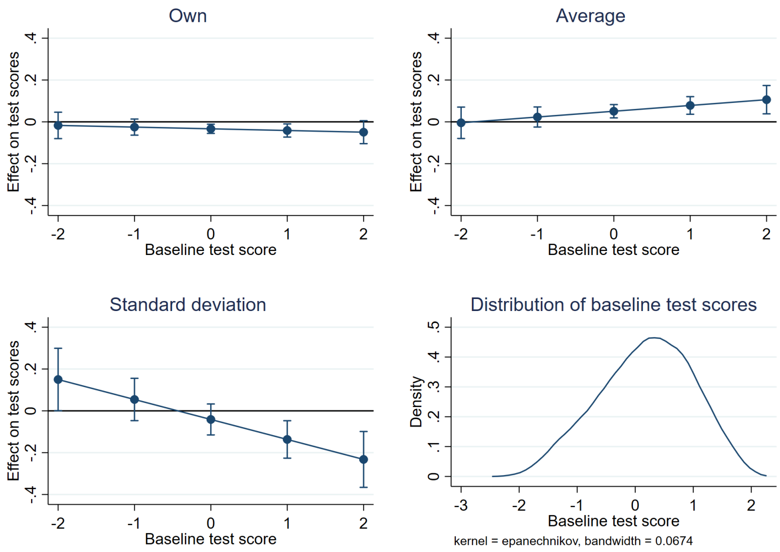


Figure 8: Marginal effects on standardized eighth-grade test scores by baseline test score. *Notes*: Marginal effects of own damage, leave-one-out average damage among classmates, and leave-one-out standard deviation of damage among classmates. Effects obtained from estimating the regression model in equation (3) (without school-by-cohort fixed effects). 90% confidence intervals reported.

3.4 Robustness

This section evaluates the robustness of the main results with regards to assumptions about earthquake damage measurement and potential spatial correlation of the regression residuals.

The analyses restricted the sample to non-coastal towns to mitigate potential attenuation bias from damages from the tsunami, which are not adequately accounted for by damage ratios. A town is defined as coastal if it is within a 0.5 km strip of the coast. I repeated the analyses defining coastal proximity as within 1 and 5km of the coast. I also repeated the analyses in the unrestricted sample that includes coastal towns. As shown in Appendix Table A10, the results are robust to different definitions of coastal proximity. The conclusions stand even considering the entire sample, but, as expected, the estimates are attenuated towards zero in this case.

The analyses allowed for correlation in the error terms of an unknown form between students in the same school and cohort. But error terms of students in different schools that are geographically close may correlate, as shaking is similar in nearby schools. I employ two methods to account for this. First, I cluster the standard errors at the school-town-by-cohort rather than the school-by-cohort level. Second, I use Conley's method (Conley (1999)) to compute the standard errors, allowing for a more flexible spatial correlation in the residuals. The method assumes that the spatial dependence between two students residing in different towns is a decreasing function of the distance between the towns, and that beyond a pre-specified distance cutoff, there is no dependence. I present results for different cutoff distances (10km, 25km, 50km, 100km, 587km), up to the distance between the asperity and the farthest municipality experiencing damages (586.3 km). As shown in Appendix Tables A8 and A9, the standard errors are very similar across methods and distance thresholds, suggesting that clustering at the school-by-cohort level accurately captures the spatial correlation in the data-generating process.

4 Mediating Relationships

Tables 5 and 6 show impacts on potential mediators, using administrative and survey data (survey items and variable construction are described in Appendix A.2).

Table 5: Impacts of earthquake damages on student cost of effort, course engagement, GPA

	(1) Eff. cost	(2) Eff. cost	(3) Engage.	(4) Engage.	(5) GPA (std)	(6) GPA (std)
Damage	0.038**	0.038*	-0.030	-0.022	-0.028*	-0.035**
	(0.018)	(0.020)	(0.018)	(0.021)	(0.015)	(0.016)
Damage average	-0.043**	0.047	0.022	0.120	0.047*	-0.032
	(0.022)	(0.118)	(0.022)	(0.180)	(0.025)	(0.171)
Damage standard deviation	0.083**	0.041	0.008	0.095	-0.100*	-0.107*
	(0.034)	(0.067)	(0.045)	(0.085)	(0.052)	(0.063)
Observations	156978	156978	137444	137444	156978	156978
R^2	0.044	0.042	0.020	0.012	0.251	0.254
School-by-cohort fixed effects	No	Yes	No	Yes	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and resding more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (3) and (3'). The outcome variables in columns 1-4 (perceived cost of study effort and engagement with the course) are built from items from the survey administered in eighth grade, using the procedure described in Appendix A.2. The outcome variable in columns 5-6 is built from administrative GPA records in eighth grade. GPA is standardized to have mean 0 and variance 1. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Study effort cost, course engagement and instruction. The first four columns of Table 5 present the impacts of earthquake damage on students' perceptions. A one-standard-deviation increase in damage to a student's home significantly increased their perceived cost of study effort, by around 0.4 standard deviations, up to 22 months post-event. At the same time, their ability to engage with the course material diminished (insignificantly) by 0.02-0.03 standard deviations. Potential reasons include logistical disruptions and psychological challenges. The medical literature has reported that earthquake survivors, especially children, are prone to long-lasting Post Traumatic Stress Disorder (PTSD).[30] In the case of the 2010 Maule earthquake, children living in strongly shaken areas displayed significantly higher PTSD rates compared to similar children in unaffected areas;[31] and adverse impacts on psychological functioning were detected among preschoolers and primary school students.[32] The results, therefore, are consistent with the notion that post-earthquake trauma affects human capital accumulation in schools.[33]

Keeping fixed a student's home damage, an increase in the average damage suffered by peers had a negative effect on own effort cost (Table 5 column 1). This result aligns with the previous findings on achievement impacts and likely reflects schools' compensatory actions. But once we account for the schools' response using school-by-cohort fixed effects (column 2), the impact on effort cost becomes insignificant. Keeping fixed a student's home damage, an increase in the damage dispersion in the classroom had a positive effect on own effort cost, but this result is not robust to the inclusion of the school-by-cohort fixed effects, suggesting that learning was more difficult in schools with larger damage dispersion, but within schools, students in classrooms with different damage dispersion had similar effort costs. The impacts on course engagement of the mean and the standard deviation of damages are imprecisely estimated; we cannot rule out null effects.

Next, I examine the impacts on classroom instruction using teacher survey data on the fraction of the curriculum covered. On average, Language teachers cover 64.3% of the curriculum in class, and Mathematics teachers 61.6%. Table 6 shows that the distribution of damages among students in the classroom did not affect these figures. The point estimates of the impacts of the classroom average and standard deviation of damages are close to zero, and the confidence intervals are narrow, especially with regards to the impacts of the standard deviation.

The lack of instructional pace adaptation suggests that the mitigating effort taken by schools in response to the average level of damages among their students did not take the form of teachers slowing down. Instead, other adaptations within the schools led to the lower effort cost (Table 5 column 1) which, combined with teachers not changing their instructional pace, resulted in higher achievement and GPA on average

[30] See, for example, Altindag, Ozen et al. (2005), Lui et al. (2009), Giannopoulou et al. (2006). Children living closer to earthquake epicenters have been found to experience more severe PTSD (Groome and Soureti (2004)).

[31] Zubizarreta, Cerda, and Rosenbaum (2013) measured PTSD using the self-rated Davidson Trauma Scale, administered 3-4 months post-earthquake, and compared students in similar-quality homes but with varying exposure to shaking.

[32] See Dutta et al. (2022), who find impacts up to one year after the earthquake. See also Gomez and Yoshikawa (2017).

[33] Other papers have estimated earthquake impacts on student achievement (e.g. Shidiqi, Di Paolo, and Choi (2023)), but exposure has typically been measured solely through location, abstracting from housing quality conditional on location, which I find to be an important source of inequality.

(Table 2 column 1 and Table 5 column 5). However, the lack of instructional pace adaptation cannot help explain why we observed heterogeneous impacts of damage dispersion. The evidence does not support the notion that in classrooms with higher damage dispersion, teachers reduced the instructional pace to focus on the lower-ability students — a scenario that could have explained the positive impact of damage dispersion on the achievement of lower-ability students and detrimental impact on that of higher-ability students.

Table 6: Impacts of earthquake damages on the percentage of the curriculum covered in class

	(1) Language	(2) Language	(3) Mathematics	(4) Mathematics
Effect of average damage among classmates	-0.000	-0.087	-0.002	0.064
	[-0.012,0.012]	[-0.218,0.044]	[-0.017,0.013]	[-0.089,0.217]
Effect of standard deviation of damage among classmates	-0.025	0.019	-0.001	0.025
	[-0.064,0.015]	[-0.033,0.070]	[-0.047,0.044]	[-0.041,0.091]
Observations	6803	6803	6858	6858
R^2	0.032	0.019	0.039	0.017
School-by-cohort fixed effects	No	Yes	No	Yes

Notes: Schools in regions affected by the earthquake, located more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (3) and (3'). The unit of observation is the classroom. The outcome variables were collected through surveys administered to Language and Spanish teachers. They are the percentages of the Language (columns 1-2) and Mathematics (columns 3-4) curricula they covered. Regressions include the following school and classroom characteristics: class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education, dummy for public school, dummy for rural school. Regressions with school-by-cohort fixed effects omit the school characteristicsy and cohort dummy. 95% confidence intervals shown in brackets, constructed from standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

GPA and GPA rank. The last two columns of Table 5 present the impacts of earthquake damage on GPA (standardized to have mean 0 and variance 1). The impact of damage to a student's home closely mirrors the test score impact shown in Table 2, suggesting no change in grading standards. The alignment between GPA and test score effects is further confirmed by the top panel of Figure 9, mirroring Figure 8. Yet, as shown in the bottom panel of Figure 9, the changes in GPA induced by changes in the distribution of peer damages did not result in changes in GPA rank patterns.[34] The null impacts on GPA rank of the standard deviation of damages are particularly striking, because the standard deviation did have heterogeneous impacts on GPA across the baseline test score distribution. This implies that while higher ability students experienced relatively large drops in GPA, they did not experience any drop in their GPA rank.

Summary. At the individual student level, damage seemed to inhibit the ability to study and engage with course content. At the classroom level, there's no indication of instructional adaptation: teachers did not change their pace. While this finding could help explain why the mitigating efforts of schools resulted in positive learning impacts,

[34] See also Appendix Figure A3 for the version with school-by-cohort fixed effects.

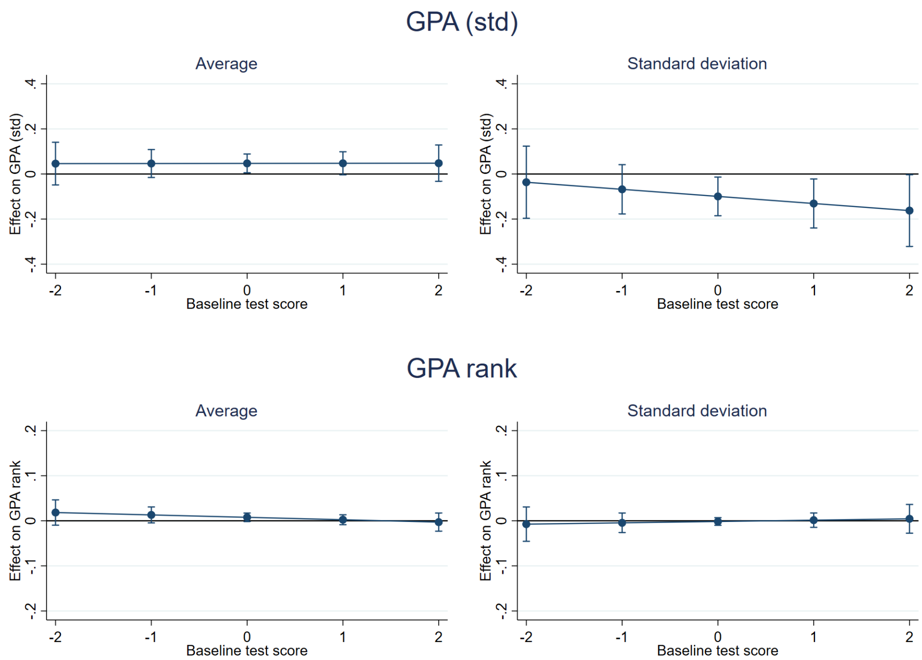


Figure 9: Marginal effects on GPA and within-classroom GPA rank by baseline test score. *Notes*: GPA rank is the classroom rank, it ranges from 0 (worst GPA) to 1 (top GPA). Marginal effects of the leave-one-out average and standard deviation of damage among classmates. Effects obtained from estimating the regression model in equation (3) (without school-by-cohort fixed effects). 90% confidence intervals reported.

it cannot easily explain why damage dispersion had heterogeneous impacts across the ability distribution. Teachers do not appear to have focused on lower-ability students by slowing down their pace, which could have generated such impacts.

The results on GPA and GPA rank are consistent with the notion that students care about GPA rank. Faced with changed study effort costs among their peers, students adjusted their effort and learning, but not at the expense of their classroom standing. To ascertain whether this channel could rationalize the empirical findings, the next section formalizes this notion through a simple model that introduces rank concerns as a mechanism behind peer interactions.

5 A potential mechanism: peer interactions

In this section I propose a conceptual framework to interpret the empirical findings. I follow the approach adopted in Blume, Brock, Durlauf, and Jayaraman (2015) of micro-founding observed spillover effects through a model of behavior.

Motivated by the empirical evidence, I present a new theory of peer influence where changing the ability to study of peers affects own outcomes through a competition motive: when students compete for academic standing, changing the academic ability of peers changes the competition they face, resulting in different effort choices and achievements.[35] Empirically, this appears like an ability peer effect.

I adapt the model to the earthquake setting in two ways. I incorporate schools' mitigating actions in response to the severity of the disruptions, and I assume that damages from the earthquake act as an additive shock to the cost of exerting study effort (or, equivalently, the ability to study) of each student, an assumption that is supported by the evidence (columns 1 and 2 of Table 5). A result of this assumption is that classrooms with different damage distributions, *ceteris paribus*, have different distributions of the effort cost.[36]

The model is what allows me to extrapolate beyond the context of the earthquake. I micro-found the choices of students of how much costly study effort to exert in a strategic setting with competitive motives, and derive comparative statics on the achievement impacts of varying the distribution of damages in a classrooms, keeping the composition of classmate characteristics constant. I compare these predictions to the empirical findings on the effects of varying the distribution of damages in a classroom, and show that the theory can explain all the empirical results, including seemingly unrelated ones, in a simple and intuitive way.

5.1 A theory of peer influence

Within a reference group there is a continuum of students, each indexed by i. Students are heterogeneous in terms of effort cost type c_i, which is distributed in the reference group according to a twice continuously differentiable cumulative distribution function (c.d.f.) $G(\cdot)$ on $[\underline{c}, \bar{c}]$, with $\underline{c} \geq 0$. The reference group is where interpersonal interactions occur, such as the classroom.

Students choose how much costly effort e_i to exert, and effort increases GPA y_i. Utility is increasing in own GPA and in the GPA rank in the reference group. Students with a higher effort cost type c_i incur a larger cost of exerting study effort for each

[35] Unlike Blume, Brock, Durlauf, and Jayaraman (2015), who assume that students choose achievement directly, I assume that students choose effort, and that effort affects achievement monotonically like in Fruehwirth (2013). This assumption allows me to derive model implications in terms of the observed achievement outcomes. Several studies show empirically that effort increases achievement (Stinebrickner and Stinebrickner (2004, 2008); De Fraja, Oliveira, and Zanchi (2010)), providing strong empirical support to this model's assumption. Good measures of effort are typically unavailable in large scale administrative datasets like the ones used in this study, as they require costly data collections to obtain detailed time diaries; researchers have been able to collect them from a few hundred students at a time (see e.g. Conley, Mehta, Stinebrickner, and Stinebrickner (2015)).

[36] It is easy to show, under the assumption that cost of study effort is a linear function of damages and other characteristics, that shifting the mean and variance of damages shifts the mean and variance of effort costs when the classroom composition is held constant (Appendix C.1).

effort level.[37] Cost type c_i captures all student characteristics, physical, psychological and socioeconomic, that affect the ability to study. For each student i, it depends on her baseline test score a_i, family characteristics x_i, and damages her home incurred from the earthquake d_i:

$$c_i = \theta_0 + \theta_1 a_i + \theta_2 x_i + \theta_3 d_i. \tag{4}$$

The cost type c_i is assumed to be decreasing in the baseline test score a_i and increasing in the damages d_i, assumptions that are supported in the data (see Table 5 and Appendix Figure A4). Each student's cost type is private information, but the distribution of cost types in the reference group, $G(\cdot)$, is common knowledge. There are no distributional assumptions on $G(\cdot)$, ensuring wide model applicability.

The cost of effort is determined by a strictly increasing and strictly convex function of effort: $q(e_i; c_i)$. Higher cost types c_i incur larger costs for every level of effort e_i, i.e., $\frac{\partial q(e_i,c_i)}{\partial c_i} > 0$ for all e_i. Moreover, at higher cost types the marginal cost of effort is (weakly) higher: $\frac{\partial^2 q(e_i;c_i)}{\partial c_i \partial e_i} \geq 0$. Effort increases GPA according to the production function:

$$y(e_i) = (a_0 + a_1(\mu_d))e_i + u_0 + u_1(\mu_d), \qquad \text{with } a_0 + a_1(\mu_d) > 0, \tag{5}$$

where μ_d is the mean of damages among peers. The functions $a_1(\mu_d)$ and $u_1(\mu_d)$, weakly increasing in μ_d, capture mitigating, compensatory actions taken by schools in response to mean damages in the classroom.[38] Mitigation is allowed to affect either the level of achievement (through u_1), or the productivity of effort (through a_1), or both; the model is therefore agnostic about which channel drives mitigation efforts.

The utility function for student i can be decomposed into a utility that depends only on own GPA y_i in absolute terms and on effort cost $q_i = q(e_i, c_i)$, $u_i = V(y_i, q_i)$, and a utility that depends on GPA rank in the classroom. Function V does not have an i subscript because it is the same for all students. The utility from GPA in absolute terms net of effort cost is non-negative, strictly increasing and linear in GPA, strictly decreasing and linear in q_i, and it admits an interaction between utility from GPA and from effort cost such that at higher costs, the marginal utility from GPA is (weakly) lower ($V_{12} \leq 0$).[39] No functional form assumptions are made on $q(\cdot)$

[37] This aspect of the model could be recast in terms of students being heterogeneous in terms of how productive their effort is.

[38] Alternatively, one could assume that the mitigating action in response to μ_d directly affects the average cost type in the reference group, thus indirectly affecting y_i in equilibrium. The model's implications would stand.

[39] All results are valid under an alternative set of assumptions for the utility V and cost function q. These are: strictly quasi-concave utility from GPA, strictly decreasing and linear utility from cost of effort ($V_2 < 0, V_{22} = 0$) with a linear cost function ($\frac{\partial^2 q}{\partial^2 e_i} = 0$) and additive separability between utility from GPA and cost of effort ($V_{12} = 0$).

or on the interaction between y_i and q_i; the results are valid under a broad class of preferences. For example, students with lower effort cost type c_i may (or may not) have higher marginal utilities from GPA.

A student's GPA rank in the classroom is given by the cumulative distribution function (c.d.f.) of GPA computed at her own GPA, $F_Y(y_i)$. This is the fraction of students with GPA lower than one's own. Because GPA is an increasing deterministic function of effort, GPA rank equates effort rank: $F_Y(y(e_i)) = F_E(e_i)$, where $F_E(\cdot)$ is the c.d.f. of effort. The utility from rank, $S\big(F_Y(y(e_i))\big)$, equals $F_E(e_i) + \phi$, with $\phi > 0$. Overall utility $U(y_i, q_i; c_i)$ is the product of utility from GPA and GPA rank: $V(y_i, q_i; c_i)\,(F_E(e_i) + \phi)$. Each student chooses effort to maximize overall utility.

In a symmetric Nash equilibrium in pure strategies, every student follows the same strategy $e(c_i)$ that is such that, given this common strategy, no student i can increase her expected utility by deviating unilaterally. Focusing on such equilibria, and initially assuming that the equilibrium strategy $e(c_i)$ is strictly decreasing and differentiable with inverse function $c(e_i)$, GPA rank in equilibrium can be rewritten as $1 - G\big(c(e_i)\big)$, and i's utility as $V\big(y(e_i), q(e_i, c_i)\big)\big(1 - G\big(c(e_i)\big)\big)$.[40] The first-order condition then is:

$$\underbrace{V_1 \overbrace{(a_0 + a_1(\mu_d))}^{\text{mg. GPA increase}}}_{\text{mg. ut. from increased GPA}} + \underbrace{\frac{V(y_i, q_i)}{1 - G\big(c(e_i)\big) + \phi} \overbrace{g\big(c(e_i)\big)\big(-c'(e_i)\big)}^{\text{mg. GPA rank increase}}}_{\text{mg. ut. from increased GPA rank}} = \underbrace{-V_2 \frac{\partial q}{\partial e_i}}_{\text{mg. cost}}. \tag{6}$$

The model is an application of the status game in Hopkins and Kornienko (2004).[41] Proposition A1 in Appendix C.2 establishes equilibrium existence and uniqueness and that the equilibrium strategy is indeed strictly decreasing, confirming equation (6) as the appropriate first-order condition.

5.2 Model predictions and their empirical counterparts

Impacts of mean damages on GPA. The first set of model implications regards the impacts on GPA of increasing mean damages in the classroom while preserving

[40] Strict monotonicity and differentiability of equilibrium $e(c_i)$ are initially assumed, and subsequently proven (see the proof of Proposition A1 in Appendix C.2). GPA rank can be written as $1 - G(c(e_i))$ in equilibrium because the probability that a student i of type c_i with effort choice $e_i = e(c_i)$ chooses a higher effort, obtaining a higher GPA, than another arbitrarily chosen student j is $F_E(e_i) = Pr\big(e_i > e(c_j)\big) = Pr\big(e^{-1}(e_i) < c_j\big) = Pr\big(c(e_i) < c_j\big) = 1 - G\big(c(e_i)\big)$ where $G(\cdot)$ is the c.d.f. of c_i and $c(\cdot) = e^{-1}(\cdot)$. The function c maps e_i into the type c_i that chooses effort e_i under the equilibrium strategy, it exists by strict monotonicity and, therefore, invertibility of $e(\cdot)$.

[41] For related games of status models, see also Hoppe, Moldovanu, and Sela (2009) and Moldovanu, Sela, and Shi (2007).

damage dispersion. I consider an identical increase in d_i for all classmates. Consider two classrooms A and B with identical distributions of a_i and x_i (i.e., identical peer compositions), but with different damage distributions $D(\cdot)$: $D_B(d) = D_A(d-k)\ \forall d$, where k is a positive constant. That is, the damage distribution in classroom B is shifted to the right by k.

Proposition 1. *Let $E_A[\cdot]$ and $E_B[\cdot]$ denote classroom-specific expectations. At the Nash Equilibrium in each classroom:*

(i) If $\frac{\partial^2 q}{\partial e_i \partial c_i} = 0$, then $E_B[y_i] \geq E_A[y_i]$, holding with equality only if $\frac{da_1}{d\mu_d} = 0$ and $\frac{du_1}{d\mu_d} = 0$, i.e., only in the absence of compensatory action.

(ii) If $\frac{\partial^2 q}{\partial e_i \partial c_i} > 0$ and $\frac{da_1}{d\mu_d} > 0$, then $\exists \gamma > 0$ such that if $\frac{\partial^2 q}{\partial e_i \partial c_i} \leq \gamma$, $E_B[e_i] \geq E_A[e_i]$, so that $E_B[y_i] > E_A[y_i]$. If $\frac{\partial^2 q}{\partial e_i \partial c_i} > \gamma$, then $E_B[e_i] < E_A[e_i]$, and $E_B[y_i] \geq E_A[y_i]$ or $E_B[y_i] < E_A[y_i]$ depending on the magnitude of $\frac{da_1}{d\mu_d}$ and $\frac{du_1}{d\mu_d}$, i.e. depending on whether school action compensates for decreased effort.

(iii) If $I\frac{\partial^2 q}{\partial e_i \partial c_i} > 0$ and $\frac{da_1}{d\mu_d} = 0$, $E_B[e_i] < E_A[e_i]$, and $E_B[y_i] \geq E_A[y_i]$ or $E_B[y_i] < E_A[y_i]$ depending on the magnitude of $\frac{du_1}{d\mu_d}$, i.e. depending on whether school action through u_1 compensates for decreased effort.

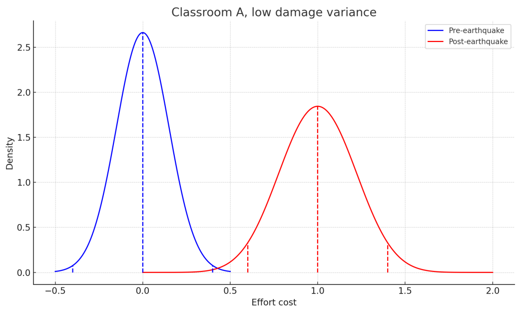
Proof: see Appendix C.2.

Proposition 1 states that the impacts on GPA of increasing mean damages in the classroom through a dispersion-preserving shift in the damage distribution is either null or negative if schools do not respond with compensatory action ($\frac{da_1}{d\mu_d} = 0, \frac{du_1}{d\mu_d} = 0$). But if schools respond (through $\frac{da_1}{d\mu_d} > 0$ or $\frac{du_1}{d\mu_d} > 0$ or both), then the impact on GPA will be positive, provided each student's marginal effort cost increases with own damage sufficiently slowly such that effort does not decrease ($0 \leq \frac{\partial^2 q}{\partial e_i \partial c_i} < \gamma$), or provided the compensatory action over-compensates for any decrease in effort.

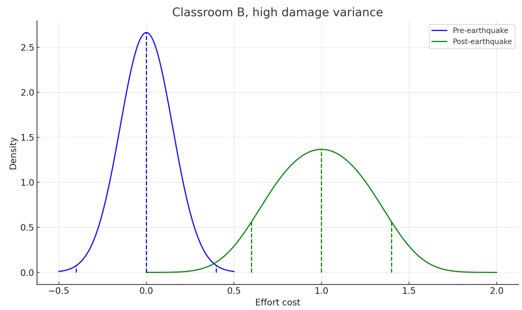
This result rationalizes the empirical findings that achievement and GPA increased with mean damage, suggesting schools took compensatory actions (column 1 of Table 2 and column 5 of Table 5), and that mean damages had insignificant, potentially negative impacts once the effects of schools' compensatory actions are removed using school-by-cohort fixed effects (column 2 of Table 2 and column 6 of Table 5).

Impacts of dispersion in damages on GPA. The second set of model implications regards the impacts on GPA of increasing damage dispersion in the classroom while preserving mean damages. I consider an increase in dispersion in the unimodal likelihood ratio (ULR) sense. Consider two classrooms A and B with identical distributions of a_i and x_i (i.e., identical peer compositions), but with different damage distributions $D(\cdot)$: $D_A \succ_{ULR} D_B$, that is, the ratio of the densities $L(d_i) = \frac{d_A(d_i)}{d_B(d_i)}$ is strictly increasing for $d_i < \tilde{d}$ and strictly decreasing for $d_i > \tilde{d}$ for some $\tilde{d} \in [\underline{d}, \bar{d})$

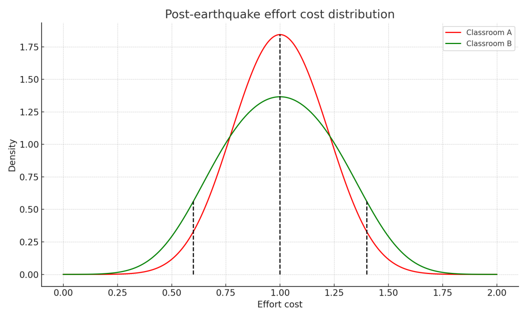
and if $\mu_d^A = \mu_d^B$. In particular, if B has the same mean but higher variance than A, then $D_A \succ_{ULR} D_B$. As the distributions of a_i and x_i are identical in classrooms A and B, and effort cost type is a weighted sum of a_i, x_i, and d_i (equation (4)), when $D_A \succ_{ULR} D_B$, the effort cost type distributions satisfy the ULR order $G_A \succ G_B$, with cutoff point $\tilde{c} \in [\underline{c}, \bar{c})$. Figure 10 visualizes the effort cost type distributions of two classrooms where the distributions of a_i and x_i are identical (blue density functions in the two top panels), and the damage distribution in classroom B is a mean-preserving spread of that in classroom A. The resulting effort cost type distribution in classroom B is a mean-preserving spread of that in classroom A (bottom panel).



(a) Classroom A, low damage variance



(b) Classroom B, high damage variance



(c) Classrooms A and B: Post-Earthquake effort cost type distributions

Figure 10: Effect of different damage shock distributions on the effort cost type distributions of two initially identical classrooms. *Notes:* The pre-earthquake effort cost type distribution is represented by a normal distribution $X \sim N(0, 0.15)$, drawn in blue. It captures the portion of effort cost type influenced only by student ability and individual characteristics. After the earthquake, the damage distribution in classroom A is described by $D_A \sim N(1, 0.21)$ and in classroom B by $D_B \sim N(1, 0.38)$. The post-earthquake effort cost type is the summation of component X (influenced by student characteristics and ability) and the damage. Specifically, for classroom A it is given by $X_{\text{post,A}} = X + D_A$ and for classroom B by $X_{\text{post,B}} = X + D_B$, whose distributions are drawn in red and green.

Proposition 2. (Adapted from Proposition 4 in Hopkins and Kornienko (2004)). *Let $y_A(c_i)$ and $y_B(c_i)$ denote the GPA each effort cost type c_i obtains at the Nash Equilibrium choices of effort in classrooms A and B, and let c^- and c^+ denote the extremal points of the ratio $(1 - G_A(c_i))/(1 - G_B(c_i))$ over the interval $[\underline{c}, \bar{c}]$, where $\underline{c} < c^- < c^+ \leq \bar{c}$. Then:*

(i) $y_A(c_i) < y_B(c_i)$ *for all* $c_i \in [c^+, \bar{c}]$*; i.e., the damage dispersion increase raises the GPA of high-cost-type students.*

(ii) $y_A(c_i) > y_B(c_i)$ *for all* $c_i \in [\tilde{c}, c^{cross})$*, where* $c^{cross} \in (\tilde{c}, c^+)$ *is the point where* y_A *and* y_B *cross; i.e., the damage dispersion increase lowers the GPA of medium-cost-type students.*

(iii) $y_A(c_i) > y_B(c_i)$ *for all* $c_i \in [\underline{c}, \tilde{c})$ *or* $y_A(c_i) < y_B(c_i)$ *for all* $c_i \in [\underline{c}, c^{cross2})$*, where* $c^{cross2} \in [\underline{c}, c^-)$ *is the point where* y_A *and* y_B *cross, i.e., the damage dispersion increase may lower or increase the GPA of low-cost-type students.*

Proof: see Appendix C.2.

The intuition is that when students have rank concerns, the cost type density at one's own type determines how easy it is to improve one's rank. If there are more peers with a similar effort cost type to one's own, more students can be surpassed for a unitary increase in effort, causing a higher marginal utility of effort. We expect heterogeneous effects because increasing the type dispersion affects the type density differently at different points, increasing it at the tails and lowering it in the middle of the distribution, as can be seen in Panel (c) of Figure 10.

High- and low-cost-type students face an incentive to increase effort, and medium-cost-type students to decrease it, because of how the type density changes at their type level when the type dispersion increases. The model predicts that high- and middle-cost-type students behave according to these incentives. Low-cost-type students, however, also face the opposite incentive to decrease effort due to the lower competition from above (from the middle-cost types), which allows them to save on effort cost while not sacrificing rank. The model is agnostic as to which incentive prevails for low-cost-type students.

Lemma 1. *Proposition 2 can be recast in terms lagged test score instead of effort cost type. Given equation* (4)*, if* $x_i = x_j$ *and* $d_i = d_j$ *for* $i \neq j$*, then* $c_i > c_j \iff a_i < a_j$*.*

Proposition 2 and Lemma 1 rationalize the empirical findings that, keeping a student's own characteristics and damage constant, achievement and GPA decreased for high-ability students and increased for low-ability students as an effect of increased damage dispersion (Tables 4 and A12, and Figures 8, A2, 9, and A3).

Impacts on GPA rank. Changing the classroom distribution of damages changes that of effort cost types. What are the implications on GPA rank, when students draw utility from rank? Consider two classrooms A and B with identical distributions of a_i and x_i (i.e., identical peer compositions), but different distributions of damages d_i. The resulting cumulative distribution functions of effort cost types, G_A and G_B, are assumed to be twice continuously differentiable, so that Proposition A1 applies.

Proposition 3. *Let $y_A(c_i)$ and $y_B(c_i)$ denote the GPA each cost type c_i obtains at the Nash Equilibrium choices of effort in classrooms A and B. Let $F_Y^J(\cdot)$ denote the c.d.f. of GPA in classroom $J \in \{A, B\}$, and $F_T(\cdot)$ the c.d.f. of baseline test score a_i in classrooms A and B. Then, $F_Y^J(y_i)|_{x,d} = F_T(a_i)|_{x,d}\ \forall J, a_i$; i.e., at given values of x_i and d_i, rank in GPA conditional on the baseline test score is identical across classrooms, for all baseline test scores.*

Proof: see Appendix C.2.

Proposition 3 states that, keeping fixed characteristics x_i and damage d_i, the mapping between a student's baseline test score and her classroom GPA rank stays constant, regardless of the distribution of damages in the classroom. As we change the damage distribution, students with higher baseline test scores — *ceteris paribus* — remain those with higher GPA rank.

This result rationalizes the empirical finding that changing the mean or the standard deviation of damages in the classroom, controlling for students' characteristics and individual damages, does not affect GPA rank at any point of the baseline test scores distribution (bottom panels of Figures 9 and A3), even when it affects GPA.

5.3 Summary of results

The model of rank concerns introduced in this section does not only intuitively explain the lack of shifts to GPA rank despite shifts to GPA, but it also rationalizes the heterogeneous effects of damage dispersion among students with different initial performance. These seemingly unrelated findings can be explained through one simple modification to standard models of social interactions in schools: the introduction of a desire to compete for grades.

Since competition for grades is likely common, the theory provides insights on the nature of social interactions in schools that apply beyond the quasi-experimental empirical context used to formulate it.

6 Conclusions

Across education contexts spanning several countries and education levels, peer ability has been shown to influence academic achievement (Sacerdote (2011)). Understanding the mechanisms behind peer influence could shed light on how school environments shape early differences in achievement across students, which are known to persist over time, with major lifelong consequences (Cunha, Heckman, Lochner, and Masterov (2006); Heckman and Mosso (2014)). But empirical challenges have hindered progress towards this goal (Blume, Brock, Durlauf, and Ioannides (2011)). This article exploits a new empirical context and rich data on how students respond to disruptions to their environment to shed light on the mechanisms through which students' ability to study influences their peers' learning.

Exploiting the context of one of the most violent earthquakes ever recorded, the study finds evidence that disruptions to a student's environment can lower their reported ability to study and engage with course content, with negative consequences for their achievement that persist for at least 22 months. Notably, such disruptions can spill over to their classmates.[42] Exploiting detailed data on the shock to each student's home environment, the article examines how student outcomes depend on the distribution of shocks within the classroom. Following the approach in Blume, Brock, Durlauf, and Jayaraman (2015), it micro-founds observed spillovers through a model of student interactions, deriving comparative statics that rationalize the empirical findings. I show that the empirical evidence is consistent with a mode of interaction that has not received much attention in the peer effects literature before: competition for classroom rank. Unlike a desire to conform, the most common assumption in models of peer interactions, a desire to compete implies that moments beyond the mean of peer ability matters, which is an empirical fact across several settings.[43]

The results offer new insights for policy. Peer assignment policies, such as tracking students by ability, are one of the most commonly studied policies in the schooling context (e.g. Duflo, Dupas, and Kremer (2011); Garlick (2018)). My results suggest that their impacts could interact with whether performance rank is intrinsically or extrinsically rewarded. For example, ability tracking may improve the achievement of all students, even those in the lower-tracks, in settings in which students intrinsically care about their performance rank, by increasing the number of nearby competitors. In other settings, they could yield across-the-board achievement gains if they are combined with rewards such as grades or college admissions based on within-track performance rank.

Much is still unknown about the interaction between rank-based rewards and classroom allocation rules. Measuring intrinsic rank concerns in schools could become a way to inform the design of grouping policies. Future research could also compare the achievement gains from optimally designing rank rewards and group allocations to the potential labor market losses from lower prosociality due to enhanced competition (Chen and Hu (2022); Kosse, Rajan, and Tincani (2023); Kosse and Tincani

[42] There is evidence that environmental risks can spill over to classmates also in the context of lead exposure (Gazze, Persico, and Spirovska (2023)).

[43] The desire-to-conform assumption underlies empirical identification strategies that contrast within- and across-group variances in outcomes to identify excess variance across groups that cannot be explained by individual and group heterogeneity and/or selection (Graham (2008) and Glaeser, Sacerdote, and Scheinkman (1996)). Whenever a desire to compete is the true interaction mode, such methods may fail to detect peer effects when they are present, a false negative result.

(2020)). Answering these open questions could significantly advance our understanding of social interactions in school, and expand our toolkit of cost-effective policy interventions.

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Appendix

A Measurements

A.1 Predicting Seismic Vulnerability of a Household's Home

This section describes the model used to predict seismic vulnerability as a function of household characteristics.

For each household in the census data (restricted to households with at least one school-aged child), I link the vulnerability class distribution obtained from the latent-class analysis to the household characteristics that are available both in the census and in the education data. These are: the age of the household head, the average years of education of mothers and fathers, the region of residence. I then estimate regularized linear regression models (lasso) using census data restricted to households with at least one school-aged child. The outcome variables are p_i^j, the probability that household i lives in a home of seismic vulnerability $j \in \{LV, MV, HV\}$, obtained from the latent-class analysis. The independent variables are parental education and age with exponents one, two and three, and region of residence. All independent variables appear uninteracted and interacted with each other (from pair-wise interactions to the interaction of all variables).

I apply the estimated predictive regression model to the education dataset to obtain a predicted likelihood of belonging to each vulnerability class for each student in my sample: $\hat{p}_i^j = p^j(x_i)$, $j = LV, MV, HV$.[44]

A.2 Survey Measures of Perceived Cost of Study Effort and Course Engagement

Students from both cohorts were asked to fill out a questionnaire when they were in eighth grade, the grade in which outcomes were measured. The pre-earthquake cohort filled it out in 2009 and the post-earthquake cohort in 2011. The questionnaire asked about the ability to engage with the course and the perceived cost of study effort. The structure of the questions was as follows: "Thinking of your experience in your school, how much do you agree with the following statements?", followed by a list of statements. Between 2009 and 2011 the number of options in the Likert-scale options changed. In 2009 the possible answers were "I agree very much", "I agree", "I do not agree nor disagree", "I disagree", "I disagree very much". In 2011 the middle option, "I do not agree nor disagree", was eliminated.

[44] Since the outcome variable is a probability, I assign a 0 to negative predictions and a 1 to those above 1.

From the raw data, I build measures of perceived effort cost and engagement with course content that are comparable across cohorts. For each statement I build two dummy variables: one equal to 1 if a student answers “I agree very much”, and 0 if she gives a different answer, and another equal to 1 if a student answers “I disagree very much”, and 0 if she gives a different answer. Perceived effort cost is a categorical variable recording whether a student reported agreeing very much, disagreeing very much, or neither agreeing very much or disagreeing very much with the statement “It costs me to concentrate and pay attention in class”, standardized to have mean 0 and unit variance. Engagement with course content is the score based on the first principal component of a principal component analysis on the six dummy variables obtained from the students’ level of agreement with the statements listed at the bottom of Table A1. I standardize the score to have mean 0 and unit variance.

The statements with which students recorded their level of agreement are the following:

Construct	**Survey Items**
Perceived cost of effort	It costs me to concentrate and pay attention in class.
Course engagement	I do the homework even when it is difficult. My notebooks are generally incomplete. During class I take notes of all that our teachers teach us.

Table A1: Constructs and Corresponding Survey Items

Note: Source: English translation of SIMCE questionnaire administered to all 8^{th} grade students.

B Additional Tables and Figures

Table A2: Correlates of damages and of seismic vulnerability of students' homes, without using school-by-cohort fixed effects.

	(1) Damage	(2) Prob H	(3) Prob M	(4) Prob L
Baseline test score	0.022***	-0.002***	-0.000	0.002***
	(0.002)	(0.000)	(0.000)	(0.000)
Female student	0.004	0.001***	-0.003***	0.002***
	(0.004)	(0.000)	(0.000)	(0.000)
Student resides in same town as school's	-0.006	-0.003***	0.014***	-0.012***
	(0.005)	(0.000)	(0.001)	(0.000)
Age of parent-respondent	-0.001***	-0.002***	-0.001***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Parental education (years)	-0.029***	-0.037***	0.003***	0.033***
	(0.001)	(0.000)	(0.000)	(0.000)
Public school	0.055***	0.005***	-0.004***	-0.001**
	(0.004)	(0.000)	(0.000)	(0.000)
Rural school	-0.029***	0.010***	-0.030***	0.021***
	(0.006)	(0.000)	(0.001)	(0.000)
POST	-0.038***	0.000	0.000	-0.000
	(0.004)	(0.000)	(0.000)	(0.000)
Observations	156718	157107	157107	157107
R^2	0.447	0.971	0.688	0.813
School-by-cohort fixed effects	No	No	No	No

Notes: Results from OLS regressions estimated on the sample of students in earthquake-affected regions and residing more than 0.5 km from the coast. Damage is measured by the standardized damage ratio. Seismic vulnerability is measured by the predicted probabilities that a student lives in a home of High (column 2), Medium (column 3) or Low (column 4) seismic vulnerability class. The class probabilities are predicted using the LASSO model in Appendix A.1. The baseline test score is the average between the Mathematics and language SIMCE test scores in the fourth grade, standardized in the population of test takers. All regressions include dummies for the region of residence. POST is a dummy equal to 1 if the student belongs to the post-earthquake cohort, 0 otherwise. *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Correlates of damages and of seismic vulnerability of students' homes, using school-by-cohort fixed effects.

	(1) Damage	(2) Prob H	(3) Prob M	(4) Prob L
Baseline test score	-0.002**	-0.002***	0.002***	-0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Female student	0.001	0.001***	-0.002***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Student resides in same town as school's	0.011***	-0.000	0.001	-0.001
	(0.002)	(0.000)	(0.001)	(0.000)
Age of parent-respondent	-0.001***	-0.002***	-0.001***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Parental education (years)	-0.029***	-0.036***	0.004***	0.032***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	156718	157107	157107	157107
R^2	0.157	0.883	0.073	0.708
School-by-cohort fixed effects	Yes	Yes	Yes	Yes

Notes: Results from OLS regressions estimated on the sample of students in earthquake-affected regions and residing more than 0.5 km from the coast. Damage is measured by the standardized damage ratio. Seismic vulnerability is measured by the predicted probabilities that a student lives in a home of High (column 2), Medium (column 3) or Low (column 4) seismic vulnerability class. The class probabilities are predicted using the LASSO model in Appendix A.1. The baseline test score is the average between the Mathematics and language SIMCE test scores in the fourth grade, standardized in the population of test takers. All regressions include dummies for the region of residence. *** p<0.01, ** p<0.05, * p<0.10.

	Freq.	Percent
Walls		
Reinforced concrete, stone	85,152	9.21
Brick	371,457	40.16
Structural panels, prefabricated	72,285	7.81
Wood, lined partition	312,517	33.79
Eternit	41,283	4.46
Adobe, soggy mud	40,291	4.36
Makeshift materials	2,032	0.22
Roof		
Roof tiles (clay, metal, cement)	80,385	8.69
Shingle (wood, asphalt)	23,101	2.50
Concrete slab	10,056	1.09
Zinc	380,640	41.15
Slate	421,946	45.61
Fiberglass, femocolor	612	0.07
Clickstone	6,172	0.67
Mud straw	73	0.01
Makeshift materials	2,032	0.22
Floor		
Hardwood floor	30,183	3.26
Ceramic tiles	189,075	20.44
Wooden decking	334,824	36.20
Wall to wall carpet	48,905	5.29
Cement tiles	42,202	4.56
Plastics (flexit, linoleum, etc.)	196,327	21.22
Radier	78,813	8.52
Earthen	4,688	0.51

Table A4: Distribution of building materials in the population of households with at least one school-aged child, N=925,017. Chilean census, 2002.

Table A5: Impacts of earthquake damages on standardized eighth-grade test score, all treatment variables measured in standard deviations

	(1)	(2)
Effect of damage to own home	-0.033**	-0.036***
	(0.013)	(0.014)
Effect of average damage among classmates	0.049***	-0.000
	(0.018)	(0.122)
Effect of standard deviation of damage among classmates	-0.014	-0.005
	(0.012)	(0.014)
Observations	154900	154900
R^2	0.581	0.505
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variable is the average between Mathematics and Language SIMCE scores, standardized to have mean 0 and variance 1. The treatment variables are measured in standard deviations. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors are clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Impacts of earthquake damages on standardized eighth-grade test scores in Spanish and Mathematics

	(1) Language	(2) Language	(3) Mathematics	(4) Mathematics
Effect of damage to own home	-0.042***	-0.041***	-0.018	-0.026*
	(0.014)	(0.016)	(0.014)	(0.015)
Effect of average damage among classmates	0.060***	0.086	0.034	-0.069
	(0.019)	(0.119)	(0.021)	(0.156)
Effect of standard deviation of damage among classmates	-0.061	-0.048	-0.033	-0.011
	(0.041)	(0.061)	(0.048)	(0.061)
Observations	155664	155664	156149	156149
R^2	0.485	0.418	0.510	0.411
School-by-cohort fixed effects	No	Yes	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variables are Language (columns 1-2) and Mathematics (columns 3-4) SIMCE scores, standardized to have mean 0 and variance 1. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regressions with school-by-cohort fixed effects omit school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors are clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Impacts of earthquake damages on standardized eighth-grade test score, alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Effect of damage to own home	-0.095***	-0.057***	-0.046***	-0.039***	-0.043***	-0.039***
	(0.024)	(0.017)	(0.015)	(0.014)	(0.015)	(0.014)
Effect of average damage among classmates	0.102***	-0.207	0.058***	-0.035	0.074***	-0.035
	(0.032)	(0.213)	(0.020)	(0.141)	(0.021)	(0.141)
Effect of standard deviation of damage among classmates	0.008	0.007	-0.036	-0.013	-0.034	-0.013
	(0.072)	(0.083)	(0.046)	(0.057)	(0.046)	(0.057)
Observations	176629	176629	154902	154902	154902	154902
R^2	0.107	0.020	0.570	0.504	0.571	0.504
School-by-cohort fixed effects	No	Yes	No	Yes	No	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
School building damage	No	No	No	No	Yes	Yes
School and classroom characteristics	No	No	No	No	No	No

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variable is the average between Mathematics and Language SIMCE scores, standardized to have mean 0 and variance 1. All regressions include controls for the student characteristics used to predict home quality (age of household head, parental education, region of residence). The first two columns include no other control variables. Columns 3 and 4 add all other student characteristics (fourth-grade test score, gender, whether the student lives in the school's town). Columns 5 and 6 control for damage to the school building (obtained by adding shaking intensity in the school's town interacted with the public school and cohort dummies, and the cohort and public school dummies interacted). The regressions with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors are clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Impacts of earthquake damages on standardized eighth-grade test score, accounting for spatial correlation in the residuals

	(1)	(2)
Effect of damage to own home	-0.033***	-0.036***
	(0.010)	(0.010)
Effect of average damage among classmates	0.052***	-0.000
	(0.019)	(0.121)
Effect of standard deviation of damage among classmates	-0.049	-0.020
	(0.046)	(0.053)
Observations	154900	154900
R^2	0.581	0.505
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variable is the average between Mathematics and Language SIMCE scores. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-municipality-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A9: Impacts of earthquake damages on standardized eighth-grade test score, accounting for spatial correlation in the residuals using the Conley method

	(1)	(2)	(3)	(4)	(5)	(6)
Effect of damage to own home	-0.030**	-0.030**	-0.030*	-0.030**	-0.030**	-0.030***
	(0.013)	(0.015)	(0.016)	(0.013)	(0.012)	(0.009)
Effect of average damage among classmates	0.048**	0.048**	0.048**	0.048**	0.048**	0.048***
	(0.019)	(0.018)	(0.017)	(0.018)	(0.017)	(0.008)
Effect of standard deviation of damage among classmates	-0.051	-0.051	-0.051	-0.051	-0.051	-0.051
	(0.047)	(0.044)	(0.049)	(0.046)	(0.039)	(0.038)
School-by-cohort fixed effects	No	No	No	No	No	No
Threshold distance	N/A	10 km	25 km	50 km	100 km	587 km

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ obtained from OLS estimation of regression (2). The first column reports the original standard errors clustered at the school-by-cohort level and corresponding significance levels. Columns (2) to (6) report standard errors and significance levels calculated according to the method in Conley (1999), under different distance thresholds. 587 km represents the distance between the asperity and the farthest town with positive shaking intensity. Parameter estimates slightly differ from those in Table 2 because regional fixed effects are omitted for computational reasons. *** p<0.01, ** p<0.05, * p<0.10.

Table A10: Impacts of earthquake damages on standardized eighth-grade test score under different geographical sample restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
Effect of damage to own home	-0.039***	-0.038**	-0.033**	-0.036**	-0.022**	-0.025**
	(0.014)	(0.016)	(0.014)	(0.015)	(0.010)	(0.012)
Effect of average damage among classmates	0.058**	0.059	0.051**	0.045	0.041***	-0.001
	(0.023)	(0.139)	(0.022)	(0.138)	(0.016)	(0.116)
Effect of standard deviation of damage among classmates	-0.044	-0.040	-0.046	-0.036	-0.037	-0.035
	(0.048)	(0.053)	(0.047)	(0.052)	(0.038)	(0.046)
Observations	150540	150540	153094	153094	190271	190271
R^2	0.581	0.504	0.581	0.504	0.582	0.504
School-by-cohort fixed effects	No	Yes	No	Yes	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake. Columns 1-2 restrict the sample to towns more than 5km from the coast, columns 3-4 to towns more than 1km from the coast, columns 5-6 are based on all towns, including coastal ones. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variable is the average between Mathematics and Language SIMCE scores. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A11: Heterogeneous impacts of earthquake damages on standardized eighth-grade test score, all treatment variables measured in standard deviations

	(1)	(2)
Effect of damage to own home	-0.033**	-0.039***
	(0.013)	(0.014)
Interacted with baseline test score	-0.008	-0.009
	(0.017)	(0.016)
Effect of average damage among classmates	0.048***	-0.013
	(0.018)	(0.122)
Interacted with baseline test score	0.026	0.019
	(0.019)	(0.018)
Effect of standard deviation of damage among classmates	-0.011	-0.005
	(0.012)	(0.014)
Interacted with baseline test score	-0.026***	-0.023***
	(0.010)	(0.008)
Observations	154900	154900
R^2	0.581	0.505
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (3) and (3'). The outcome variable is the average between Mathematics and Language SIMCE scores. The treatment variables are measured in standard deviations. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A12: Heterogeneous impacts of earthquake damages on standardized eighth-grade test scores by deciles of baseline test scores

	(1)	(2)
	Score	Score
Effect of damage to own home for decile 1 ability	-0.025	-0.039
	(0.040)	(0.041)
Additional effect for decile 2 ability	-0.002	0.012
	(0.051)	(0.053)
Additional effect for decile 3 ability	-0.052	-0.059
	(0.056)	(0.054)
Additional effect for decile 4 ability	-0.031	-0.007
	(0.051)	(0.050)
Additional effect for decile 5 ability	0.011	0.061
	(0.058)	(0.057)

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Additional effect for decile 6 ability	0.021	0.034
	(0.063)	(0.058)
Additional effect for decile 7 ability	0.007	-0.006
	(0.062)	(0.058)
Additional effect for decile 8 ability	-0.019	-0.023
	(0.059)	(0.057)
Additional effect for decile 9 ability	-0.018	-0.023
	(0.054)	(0.054)
Additional effect for decile 10 ability	-0.054	-0.022
	(0.063)	(0.059)
Effect of average damage among classmates for decile 1 ability	0.009	0.040
	(0.046)	(0.141)
Additional effect for decile 2 ability	0.029	0.003
	(0.059)	(0.061)
Additional effect for decile 3 ability	0.081	0.086
	(0.060)	(0.061)
Additional effect for decile 4 ability	0.079	0.043
	(0.057)	(0.056)
Additional effect for decile 5 ability	0.011	-0.027
	(0.066)	(0.064)
Additional effect for decile 6 ability	0.024	0.001
	(0.073)	(0.066)
Additional effect for decile 7 ability	0.020	0.030
	(0.071)	(0.068)
Additional effect for decile 8 ability	0.064	0.053
	(0.067)	(0.066)
Additional effect for decile 9 ability	0.056	0.042
	(0.061)	(0.062)
Additional effect for decile 10 ability	0.149^{**}	0.062
	(0.072)	(0.069)
Effect of standard deviation of damages among classmates for decile 1 ability	0.158^{**}	0.134^{*}
	(0.066)	(0.077)
Additional effect for decile 2 ability	-0.206^{**}	-0.136
	(0.095)	(0.098)
Additional effect for decile 3 ability	-0.151^{**}	-0.170^{**}
	(0.077)	(0.086)
Additional effect for decile 4 ability	-0.276^{***}	-0.261^{***}
	(0.085)	(0.089)
Additional effect for decile 5 ability	-0.172^{**}	-0.218^{**}

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	(0.087)	(0.087)
Additional effect for decile 6 ability	-0.208^{**}	-0.203^{**}
	(0.094)	(0.087)
Additional effect for decile 7 ability	-0.140	-0.140^{*}
	(0.093)	(0.081)
Additional effect for decile 8 ability	-0.209^{**}	-0.207^{**}
	(0.088)	(0.084)
Additional effect for decile 9 ability	-0.243^{***}	-0.183^{**}
	(0.094)	(0.090)
Additional effect for decile 10 ability	-0.438^{***}	-0.295^{***}
	(0.095)	(0.100)
Observations	150540	150540
R^2	0.590	0.514
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (3) and (3'), where a is replaced by dummy variables identifying a student's baseline ability category. Students are categorized by deciles of their baseline test score (SIMCE in fourth grade). Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regressions with school-by-cohort fixed effects omit school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A13: Heterogeneous impacts of earthquake damages on standardized eighth-grade test score by student characteristics

	(1)	(2)
Effect of damage to own home	0.002	0.002
	(0.028)	(0.029)
Interacted with baseline test score	-0.008	-0.011
	(0.022)	(0.022)
Interacted with parental education	-0.016	-0.007
	(0.016)	(0.015)
Interacted with female dummy	-0.025	-0.036
	(0.030)	(0.029)
Interacted with income	-0.003	-0.005
	(0.011)	(0.011)
Effect of average damage among classmates	0.020	-0.037
	(0.031)	(0.142)
Interacted with baseline test score	0.017	0.016
	(0.025)	(0.024)
Interacted with parental education	0.043**	0.020
	(0.018)	(0.017)
Interacted with female dummy	0.030	0.029
	(0.033)	(0.033)
Interacted with income	0.003	0.008
	(0.013)	(0.012)
Effect of standard deviation of damage among classmates	-0.020	0.007
	(0.048)	(0.060)
Interacted with baseline test score	-0.081**	-0.071**
	(0.038)	(0.033)
Interacted with parental education	-0.039	-0.020
	(0.029)	(0.028)
Interacted with female dummy	-0.076	0.005
	(0.060)	(0.044)
Interacted with income	0.010	-0.016
	(0.022)	(0.026)
Observations	119909	119909
R^2	0.582	0.506
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (3) and (3'). The outcome variable is the average between Mathematics and Language SIMCE scores. The treatment variables are measured in standard deviations. Lagged test score, parental education and lagged household income are standardized to have mean 0 and unit variance. Regressions include student and classroom characteristics controls. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence, household income during fourth grade. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A14: Heterogeneous impacts of earthquake damages on standardized eighth-grade test score, alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Effect of damage to own home	-0.048***	-0.041***	-0.046***	-0.041***	-0.044***	-0.041***
	(0.016)	(0.014)	(0.016)	(0.014)	(0.015)	(0.014)
Interacted with baseline test score	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)
Effect of average damage among classmates	0.059***	-0.046	0.057***	-0.047	0.073***	-0.047
	(0.020)	(0.140)	(0.020)	(0.140)	(0.021)	(0.140)
Interacted with baseline test score	0.028	0.019	0.027	0.019	0.028	0.019
	(0.020)	(0.018)	(0.020)	(0.018)	(0.020)	(0.018)
Effect of standard deviation of damage among classmates	-0.026	-0.011	-0.027	-0.011	-0.024	-0.011
	(0.046)	(0.056)	(0.045)	(0.056)	(0.045)	(0.056)
Interacted with baseline test score	-0.096***	-0.079***	-0.095***	-0.078***	-0.098***	-0.078***
	(0.034)	(0.029)	(0.034)	(0.029)	(0.034)	(0.029)
Observations	154902	154902	154902	154902	154902	154902
R^2	0.570	0.504	0.570	0.504	0.571	0.504
School-by-cohort fixed effects	No	Yes	No	Yes	No	Yes
Individual characteristics	No	No	Yes	Yes	Yes	Yes
School building damage	No	No	No	No	Yes	Yes
School and classroom characteristics	No	No	No	No	No	No

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\bar{\delta}$ obtained from OLS estimation of regressions (3) and (3'). The outcome variable is the average between Mathematics and Language SIMCE scores, standardized to have mean 0 and variance 1. All regressions include controls for the student characteristics used to predict home quality (age of household head, parental education, region of residence). The first two columns include no other control variables. Columns 3 and 4 add all other student characteristics (fourth-grade test score, gender, whether the student lives in the school's town). Columns 5 and 6 control for damage to the school building (obtained by adding shaking intensity in the school's town, uninteracted and interacted with the public school and cohort dummies, and the cohort and public school dummies interacted). The regressions with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors are clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Figure A1: *Source*: Comerio (2013). Handmade sign found in Cauquenes, Chile, on February 2, 2012, nearly two years after the earthquake. Translation: "Reconstruction is like God. Everyone knows it exists. But nobody sees it."

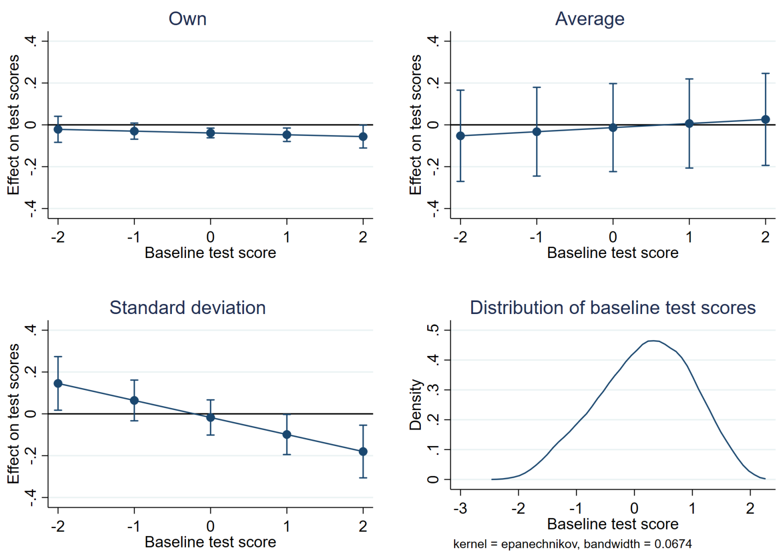

Figure A2: Marginal effects on standardized eighth-grade test scores by baseline test score. *Notes*: Marginal effects of own damage, leave-one-out average damage among classmates, and leave-one-out standard deviation of damage among classmates. Effects obtained from estimating the regression model in equation (3') (with school-by-cohort fixed effects). 90% confidence intervals reported.

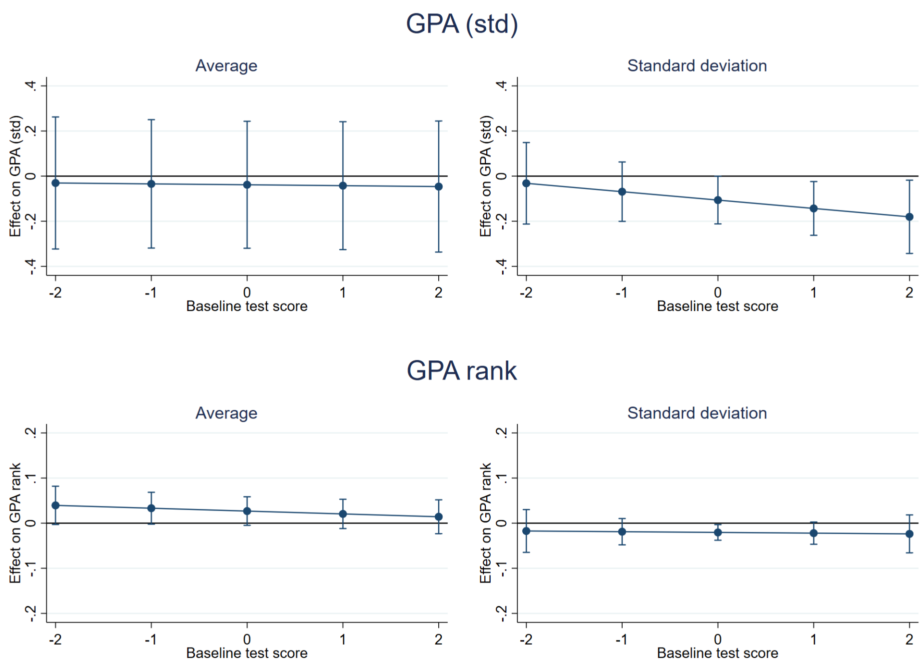

Figure A3: Marginal effects on GPA and within-classroom GPA rank by baseline test score. *Notes*: GPA rank is the classroom rank, it ranges from 0 (worst GPA) to 1 (top GPA). Marginal effects of the leave-one-out average and standard deviation of damage among classmates. Effects obtained from estimating the regression model in equation (3') (with school-by-cohort fixed effects). 90% confidence intervals reported.

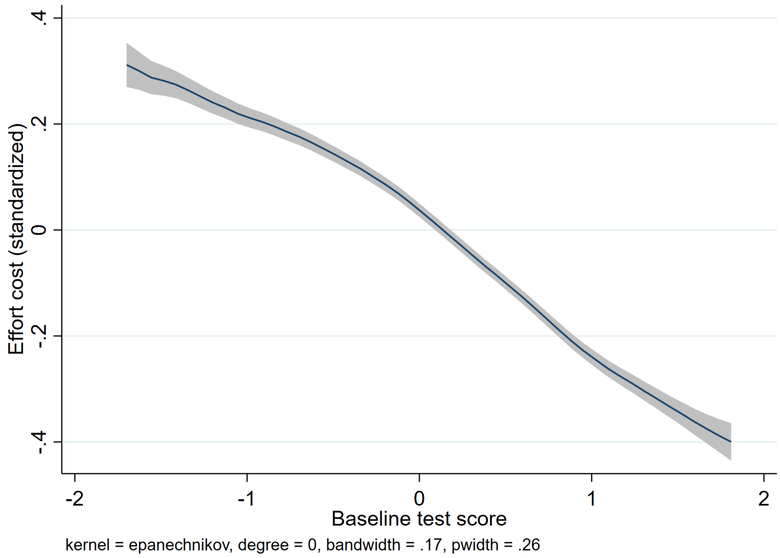

Figure A4: Relationship between reported effort cost and baseline test score. *Notes*: Local polynomial regression estimated on the sample of students in earthquake regions and in the cohort affected by the earthquake. 95% confidence intervals reported.

C Theoretical Appendix

C.1 Earthquake Shocks and Peers' Cost of Effort

Suppose that students' costs of study effort (or, conversely, abilities to study) are determined by their baseline test scores, a_i, demographic characteristics and family backgrounds, x_i, and how badly their homes were damaged by the earthquake, d_i. For ease of notation, let us group a_i and x_i into vector w_i:

$$c_i = \theta_0 + \theta_1 w_i + \theta_2 d_i \quad \forall i.$$

The average effort cost among classmates is given by:

$$E[c] = \theta_0 + \theta_1 E[w] + \theta_2 E[d],$$

where the averages are taken with respect to classroom distributions. When $\theta_2 > 0$, increasing the average damages $E[d]$ while keeping classroom composition $E[w]$ constant increases the average effort cost.

Letting $w_{[j]}$ indicate element j of vector w, and θ_{1j} its coefficient, the variance of the cost of effort among classmates is given by:

$$Var[c] = \sum_{j=1}^{m} \theta_{1j}^2 Var[w_{[j]}] + \theta_2^2 Var[d] + \sum_{j=1}^{m} \sum_{j':j'>j}^{m} \theta_{1j}\theta_{1j'} Cov(w_{[j]}, w_{[j']}) + \sum_{j=1}^{m} \theta_{1j}\theta_2 Cov(w_{[j]}, d),$$

where the variances and covariances are taken with respect to classroom distributions. When $\theta_2 > 0$, increasing the variance in damages $Var[d]$, while keeping the other variances and the covariances constant, increases the effort cost variance. As can be seen in Tables A15 and A16, the findings stand when adding the variances and covariances as controls, suggesting that effort cost dispersion could be a mediator.

Table A15: Impacts of earthquake damages on standardized eighth-grade test score, controlling for variance and covariance terms

	(1)	(2)
Effect of damage to own home	-0.031**	-0.037***
	(0.013)	(0.014)
Effect of average damage among classmates	0.052***	-0.011
	(0.019)	(0.124)
Effect of standard deviation of damage among classmates	-0.048	-0.027
	(0.042)	(0.053)
Observations	154889	154889
R^2	0.582	0.505
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (2) and (2'). The outcome variable is the average between Mathematics and Language SIMCE scores, standardized to have mean 0 and variance 1. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education, classroom variance of gender and local residency, all pairwise covariances between the following variables: damage, gender, parental education, local residency, lagged test score. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors are clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

Table A16: Heterogeneous impacts of earthquake damages on standardized eighth-grade test score, controlling for variance and covariance terms

	(1)	(2)
Effect of damage to own home	-0.031**	-0.039***
	(0.013)	(0.014)
Interacted with baseline test score	-0.011	-0.009
	(0.017)	(0.016)
Effect of average damage among classmates	0.050***	-0.025
	(0.019)	(0.124)
Interacted with baseline test score	0.029	0.020
	(0.019)	(0.019)
Effect of standard deviation of damage among classmates	-0.041	-0.026
	(0.042)	(0.053)
Interacted with baseline test score	-0.094***	-0.081***
	(0.035)	(0.029)
Observations	154889	154889
R^2	0.583	0.505
School-by-cohort fixed effects	No	Yes

Notes: Students enrolled in schools in regions affected by the earthquake and residing more than 0.5 km from the coast. Parameters δ and $\tilde{\delta}$ obtained from OLS estimation of regressions (3) and (3'). The outcome variable is the average between Mathematics and Language SIMCE scores. Regressions include student and classroom characteristics. Student characteristics: fourth-grade test score, gender, whether the student lives in the school town, parental education, age of household head, dummy for region of residence. Classroom characteristics: public school dummy, rural school dummy, shaking intensity in school's town interacted with public and cohort dummies, cohort and public dummies interacted, class size, classroom fractions of females and of local residents; classroom average and standard deviation of lagged test scores and of parental education, classroom variance of gender and local residency, all pairwise covariances between the following variables: damage, gender, parental education, local residency, lagged test score. The regression with school-by-cohort fixed effects omits school-level controls and the cohort dummy. Damages' mean and standard deviation are leave-one-out moments. Standard errors clustered at the school-by-cohort level. *** p<0.01, ** p<0.05, * p<0.10.

C.2 Proofs

Rearranging equation (6) and substituting $c'(e_i) = \frac{1}{e'(c_i)}$, the following first-order differential equation characterizes the equilibrium strategies:

$$\begin{aligned} e'(c_i) &= \left(\frac{g(c_i)}{1-G(c_i)+\phi}\right)\left(\frac{V(y(e(c_i)),q(e(c_i),c_i))}{(a_0+a_1(\mu_d))V_1+V_2\frac{\partial q}{\partial e_i}}\right) \\ &= \frac{g(c_i)}{1-G(c_i)+\phi}\psi(e(c_i),c_i), \end{aligned} \tag{7}$$

where $\psi(e(c_i),c_i) = \frac{V(y(e(c_i)),q(e(c_i),c_i))}{(a_0+a_1(\mu_d))V_1+V_2\frac{\partial q}{\partial e_i}}$.

Proposition A1. (Adapted from Proposition 1 in Hopkins and Kornienko (2004)). *The unique solution to the differential equation* (7) *with the boundary condition* $e(\bar{c}) =$

$e_{nr}(\bar{c})$, *where* e_{nr} *solves the first-order condition absent rank concerns*

$$V_1(a_0 + a_1(\mu_d))|_{e_i=e_{nr}} = -V_2 \frac{\partial q}{\partial e_i}|_{e_i=e_{nr}},$$

is a unique symmetric Nash Equilibrium of the game of status. Equilibrium effort $e(c_i)$ *and equilibrium GPA* $y(c_i)$ *are both continuous and strictly decreasing in student's type* c_i.

Proof of Proposition A1. First, as in the proof of Proposition 1 in Hopkins and Kornienko (2004), it is easy to show that the boundary condition is optimal for the student with the highest cost, $\bar{c}$. Such student chooses the effort that maximizes utility V in the absence of rank concerns. In equilibrium, her utility from rank is zero, therefore, she maximizes V, because $V \times F + \phi \times V = V \times 0 + \phi \times V = \phi V$.

Next, I adapt the proof in Hopkins and Kornienko (2004) to show that if the strategy $e^*(c_i)$ is a best response to other students' effort choices, then it is decreasing (while Hopkins and Kornienko (2004) deal with increasing functions). If a student i of type c_i exerts effort $e_i = e^*(c_i)$ and this is a best response to the efforts of the other students as summarized by the effort distribution $F_E(\cdot)$, then it must be that $e_i \geq e_{nr}(c_i)$, where $e_{nr}(c_i)$ solves the first-order condition in the absence of rank concerns, i.e., $V_1(a_0 + a_1(\mu_d))|_{e_i=e_{nr}} = -V_2 \frac{\partial q}{\partial e_i}|_{e_i=e_{nr}}$. This is because if $e_i < e_{nr}(c_i)$, then $F_E(e_i) + \phi < F_E(e_{nr}) + \phi$, because F_E is strictly increasing, and $V(y(e_i), q(e_i; c_i)) < V(y(e_{nr}(c_i)), q(e_{nr}(c_i); c_i))$, because $V_1 > 0, V_2 < 0$, and $q_1 > 0$. Therefore, $V(y(e_i), q(e_i; c_i))(F_E(e_i) + \phi) < V(y(e_{nr}), q(e_{nr}; c_i))(F_E(e_{nr}) + \phi)$, i.e., any level of effort below the no-rank-concerns level is strictly dominated by the no-rank-concerns level. Suppose that equality holds, so $e_i = e_{nr}(c_i)$. Then $e^*(c_i)$ is decreasing because $e_{nr}(c_i)$ is decreasing. This follows from the assumptions that $V_{11} = 0$, $V_{22} = 0$, $V_{12} \leq 0$, and from the assumptions that $q_1 > 0, q_2 > 0, q_{11} > 0$, and $q_{12} \geq 0$. To see why, let $FOC(e_i, c_i) = V_1(a_0 + a_1(\mu_d)) + V_2 q_1$ and notice that by the Implicit Function Theorem:

$$\frac{de_{nr}}{dc_i} = -\frac{\partial FOC/\partial c_i}{\partial FOC/\partial e_i}.$$

The numerator is:

$$\frac{\partial FOC}{\partial c_i} = (a_0 + a_1(\mu_d))V_{12}\frac{\partial q}{\partial c_i} + V_{22}\frac{\partial q}{\partial e_i}\frac{\partial q}{\partial c_i} + V_2\frac{\partial^2 q}{\partial e_i \partial c_i} \leq 0.$$

The denominator is:

$$\frac{\partial FOC}{\partial e} = (a_0+a_1(\mu_d))^2 V_{11} + (a_0+a_1(\mu_d))V_{12}\frac{\partial q}{\partial e_i} + \left((a_0 + a_1(\mu_d))V_{21} + V_{22}\frac{\partial q}{\partial e_i}\right)\frac{\partial q}{\partial e_i} + V_2\frac{\partial^2 q}{\partial^2 e_i} \leq 0.$$

As a result, $e^*(\cdot)$ is decreasing in c_i when it is equal to optimally chosen effort in the absence of rank concerns, because $\frac{de_{nr}}{dc_i} \leq 0$.

If equality does not hold, we want to show that if e_i is a best-response and $e_i > e_{nr}(c_i)$, then it is still the case that e_i is decreasing in c_i. First, I show that for any other choice $\tilde{e} \in (e_{nr}(c_i), e_i)$,

$$\frac{\partial V}{\partial c_i}(y(e_i), q(e_i, c_i))(F_E(e_i) + \phi) < \frac{\partial V}{\partial c_i}(y(\tilde{e}), q(\tilde{e}, c_i))(F_E(\tilde{e}) + \phi). \tag{8}$$

Rewrite the left-hand side as:

$$\frac{\partial V}{\partial c_i}(y(e_i), q(e_i, c_i))(F_E(\tilde{e} + \phi) + \frac{\partial V}{\partial c_i}(y(e_i), q(e_i, c_i))(F_E(e_i) - F_E(\tilde{e})).$$

The first term is smaller or equal to the right-hand side of equation (8), because $\frac{\partial V}{\partial c_i}$ is decreasing in e_i, as $V_{21} \leq 0, V_{22} = 0, \frac{\partial q}{\partial c_i} > 0, V_2 < 0$, and $\frac{\partial^2 q}{\partial c_i \partial e_i} \geq 0$. To see why, notice that $\frac{\partial^2 V}{\partial c_i \partial e_i} = \left(V_{21}(a_0 + a(\mu_d) + V_{22}\frac{\partial q}{\partial e_i}\right)\frac{\partial q}{\partial c_i} + V_2 \frac{\partial q}{\partial c_i \partial e_i} \leq 0$. The second term is strictly negative, because first, $\frac{\partial V}{\partial c_i}$ is strictly negative because $V_2 < 0$ and $\frac{\partial q}{\partial c_i} > 0$, and second, $F_E(e_i) - F_E(\tilde{e}) > 0$. To see why the latter is true, notice that for $e_i > e_{nr}$, $V(y(e_i), q(e_i, c_i))$ is decreasing in e_i. Therefore, if e_i is a best-response, it must be the case that $F_E(e_i) > F_E(\tilde{e})$, otherwise a student could lower effort and obtain a higher utility, while not lowering her status. This establishes the inequality in (8), so that at e_i, the overall marginal utility with respect to c_i, $(\frac{\partial}{\partial c_i}(V(y_i, q_i)(F_E(e_i) + \phi)))$, is strictly decreasing in e_i. This implies that an increase in cost type c_i leads to a decrease in the marginal return to e_i, therefore, the optimal choice of effort e_i must decrease.

To show that if an effort function is an equilibrium strategy, then it must be continuous, we can follow the proof in Hopkins and Kornienko (2004) with a minor adaptation to account for the fact that the equilibrium strategy in this paper is a decreasing rather than increasing function. Specifically, suppose the equilibrium strategy was not continuous. That is, suppose that that there was a jump downwards in the equilibrium effort function $e^*(c_i)$ at $\tilde{e}$, so that $\lim_{c_i \to \tilde{c}} e^*(c_i) = \tilde{e} < e^*(\tilde{c})$. Then, there would exist an $\epsilon > 0$ small enough, such that the student of type $\tilde{c} - \epsilon$ can reduce her effort to $\tilde{c}$, which is below $e^*(\tilde{c} - \epsilon)$, and obtain a discrete increase in utility because of the lower effort, while her rank would decrease by less, by continuity of the rank function $S(\cdot)$ at $\tilde{c}$. Therefore, there exists a student with an incentive to deviate, and such discontinuous $e^*(c_i)$ function cannot be an equilibrium strategy.[45]

[45] That the equilibrium strategy is *strictly* decreasing and differentiable follows from Hopkins and Kornienko (2004) after replacing z_i with c_i, x_i with e_i, and $x(z_i)$ with $e(c_i)$ (with the only difference that $e(\cdot)$ is decreasing and $x(\cdot)$ is increasing), and setting $\alpha > 0$.

Finally, if $e^*(c_i)$ is continuous and decreasing then it must be that $y^*(c_i) = y(e^*(c_i))$ is continuous and decreasing, because $y(\cdot)$ is a continuous function of e_i and $\frac{dy}{de_i} > 0$ $\forall e_i$ as per equation (5).

Uniqueness of the solution to the differential equation in (7), and therefore uniqueness of the equilibrium, follows from the fundamental theorem of differential equations. The boundary condition pins down the unique solution.

□

Proof of Proposition 1. Let $e_A(c_i)$ and $e_B(c_i)$ denote the equilibrium effort choices in classrooms A and B. Proposition A1 established that $e_A(c_i)$ and $e_B(c_i)$ are strictly decreasing functions of c_i. Moreover, for the highest value of c_i in each classroom, denoted by $\bar{c}_J$ for $J = A, B$, these effort choices satisfy the following first-order condition for maximization in the absence of rank concerns:

$$V_1(a_0 + a_1(\mu_d^J)) = -V_2 \frac{\partial q}{\partial e_i} \quad \text{for } J = A, B. \tag{9}$$

Given this, we can focus on the optimal effort choice for the student with the highest c_i in each classroom. This is because if $e_B(\bar{c}_B) > e_A(\bar{c}_A)$, then $E_B[e_i] > E_A[e_i]$. Similarly, if $e_B(\bar{c}_B) = e_A(\bar{c}_A)$, then $E_B[e_i] = E_A[e_i]$, and if $e_B(\bar{c}_B) < e_A(\bar{c}_A)$, then $E_B[e_i] < E_A[e_i]$. Recall that $y(e_i) = (a_0 + a_1(\mu_d))e_i + u_0 + u_1(\mu_d)$, with $\frac{da_1}{d\mu_d} \geq 0$ and $\frac{du_1}{d\mu_d} \geq 0$ representing the multiplicative and additive compensatory actions by schools. The damage distribution shift implies that $\mu_d^B > \mu_d^A$. Then:

- If $\frac{\partial^2 q}{\partial e_i \partial c_i} = 0$ and $\frac{da_1}{d\mu_d} = 0$, then the right-hand side (RHS) and left-hand side (LHS) of equation (9) are identical in classrooms A and B, resulting in $e_B(\bar{c}_B) = e_A(\bar{c}_A)$. If $\frac{du_1}{d\mu_d} = 0$, this results in $E_B[y_i] = E_A[y_i]$, while if $\frac{du_1}{d\mu_d} > 0$, this results in $E_B[y_i] > E_A[y_i]$.

  When there is no change to the marginal cost or marginal benefit of effort, optimal effort does not change. In the absence of any compensatory action, this results in no change in GPA. If instead schools introduce an additive compensatory action (through u_1), this results in an increase in GPA even without increased effort.

- If $\frac{\partial^2 q}{\partial e_i \partial c_i} = 0$ and $\frac{da_1}{d\mu_d} > 0$, then the LHS of equation (9) is larger in classroom B than in classroom A. As q is an increasing convex function of e_i, it must be that $e_B(\bar{c}_B) > e_A(\bar{c}_A)$, resulting in $E_B[y_i] > E_A[y_i]$.

  When compensatory action increases the marginal return to effort and there is no change to its marginal cost, students exert more effort, resulting in higher GPA both because of increased effort and of a larger coefficient on effort in the achievement production function.

- If $\frac{\partial^2 q}{\partial e_i \partial c_i} > 0$ and $\frac{da_1}{d\mu_d} > 0$, then the LHS of equation (9) is larger in classroom B than in classroom A. As $\bar{c}_B > \bar{c}_A$ because damages are larger for all students in classroom B, the RHS is larger in classroom B than in classroom A.

  For small enough $\frac{\partial^2 q}{\partial e_i \partial c_i}$, i.e. $\frac{\partial^2 q}{\partial e_i \partial c_i} \leq \gamma$ with γ a positive constant, we have $e_B(\bar{c}_B) \geq e_A(\bar{c}_A)$, resulting in $E_B[y_i] > E_A[y_i]$ (holding with strict inequality because the increased coefficient on effort in the GPA production function in classroom B causes larger GPA even in the case in which effort is equal across classrooms).

  For large enough $\frac{\partial^2 q}{\partial e_i \partial c_i}$, i.e. $\frac{\partial^2 q}{\partial e_i \partial c_i} > \gamma$, $e_B(\bar{c}_B) < e_A(\bar{c}_A)$. This can results in $E_B[y_i] \geq E_A[y_i]$ if the compensatory action (through a_1, u_1 or both) (over)compensates the reduction in effort, or in $E_B[y_i] < E_A[y_i]$ if it does not.

  When both the marginal cost and benefit of effort increase, the sign of the impact on effort depends on the relative magnitudes of such increases. When the increase in the marginal benefit due to the compensatory action is larger in magnitude than the increase in the marginal cost due to the larger damages, GPA increases in classrooms more affected by the earthquake, because of the increased effort and of the compensatory action. When the increase in the marginal benefit is lower than that in the marginal cost, GPA may increase or decrease depending on whether the compensatory action (over)compensates for the decreased effort.

- If $\frac{\partial^2 q}{\partial e_i \partial c_i} > 0$ and $\frac{da_1}{d\mu_d} = 0$, the LHS of equation (9) is identical across classrooms, while the RHS is larger in classroom B, resulting in $e_B(\bar{c}_B) < e_A(\bar{c}_A)$. This results in either $E_B[y_i] \geq E_A[y_i]$ if the compensatory action through u_1 (over)compensates the reduction in effort, or in $E_B[y_i] < E_A[y_i]$ if it does not.

  When the marginal cost of effort increases (due to the larger damages) and its marginal benefit stays constant (due to lack of compensatory action through a_1), effort decreases. GPA may increase or decreased depending on whether the additive compensatory action (u_1) overcompensate for decreased effort.

$\square$

Proof of Proposition 2. The results follow from Proposition A1 and Proposition 4 in Hopkins and Kornienko (2004) for the case $\alpha > 0$ (where α there is the equivalent of ϕ in this paper), noting that e_i in this paper corresponds to x_i in theirs, c_i corresponds to z_i, $e^*(c_i)$ corresponds to $x^*(z_i)$. As per Proposition A1, $e^*(c_i)$ is strictly decreasing, while $x^*(z_i)$ in Hopkins and Kornienko (2004) is strictly increasing, which implies that rank $G(x^{-1}(x_i))$ in their paper's proof must be replaced by rank $1 - G(c(e_i) = 1 - G(e^{-1}(e_i))$ here, and the results follow.

□

Proof of Proposition 3. At the Nash Equilibrium in classroom $J \in \{A, B\}$, keeping d_i and x_i fixed, GPA $y(\cdot)$ is strictly increasing in a_i, and therefore invertible. This follows from the fact that y_i is strictly decreasing in c_i, and c_i is strictly decreasing in a_i. Therefore, the probability that a student i with baseline test score a_i and GPA y_i obtains a higher GPA than another student j, chosen at random among those with $x_j = x_i = x$ and $d_j = d_i = d$, is $F_Y^J(y_i)|_{x,d} = Pr\big(y_i > y(a_j)\big)|_{x,d} = Pr\big(y^{-1}(y_i) > a_j\big)|_{x,d} = Pr\big(a(y_i) > a_j\big)|_{x,d} = F_T(a_i)|_{x,d}$ where $F_T(\cdot)|_{x,d}$ is the c.d.f. of a_i conditional on x, d and $a(\cdot) = y^{-1}(\cdot)$.

Therefore, conditional on x_i, d_i, the GPA rank of a student with baseline test score a_i is constant across classrooms $\forall a_i$.

□