The Legacy of Natural Disasters: The Intergenerational Impact of 100 Years of Disasters in Latin America

Germán Daniel Caruso
The World Bank *

March 2017

Abstract

Disasters can have long lasting effects, but understanding the breadth, variety and longevity of their effects can be challenging. This paper examines the long term effects and subsequent intergenerational transmission of exposure in childhood to the natural disasters that have occurred in Latin America in the last 100 years. The identification strategy exploits the exogenous variation in geographic location, timing and exposure of different birth cohorts to natural disasters. This study measures individuals' exposure to each disaster based on their geographic location at birth to avoid any bias in the estimates due to possible selective migration caused by each disaster. The main results indicate that children in utero and young children are the most vulnerable to natural disasters and suffer the most long-lasting negative effects. These effects include less human capital accumulation, worse health and fewer assets when they are adults. Effects are found to have a non-linear relationship with the level of development of each country. Furthermore, the results provide evidence of the intergenerational transmission of shocks, indicating that children born to mothers who had been exposed to natural disasters also have less education and increased child labor.

JEL classifications: D31, I00, J13
Keywords: Long term effects; Intergenerational transmission; Natural disasters.

*Corresponding author: Germán Caruso, Poverty and Equity Global Practice, The World Bank. Address: 1850 I St NW, World Bank Group, Room I4-386 (20006), Washington, DC, USA. gcaruso@worldbank.org. I would like to thank Richard Akresh, Walter Sosa-Escudero, Elizabeth Powers and Daniel McMillen for their help and support. I would also like to thank David Albouy, Mary Paula Arends-Kuenning, Javier Baez, Kathy Baylis, Dan Bernhardt, Mark Borgschulte, Tatyana Deryugina, Guillermo Marshall, Benjamin Marx, Nathan Nunn, Adam Osman, Emmanuel Skoufias, Alex E. Winter-Nelson, Dean Spears and two anonymous referees for very useful insights. All errors and omissions are my responsibility.

1 Introduction

Over the last 50 years, the number of recorded natural disasters has been increasing significantly, especially those related to global warming (Helmer et al., 2006; Van Aalst, 2006). Governments and policy makers often evaluate the consequences of these shocks by focusing primarily on the damage to infrastructure (Prestemon and Holmes, 2000). According to these estimates, natural disasters cost an annual average of $901 million. However, this damage estimation does not consider the effect of natural disasters on other dimensions of welfare such as employment and education, which may have lasting effects (Baez et al., 2010) and which are vital to consider when attempting to assess the full impact of the shocks inflicted by a natural disaster.

In addition, there is a growing concern among economists and policy makers that negative conditions experienced early in life may have persistent effects. Recent research documents the long-lasting effects of shocks experienced in early childhood on child development (Currie, 2009) and on adult outcomes in areas such as education, height, self-reported health and socio-economic outcomes (Alderman et al., 2006; Almond et al., 2005; Maluccio et al., 2009). Despite the strong evidence that shocks in early childhood have long-term effects, and despite researchers' increasing interest in the relationship between parental and child health and education (Anger, 2010; Coneus and Spiess, 2012), there is, surprisingly, limited research on the intergenerational transmission of shocks in early life.

Given the recent increase in the recorded number of natural disasters and the long-term effects on the welfare of those exposed to these events, the primary research questions of this paper are: What is the long term effect of natural disasters on education, health, welfare and labor outcomes, and can this impact be transmitted to the next generation? This paper estimates the impact of natural disasters, including the effects on both first and second generations. In particular, the long-run effects of shocks experienced in early childhood and their intergenerational transmission are examined using *all* natural disasters occurring in Latin America in the 20^{th} century.[1] Additionally, this paper explores whether there are generalizable patterns across different types of disasters in different countries.

[1] Since some disasters may have no records, every time this paper refers to all natural disasters occurring in Latin America in the 20^{th} century, it means all the recorded natural disasters that have occurred between the years 1900 to 2000.

Specifically, this paper separately estimates the impact of each type of disaster triggered by natural hazards (floods, earthquakes, tropical cyclones, landslides and volcanoes) by including all the events of each type.[2] The identification strategy of this paper relies on the exogenous timing and geographic variation of each disaster. It identifies as affected those individuals who were exposed to natural disasters during their first 15 years of life. In particular, this study measures individuals' exposure to the disaster based on their geographic location at birth to avoid any bias in the estimates due to possible selective migration caused by the disaster. The main outcomes examined in this paper are the years of education, the probability of being disabled, the probability of being unemployed, a wealth index, fertility rate and child labor.

The heterogeneity of effects of each type of disaster and the persistence of their impact across generations is also explored. In order to explore the heterogeneity of the impacts, this study compares the impact of each natural disaster type at different ages in different countries with different levels of development. Finally, this paper estimates the intergenerational impact of these shocks by identifying as affected those individuals with a parent that has been exposed to a natural disaster during his or her first 15 years of life.

This paper makes three main contributions. First, this work takes a comprehensive approach to study the impact of natural disasters by using data about all natural disasters that affected one continent in the last 100 years. The standard approach in the literature focuses on case studies that evaluate the impact of single specific shocks,[3] but such studies mainly focus on the estimation of extreme cases. As shown in Figure 1,[4] the estimated loss of years of education due to the impact of a natural disaster is greater for those studies that only analyze extreme disasters.[5] In particular, small disasters have a 30-99% smaller impact

[2]This paper focuses only on disasters triggered by natural hazards. Every time this paper mentions the term natural disaster, it refers to disasters triggered by natural hazards. More information about the terminology used in the disaster risk management literature has been included in the appendix.

[3]Baez and Santos (2007) show that the Hurricane Mitch in 1998 negatively impacted schooling, child labor, health and nutritional outcomes between 1998 and 2001 among children in regions directly affected by Mitch compared to children in control areas. Bustelo et. al (2012) also provides evidence of the negative impact of the 1999 Colombian Earthquake on child nutrition and schooling. Moreover, Caruso (2017) demonstrates that the great flood of Tanzania in 1993 negatively affected child height of the first and second generation of affected individuals.

[4]In Figure 1 a natural disaster is classified as "Big" if it affects more individuals than the mean estimated for its type. In the same way, a disaster is defined as "Small" if it affects fewer individuals than the mean estimated for its type.

[5]Examples of studies that find relatively large effects of natural disasters due to focus on extreme disasters

than big disasters for children exposed in utero. This paper complements the existing case study analyses by obtaining an estimation of the impact of natural disasters in Latin America that incorporates the whole distribution of events.[6] Furthermore, this strategy compares how exposure to different types of natural disasters at birth, in different countries with different levels of development, leads to poor welfare outcomes, thus distinguishing the effect of the shock from the intrinsic influence of its location of occurrence and examining the role of different mechanisms like the level of destruction of each disaster.

The second contribution of this paper is an improvement in the accuracy of the estimation of the effects, since another difficulty in capturing the long-term impacts of exposure to natural disasters is that migration may occur as a consequence of the disaster. Traditional studies have used individuals' location at the time of their surveys as a measure of exposure, without recognizing the fact that selective migration may bias the estimations. This paper accounts for those movements by using the birth location data included in the national censuses to measure individuals' exposure to each disaster. Disregarding this data would lead to an incorrect classification of exposure for 7% of individuals, and the estimated negative impacts of exposure to the natural disasters on years of education would be 18% greater than if the individuals' locations at the time of the censuses were used.

Third, this paper also expands the scope of focus of previous studies in two innovative ways. The literature of shocks in childhood traditionally focuses on the effects of exposure to shocks during gestation and the first two years of life. In contrast, this paper can distinguish how exposure to different disasters at different ages, in utero to age 15, may have different long lasting effects.[7] Moreover, this paper contributes to the literature of shocks in early childhood by providing micro estimates of how the impact of these shocks can be translated to the next generation.

The main results of this paper indicate that the most fragile period for any individual to receive this kind of shock is during the first years of life through school age. In particular, those individuals exposed in childhood suffer long-lasting negative effects including less

can be found in Caruso and Miller (2015), Santos (2007) and Ureta (2005) where the effects on years of education are 29-76% larger than the estimation obtained when all the disasters are incorporated.

[6] Case studies add an important heterogeneity to the results by exploring extreme cases. So, this paper should be viewed as a complement rather than as a competing approach to identify the impacts of disasters.

[7] Some scarce literature that focuses on the long-term effects of other types of shocks (e.g., armed conflicts) investigates exposure at different ages (e.g., Akresh et al., 2012; León 2012).

human capital accumulation, worse health and less asset accumulation when they are adults. Exposure in utero to natural disasters generates an average reduction of 0.3 years of education.[8]

This study finds that unpredictable natural disasters impose the largest impact during gestation and the first two years of life. However, natural disasters that allow governments to take action before they impact, such as evacuating affected areas, are mainly relevant for school ages due to the unavoidable damage to infrastructure. This paper further finds that shocks affecting health are especially disastrous, particularly for education and employment.[9]

The empirical approach of this paper has allowed the possibility of comparing shocks and has uncovered the fact that there is a non-linear relationship between the size of impacts and the level of development in the countries where they occur. In addition, this study provides evidence of the intergenerational transmission of shocks. The results show that the children of women exposed to natural disasters are negatively affected with increased child labor and decreased education.

The remainder of the paper is organized as follows. In the next section, an overview of natural disasters and the problems caused is presented. Section 3 describes the data used in the analysis and explains the key variables. Section 4 depicts the empirical identification strategy, and Section 5 presents the main results and robustness tests followed by a discussion of the results and policy implications. Finally, Section 6 concludes.

2 The impact of natural disasters

2.1 Natural disasters in the economic literature

Every year natural disasters affect almost every country worldwide. These types of events are usually unpredictable and affect human lives in many different dimensions. At a macroeconomic level, natural disasters may destroy infrastructure affecting industries, growth and employment. However, at a microeconomic level they can destroy assets, affect

[8]Given that the average level of education in the sample is 7 years of education, which is equivalent to the average duration of primary school in Latin America, the loss 0.3 years of education significantly reduces the probability of finishing primary school.

[9]Natural disasters that affect water provision, such as floods, usually generate outbreaks of cholera among other illnesses.

nutrition and access to education and health services. In addition, natural disasters may also cause water disruptions that generate outbreaks of illness. Furthermore, depending on their intensity, disasters can directly provoke casualties in the affected areas.[10]

The literature analyzing the macroeconomic impact of natural disasters mainly focuses on their effects on growth (Barro, 2009; Dercon, 2004; Noi, 2009). These works include country level and meta-analysis studies. Some of these studies focus on the local economic disruption caused by these events using district level data and an identification strategy similar to the one used in this paper (Hornbeck, 2012; Hornbeck and Keskin, 2014).

The literature on the microeconomic effects of natural disasters has documented country specific evidence of the disasters' impact on the education of exposed individuals (Shah and Steinberg, 2016). Examples of this evidence are the Guatemalan earthquake of 1976 that was found to negatively affect school grade completion (Stein et al., 2003). Similarly, the tropical storm Stan in 2005 was found to be harmful for school enrollment (Bustelo, 2011), and the 2001 earthquake of El Salvador affected the likelihood of school attendance (Santos, 2007).

Case studies have also found effects on individual health. Maccini and Yang (2009) provided some of the best evidence for a long-term disaster-nutrition-morbidity link in Indonesia. Their research also establishes that the amount of rainfall during the birth year correlates positively with a person's reported health status, lung capacity and height in centimeters. Baez and Santos (2007) found in Nicaragua that children in areas affected by Hurricane Mitch were 30% less likely to visit the doctor when needed, and that the probability of malnourishment increased by 9 percent.

Finally, some natural disasters have labor market effects. In Bangladesh a flood was found responsible for a wage reduction of 9% (Banerjee, 2007). In addition, after the Agatha Storm in Guatemala, Baez et al. (2016) found that exposed adults coped with the shock by increasing their labor supplyand simultaneously withdrawing their children from school and relying on them for labor. Migration (Boustan et al., 2012) and agricultural production (Mardero et al., 2015) were found to be other household labor and production decisions affected by the impact of natural disasters. Other studies also find impacts on

[10]This paper follows the standard terminology of the natural disaster risk management literature. More detail about this terminology has been added in the Terminology Appendix.

poverty (De la Fuente, 2010; Rodriguez-Oreggia et al., 2013), assets accumulation (Gignoux and Menendez, 2016) and consumption (Kurosaki, 2015; Skoufias and Vinha, 2013).

All these studies are focus mainly on case studies or country studies. Yet these studies may not represent the true effect of each type of natural disaster, and more importantly, may be difficult to compare across countries. In addition, these studies focus on the direct effects on individuals that have been exposed to disaster and ignore the fact that these effects may be transmitted to the next generation of individuals.

Furthermore, these studies do not account for effects of the environment. As in any natural experiment, the environment can affect the impact of shocks by either amplifying or reducing them. For instance, it is likely that the impact of natural disasters may be different in poor countries than in rich ones (Arouri et al., 2015). The unfortunate lack of empirical studies dealing with this problem, however, makes the results of this paper unique. This study fills this gap in the literature by analyzing both very particular shocks in particular environments and more general kinds of shocks such as floods, earthquakes, tropical cyclones, landslides and volcanoes, thus exploring the heterogeneity of their impacts. All the natural disasters registered in the Latin-American continent have been analyzed with the aim of obtaining a global estimation of the effects of these kinds of shocks and then understanding the determinants of the size of the impact of each type of disaster.

2.2 Natural Disasters in Latin America

Latin America and the Caribbean form one of the regions of the world most susceptible to natural disasters. Latin America's geographic position makes it vulnerable to big geological failures that translate into frequent and severe earthquakes. Unpredictable earthquakes afflict the whole region, particularly along the fault-lines. Some of the most violent and destructive earthquakes recorded have occurred in this region (Mexico, Haiti, Chile) along with volcanic eruptions that usually cause health problems as well as important interruptions to normal economic and social activities. The Caribbean, jointly with South Asia, is also severely affected by tropical cyclones. On average at least one Caribbean island is hit by a tropical cyclone each year (World Bank, 2017).

Fortunately for researchers, Latin America and the Caribbean have the most complete publicly available data among the regions with the highest number of natural disasters. Not only are national censuses publicly available for the majority of countries in Latin America, but these censuses also contain information about the place of birth of each individual. In addition, the natural disasters data base better covers the Latin American region. This information is key for the empirical strategy, so this paper focuses on Latin America and the Caribbean Region.

2.3 The intensity of natural disasters

Latin American countries are mostly affected by floods (Table 1). Typically, more than four floods may be expected each year on the continent. Floods can be riverine floods, which are predictable with the current alert systems, and flash floods, which even with the current technology are much less predictable than other types of disasters such as tropical cyclones (Nadal, et al., 2009). The common consequences of floods include loss of life, economic losses of planted crops, damage to infrastructure, disruptions in the electric system, contamination of drinking water and loss of sewage disposal facilities. Given that this type of shock affects access to drinking water, outbreaks of waterborne diseases are usually expected after a flood. Furthermore, outbreaks after flooding (Ahern et al., 2005) are more frequently documented than after earthquakes, volcanic eruptions, or other types of natural disasters (Noji, 1997; Floret et al., 2007; Watson et al., 2007). Each year floods affect many individuals in Latin America, and even floods in the 1^{st} quartile of the distribution may affect up to 2,000 individuals. While flooding is usually a disaster with low mortality, the variability, as shown by the coefficient of variation, is significant, and the economic damages can be serious. The intensity of floods varies widely. Some generate no damage while other floods, like the ones that affected El Salvador in 1982 and generated damages of $280 million, are extremely costly. Given the direct impact on health and the high frequency and number of individuals impacted, floods that occur during early childhood are expected to have long-term effects on those individuals, according to the literature (Maccini and Yang, 2009; Ohl and Tapsell, 2000).

Tropical cyclones are the second most frequent phenomenon. On average, almost two tropical cyclones impact Latin America per year. Tropical cyclones generate strong winds that can damage and destroy infrastructure and private property and can cause even death

(Kwasinski et al., 2009; Padgett et al. 2008; Reed et al., 2010). This type of event can be highly destructive. An example of this destructive power is the 1980 Hurricane Allen that caused an estimated damage of $400 million in Haiti. In comparison with the large destruction in infrastructure, the number of people killed by tropical cyclones is usually relatively small, with 75% of them killing fewer than 60 people. Tropical cyclones are the most predictable events among the natural disasters, and this likely explains the low mortality resulting from the majority of these shocks (Charveriat, 2000). However, as highlighted by the Kurtosis coefficient, some extreme events have caused numerous casualties.

The third most numerous of the natural disasters affecting Latin America are earthquakes, with almost two earthquakes per year on the continent. Earthquakes are one of the most expensive types of shock. One out of four earthquakes generates more than $180 million in damage to infrastructure destroying buildings and other rigid structures (Samadzadegan and Zarrinpanjeh, 2008). Furthermore, when there is ground rupture the size of the damage increases because of the major risk to large engineering structures such as dams, bridges and nuclear power stations (Mimura et. al, 2011). Because of its unpredictability, this type of shock may be terribly deadly (Geller et al., 1997; Wyss, 2001). But, as shown by the Kurtosis coefficient and the coefficient of variation, the intensity of these disasters varies greatly. Some earthquakes provoke almost no casualties while other earthquakes cause extreme damage like the Chilean earthquake of 1939 that killed almost 30,000 people.

Landslides are disasters that are expected to occur an average of once per year in Latin America. Landslides vary greatly in terms of the number of people affected. Some landslides occur in isolated rural communities while others affect whole towns, like the 1966 landslide of Rio de Janeiro. This kind of event is usually predictable (Fabbri et al., 2003), which commonly reduces the number of deaths. However, each landslide has large destructive power (Fleming and Taylor, 1980). The most damaging landslides (25% of them) destroy a minimum of $400 million in infrastructure in addition to affecting property values, forestry and agriculture (Hilker et al., 2009).

Volcanoes are the least frequent natural disaster in Latin America, but even the 25% least intense volcanic eruptions may affect up to 2,000 people. There is enormous variability in terms of casualties resulting from this type of shock, which can be very deadly in some concrete cases. For example, the volcanic eruption of 1985 in Colombia, the second-deadliest volcanic disaster in the 20^{th} century, killed over 21,000 individuals. In addition to direct casualties, volcanic eruptions may generate respiratory illness as a consequence of their emission of ash (Longo and Yang, 2008) as well as other economic consequences (Annen and Wagner, 2003; Neil et al., 1998).

Finally, an important fact to point out is the existence of extreme events. The distribution of the intensity of natural disasters may be skewed by these extreme disasters. Table 1 presents the summary statistics per event in the disaster database. As shown in this table, the Skewness coefficient is positive for the three indicators of intensity for all the natural disasters. Moreover, the mean in terms of number of people killed, number of people affected and damages is usually larger than the 75^{th} percentile. This fact indicates that extreme events are outlying realizations of the probability distribution. The Kurtosis coefficient also accounts for a distribution of disasters with heavy tails. In other words, much of the variation observed in the intensity of natural disasters comes from infrequent extreme deviations from the mean.

3 Data

3.1 National Censuses

In order to analyze the impact of natural disasters on a set of outcomes that measure welfare, this paper uses the publicly available census of each country in Latin America and the Caribbean. These surveys provide information about the date and place of birth of each individual, and the information is available at district level. In particular, this study defines a district as the lowest subnational level available in each census. The size of each district depends on the political division of each country. In some countries like Colombia, the lowest subnational level is the municipality; in some others like Jamaica, the lowest subnational level available is the Parish. This data is provided by the Integrated Public Use Micro data Series (IPUMS) and includes the following countries: Argentina, Bolivia, Brazil, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

IPUMS-International is a database that contains censuses from almost all countries and is the world's largest publicly available bank of census samples. The database is organized following the same approach across time and countries to allow researchers to compare the results of their investigations across samples. These cross-sectional surveys provide information at the individual level on demographic topics such as years of education, employment status, employment disability status and fertility. The censuses also provide information about household assets such as access to clean water, access to electricity and number of rooms per capita. In order to capture the wealth of each household, this paper calculates a multidimensional measure of wealth. This is a wealth index based on a principal components approach that includes information about the assets available for each household, thus allowing to identify its financial status.[11]

3.2 Timing, location and intensity measures of each disaster

In order to get information about the place and date of the occurrence of natural disasters, this study uses data from the Emergency Events Database (EM-DAT). The EM-DAT is a database of natural disasters that includes variables measuring the intensity of each disaster. In particular, the natural disasters included in this study are geophysical natural disasters (earthquakes and volcanoes), hydrological natural disasters (floods and landslides) and meteorological natural disasters (tropical cyclones). This database covers the occurrence of natural disasters worldwide from 1900 to the present. Disasters that do not satisfy a minimum requirement in terms of intensity are not included in this database. Those disasters that are included in the EM-DAT satisfy at least one of the following conditions: if 10 or more people died because of the disaster, if 100 or more people are affected by the disaster, if the affected country declared a state of emergency, and/or if the affected country called for international assistance.

To measure the intensity of the impact of each disaster, this investigation uses three variables included in the EM-DAT: the number of people killed by each disaster, the number of people affected and the damage estimated in U.S. dollars. When these variables are missing from the database, they are supplied according to data found in another database

[11] A data appendix has been created to provide information about the construction and definition of the variables explored.

called DESINVENTAR.[12] DESINVENTAR is an inventory system of the effects of disasters that reports the number of victims, people affected and damage provoked by each natural disaster.

3.3 Natural Disasters Data Base Construction

As mentioned before, the disaster data for this paper has been drawn mainly from the EM-DAT dataset. EM-DAT is one of the most complete databases of natural disasters because it incorporates disasters that have occurred since 1900. However, some researchers have pointed out that the list of disasters in EM-DAT is incomplete; the database may not include 100 percent of the disasters that have occurred. Although EM-DAT incorporates disasters from the beginning of the 20^{th} century, some disasters may be missing because EM-DAT only registers a disaster that fits its definition according to the number of people killed or affected, or whether a state of emergency or call for international assistance is issued.

As stated by EM-DAT, the database is made up of information from various sources including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies. Priority is given to data from UN agencies, governments, and the International Federation of Red Cross and Red Crescent Societies. This prioritization is not only a reflection of the quality or value of the data, it also reflects the fact that most reporting sources do not cover all disasters and operate under political constraints.

The dataset includes three measures of the intensity of each disaster: number of deaths, total number of people affected and estimated damage. The number of deaths is defined as the number of people who lost their life because the event occurred, while "people affected" is defined as those suffering from physical injuries, trauma or illness requiring immediate medical assistance as a direct result of a disaster, those whose homes are destroyed or heavily damaged and therefore need shelter after an event, and the people requiring immediate assistance during a period of emergency, i.e. requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance. Finally, the estimated

[12] Since some authors have identified discrepancies between different natural disaster databases, only those natural disasters that have consistent information in both databases (EM-DAT and DESINVENTAR) are included in this study. However, the most relevant information for this study (location and date of occurrence of each natural disaster) was found to be consistent in 99.69% of the cases.

damage is the amount of damage to infrastructure in US dollars.

To identify missing disasters, an alternative dataset is used. DESINVENTAR is another well-known natural disasters dataset that includes disasters after 1980. DESINVENTAR is used to complete the list since coverage may be more incomplete in some countries than in others. DESINVENTAR frequently has multiple entries for the same event, since it records a separate event for each affected district. To compare the disasters in both datasets, this paper computes each disaster as one event regardless of the number of records registered. However, the majority of the disasters found in DESINVENTAR after 1980 for Latin America were also found in EM-DAT. Once the list was established, the location of disasters was obtained from the raw data of EM-DAT or DESINVENTAR. If such data was unavailable, a search for the details of each disaster was conducted until the affected locations could be identified.

Naturally, information systems have evolved across time, and the coverage of more recent events has improved significantly. Since this paper includes natural disasters from the early 20^{th} century, a potential reporting bias may affect the results of this paper. This study addresses this issue by replicating the main regressions using only recent natural disasters. The results are consistent with results derived from all the disasters of the 20^{th} century.

3.4 Preliminary observations

When analyzing differences in terms of the geographical dimension, the balance analysis shows no clear pattern in any set of districts in terms of welfare. In Table 2, the characteristics of affected individuals are compared between affected and non-affected districts. In particular, panel A compares the characteristics of the adults analyzed. In terms of education and disabilities, affected districts appear to be less deprived than non-affected districts. For other characteristics such as fertility and unemployment, the table shows no significant difference across districts. Panel B presents a comparison of the characteristics of households between the affected and the non-affected districts. This study observes that the affected areas are wealthier and enjoy greater access to electricity and current water. However, this correlation cannot be interpreted as a causal relationship between deprivation and the impact of natural disasters since the assets are recorded after the occurrence of the disasters. Finally, in Panel C, this research compares the characteristics of individuals younger than 20 years old. Among the characteristics investigated, this panel shows that only the years of education for individuals 5 to 20, and the probability of finishing primary school for individuals 15 to 20, are statistically different between the affected and the non-affected districts. This indicates that the non-affected districts are the most deprived in these dimensions.[13]

Even though the results from Table 2 indicate that the differences, if any, between districts are favorable to the affected areas, any bias resulting from pre-existing, time-invariant district differences between affected and non-affected districts is avoided with the use of district fixed effects in the identification strategy of this paper. However, outcomes such as education may follow different trends across districts that may bias the estimations. To address this potential bias, district-specific time trends are included. Of course, even controlling for these observables, in the case of selective assistance after a disaster, the results may only represent a lower bound for the pure effect of natural disasters. For example, if a government discretionally offers social plans to certain groups in a district, and that is correlated with unobservable characteristics of individuals, that also may determine the outcomes analyzed and may show a lower impact of the disasters.[14] However, remedial programs and insurance for aggregate shocks are modern approaches that are almost completely absent from the majority of shocks in this study. In addition, if another event occurs during the same time period and in exactly the same location as a disaster event, that event might correlate with both the disaster's occurrence and the changes in individuals' welfare. If this were the case, observed changes in socioeconomic status might be incorrectly attributed to the disasters.[15] For these reasons, a model using intensity measures has been estimated, and the results find no presence of this type of bias.

[13]In addition to analyzing differences across affected and non-affected regions, this paper finds no statistically significant differences in the proportion of affected individuals for any particular cohort when testing for differences in the proportion of exposed individuals per age group.

[14]In this hypothetical example, a positive correlation between the probability of being exposed to both a natural disaster and a social plan, in addition to the potential positive correlation between social plans and the socioeconomic status of individuals, may generate a positive bias that underestimates the negative impact of natural disasters.

[15]In the same direction as the last hypothetical example, a positive correlation between the probability of being exposed to both a natural disaster and another event like an economic crisis, in addition to a potential negative correlation between that event and the socioeconomic status of individuals, may generate a negative bias that overestimates the negative impact of natural disasters.

Finally, other potential biases that may affect the model presented in the next section are explored in the robustness check section of this paper. For example, to control for individual characteristics that may vary independently of the natural disasters, this study also estimates the effects of the natural disasters using the oldest census available as a control group. In addition, false experiments are performed simulating false dates and false locations for different types of natural disasters to avoid spurious results. A potential bias regarding endogenous fertility is also explored in the robustness check section. This study finds no evidence that any of these issues affect the results obtained by the empirical model explained in the next section.

4 Empirical identification strategy

The empirical identification strategy relies on a comparison of each outcome for similarly aged individuals in affected and non-affected districts. The implicit assumption is that differences across birth cohorts in each outcome of interest would be similar across affected and non-affected districts in the absence of the shock. This paper first estimates the following regression with district and birth cohort fixed effects:

$$\begin{aligned} Y_{ijt} = & \sum_{t=-1}^{14} \beta_t (Born\, in\, Affected\, Area_j * During\, Shock\, Age = t_t) \\ & + \alpha_j + \delta_t + \gamma_{jt} + \theta X_{ijt} + \mu_{ijt} \end{aligned} \tag{1}$$

where Y_{ijt} is the outcome of interest for the individual i born in district j that belongs to cohort t; $Born\, in\, Affected\, Area_j * Age = t\, During\, Shock_t$ is a dummy variable that takes value one if in district j there was a natural disaster when individual i was t years old (where -1 means during gestation); α_j are district fixed effects; δ_t are cohort fixed effects; γ_{jt} are district-specific time trends; X_{ijt} are individual control variables that include gender fixed effects; and μ_{ijt} is a random, idiosyncratic error term. β measures the impact of natural disasters on outcome Y_{ijt} for individuals who belong to cohort j at the time of the impact of the natural disaster in the affected districts.

This model measures the direct effect of natural disasters. For the model, only adults older than 20 years are included in order to consider only individuals who have finished their educational investments. The average number of years of education in Latin America is 7 for the database used in this paper, so the assumption that people older than 20 have finished with their education seems reasonable.[16] In this difference-in-difference model, an individual is classified as affected if he is part of the affected cohort and born in the affected district. For the control group this study considers those individuals born in affected cohorts but in non-affected districts, those born in affected districts in non-affected cohorts, and those born in non-affected areas in non-affected cohorts.

Additionally, in order to identify the effects of shocks and determine the intergenerational transmission of effects on the next generation, this paper uses the exposure of the parents of each child and generates the following equation:

$$\begin{aligned} &Y_{ijt} = \\ &\sum_{t=-1}^{14} \beta_t (Parent\,Born\,in\,Affected\,Area_j * During\,Shock\,Parent\,Age = t_t) \\ &+ \alpha_j + \delta_t + \gamma_{jt} + \theta X_{ijt} + \mu_{ijt} \end{aligned} \tag{2}$$

where Y_{ijt} is the outcome of interest for individual i with parents born in district j and that belong to cohort t; $Parent\,Born\,in\,Affected\,Area_j * Parent\,Age = t\,During\,Shock_t$ is a dummy variable that takes value one if in district j there was a natural disaster when the parent of individual i was t years old (where -1 means during gestation); α_j are district fixed effects; δ_t are cohort fixed effects; γ_{jt} are district-specific time trends; X_{ijt} are individual control variables that include gender fixed effects; and μ_{ijt} is a random, idiosyncratic error term. β measures the impact of natural disasters on the outcome for offspring of individuals who are part of cohort t during the natural disaster.

The last model measures the indirect impact of natural disasters. For this model, only individuals younger than 20 years are included. This assumption is made since the data supplies only the parents' information if the offspring lived with their parents (because the census follows households, not individuals). The purpose is to avoid having older individuals who still live with their parents because that could lead to a selected sample. Since the starting age of formal education is 5, the sample includes only individuals between

[16] The results are robust to the usage of different age cut-offs and to the usage of a Tobit model to avoid any censoring concern.

5 and 20 years. An individual is classified as exposed to the shocks if his parents were born in an affected district and are part of the affected cohort.

The estimation of the equations above assumes that the intensity of each shock is similar. To differentiate the effect of each shock, this study controls by its intensity, and to corroborate that the observed differences across districts and birth cohorts in each outcome are in fact due to the natural disasters, this paper estimates regressions using the intensity measures for the natural disasters in the following way:

$$\begin{aligned} Y_{ijt} = &\sum_{t=-1}^{14} \beta(Intensity\,of\,Naturaldisaster_j * Age = t\,During\,Shock_t) \\ &+ \alpha_j + \delta_t + \gamma_{jt} + \theta X_{ijt} + \mu_{ijt} \end{aligned} \tag{3}$$

where $Intensity\,of\,NaturalDisaster_j * Age = t\,During\,Shock_t$ is measured by the number of individuals affected per 10,000 individuals, the number of people killed and the damage in USD, if a disaster happened in district j when individual i was t years old (where -1 means during gestation). This paper also uses the number of deaths and the damage in US dollars caused by the disaster as robustness checks for the intensity measures. All the models include gender, cohort, and district fixed effects as well as district-specific trends.

5 Results

5.1 From case studies to comparable results

Cases studies analyze specific events that may not necessarily be replicable because of the characteristics of the environment where they occur and because of the characteristics of the event per se. Moreover, as highlighted in the introduction, the majority of studies about the impact of natural disasters focus on relatively big events that may have different impacts than medium or small disasters. To illustrate this point, in Tables 3 and 4 the main regressions are performed including all natural disasters above and below the median number of affected individuals to classify big and small natural disasters, respectively. This analysis has also been performed using the arithmetic mean as the threshold for big and small disasters. Both thresholds show similar results. The results using the mean are presented in Figure 1, which collapses the results in the in utero period and in the ages

0-2, 3-6, 7-11, and 12-15. This analysis finds persistent effects for individuals exposed by relatively large disasters in early childhood and in older ages (Table 3). However, the effects for impacts at older ages do not seem to be economically relevant for smaller disasters (Table 4). These estimations also point out the bias in comparing results from shocks that may be an extreme realization of the distribution of shocks instead of taking into account the entire distribution of natural disasters.[17]

The majority of studies that estimate the impact of natural disasters focus on extreme events. This particular type of study is valuable for explaining details of the impact of a particular disaster in a particular environment. However, generalization and comparison of those effects may lead to biased estimations. For that reason, any generalizations should be considered as the estimations of a realization of a variety of natural disasters. For instance, Caruso and Miller (2015) estimate that exposure in utero to the Ancash earthquake of 1970 generated a loss of 0.7 years of education. The Ancash Earthquake was the most severe natural disaster in the history of Peru affecting more than 3,000,000 people.[18] In contrast, this study finds that exposure in utero to earthquakes in general generates of a loss of 0.2 years of education; generalization of the results from Caruso and Miller (2015) would lead to an overestimation by 250% for the in utero estimations. These differences between general and particular estimates point out the necessity of an empirical strategy that incorporates the entire distribution of disasters instead of just the extreme cases.

In addition to the size of the natural disasters, this paper finds that when analyzing natural disasters in different countries the results may differ. For instance, the flood that affected Argentina in 1967 had an impact on years of education only if it impacted individuals during their first five years of life, while the 1966 landslide in Brazil had an effect on education if it impacted individuals in utero and in their first year. However, the analysis that includes all the natural disasters occurring in the last century (presented in the following subsection) contradicts these results. Thus, in those cases it is even harder to determine if the different results are due to the size of the disasters or due to other characteristics of the countries where the shocks occurred.

The potential negative effects of natural disasters depend on the degree of development

[17]Similar results hold if the disasters are classified according to the number of people killed or the economic damages.

[18]The Ancash earthquake is considered above of the median of affected individuals.

of each country. Figure 2 presents the average effect on years of education and the average GDP per capita of the last 50 years. Contrary to the belief that the impact of natural disasters may have a linear relationship with the countries' degree of development, the relationship is clearly not linear. In fact, this relationship follows a U-shaped pattern. On one hand, the countries on the bottom of the GDP per capita distribution usually have a lower level of human capital accumulation, independent of the occurrence of a shock. The impact of natural disasters is thus limited by the low asset accumulation of those countries. On the other hand, countries at the top of the GDP per capita distribution commonly have better infrastructure and preventive systems to resist shocks. Countries in the middle that are accumulating assets but still have not the necessary infrastructure to ameliorate the impact of natural disasters are the countries that mainly drive the results found in this paper.

Given that the discussion above highlights the relevance of analyzing many realizations across different contexts instead of focusing on the results of individual case studies, this study estimates the impact of different types of natural disasters. The next subsection expands the database to include all the natural disasters occurring in the last century, in all the countries.

5.2 Effects on Education for the First Generation

By including all the natural disasters that have occurred in different contexts, this study finds results that differ from those presented by country specific studies. This finding highlights the contribution of combining many similar shocks from different countries in the same study. In particular, this work finds that for education, the relevant age for each type of disaster varies with the specific shock. From here, this paper defines a set of hypotheses to be tested empirically and discussed in a systematic way, based on discussion in the previous sections.

Hypothesis 1a: Natural disasters hinder human capital formation when individuals are exposed during cognitive development or school age.

Hypothesis 1b: Effects in the first years of life are preventable when shocks are pre-

dictable since they allow households to evacuate potentially affected areas and avoid suffering a lack of basic goods for their children; impacts during school age are usually related to the destruction of infrastructure, such as schools and means of transport, which is hard to avoid.

Figure 3 shows the estimation of the main model for different types of shocks.[19] As mentioned before, since in Latin America schooling begins at the age of five and the average years of education in this sample is seven, this paper includes only those individuals older than 20 years in order to observe the number of completed years of education. According to Figure 3a, an individual impacted by a flood while he was in utero has 0.472 fewer years of education (equivalent to a 0.1 standard deviation) compared to those not exposed. This effect decreases if the individual is exposed after the aged of 6, except for individuals exposed at ages 12 to 15 when they are finishing primary school and beginning secondary school.

In Figure 3b the effect of earthquakes on years of education is shown. In this case, the effect on education is relevant if the individual is affected during the first four years of life or during the first years of secondary school (ages 12 to 14). Surprisingly, the results for tropical cyclones in Figure 3c show no statistically significant effects for individuals exposed during the first years of life. However, the impact becomes relevant if the individual is exposed at school age. One factor that may explain this differential result is that, in comparison with the two natural disasters previously analyzed, this disaster is predictable, thus giving people enough time to avoid risk areas. Although predictable, tropical cyclones provoke damage to infrastructure that cannot be safeguarded, which may explain the negative effects found during school age.

In Figure 3d, the estimations suggest that the impact of landslides is relevant from a statistical and economic perspective if the individual is exposed between the in utero period and the first 15 years of life. This study finds that the impact is larger for individuals younger than seven years. This type of shock can be extremely destructive and is unfortunately as unpredictable as floods and earthquakes. As a consequence, the destruction

[19]The standard errors are clustered at district level. In addition, many robustness checks have been performed where the results are consistent when clustering at the province and country levels, or when using a two-way cluster-robust covariance matrix.

includes not only schools and health centers but also basic service facilities such as water purification plants that impact individuals' health. This suggests that the destruction of infrastructure can reduce the education of an individual exposed at the in utero period by 0.486 years, and the greatest impact of this kind of shock occurs during the first seven years of life. Thus, as the size of the impact decreases, the age of the impacted individual increases.

Finally, Figure 3e shows that the impact of a volcano is relevant if the individual is exposed at the in utero period or at school age. This type of shock allows individuals to escape and avoid part of the impact, but the damage to infrastructure and access to basic services like piped water is total, with almost all infrastructure destroyed that is touched by lava from the volcano. Moreover, gases emitted by the eruption of the volcano may produce several respiratory illnesses, particularly during the in utero period (Soto-Martinez et al., 2009).[20]

In summary, we find a negative effect of natural disasters on human capital formation. Furthermore, the effect of each disaster has a pattern related to the age of affected individuals with the youngest children shown to be the most fragile group against the impact of natural disasters. This study also determines that those natural disasters that are harder to predict are the ones with the largest effects. Thus, the Hypotheses 1a and 1b could not be rejected.

5.3 Effects on Health and Labor Outcomes for the First Generation

Apart from the effects on education, natural disasters can affect other dimensions of welfare such us employment disabilities and unemployment. Therefore, this study proposes the following hypothesis:

Hypothesis 2: Natural disasters increase the likelihood that a disability prohibits an individual from working and increase unemployment in the long term.

[20] Although volcanoes may appear to be benign, the fall of the ash may not only have health impacts (Longo and Yang, 2008) but also impacts on agriculture that affect rural household income (Neil et. al, 1998). Other studies have analyzed the impact of Volcanoes and found negative impacts (Annen and Wagner, 2003).

The census data do not contain questions about health outcomes, but they do contain a self-reported employment disability status variable. This question is present in the majority of the countries and identifies individuals who are unable to work because of any kind of disability. In Figure 4 the estimation of employment disabilities for those that should be able to work is presented. To be consistent with the education estimation, the effects for adults older than 20 are analyzed. From the figure it is possible to see that all the shocks generate significant increments in the probability of being disabled, taking into account that the probability of being disabled to work in the control districts is 0.024, for all the natural disasters analyzed. Tropical cyclones are the natural disaster with the strongest impact, generating an increase of 0.030 (equivalent to 0.24 standard deviations) in the probability of being disabled if an individual is exposed to a shock in utero. Furthermore, the impact of the shock is stronger when it occurs in the first 8 years of life. However, when controlling for the intensity of each disaster, the impact on disabilities is less unequal across age groups. These results suggest that the effect is driven by the destructive power of each type of disaster. Disasters that generate bigger destruction (tropical cyclones, earthquakes and landslides) more dramatically increase the probability of suffering health problems that prevent an individual from working.

The effects of natural disasters on unemployment are shown in Figure 5. Surprisingly, the results are consistent with the findings for education. In Figure 5a, the results for the impact of floods during early childhood on unemployment in the long run are presented. Floods are found to increase the unemployment of individuals affected in utero by 0.009. This represents an increase of 10% on the probability of being unemployed. The effect of floods on unemployment is statistically and economically significant if the individuals are exposed to a shock in the first five years of life and during the first years of high school, mimicking the results from Figure 3.

Figure 5b shows the effect of earthquakes on unemployment. In particular, the results indicate that the impact of earthquakes during the first four years of life increases unemployment by 0.003. The impact of this type of shock is also significant for school age individuals.

The impact of tropical cyclones is shown in Figure 5c. For individuals in utero during a tropical cyclone, the probability of being unemployed is 0.009. The effect of tropical cyclones is relevant if the individual is impacted during the first five years of life and during the transition from primary to secondary school (ages 11 to 13). Although tropical cyclones do not impact education for individuals exposed during their first years of life, tropical cyclones do impact employment disabilities, as shown before, which may partially explain why there is no effect in the first years of life for education while there are effects for unemployment.

Events like landslides strongly affect the infrastructure and economic situation of the areas they touch. Figure 5d shows that the effect on individuals is relevant during the first years of life. Moreover, the greatest impact of landslides is found when the event occurs during the in utero period with unemployment increasing in the long run by 0.009, meaning that the destruction caused by landslides affects the health status of fetuses. This effect decreases as the age of the affected individual increases.

Finally, Figure 5e shows the effect of volcanoes on unemployment. The effect of these shocks is significant in the first seven years of life. For instance, an individual exposed to a shock in the first year of life suffers an increase in his probability of being unemployed in the long run by 0.015 (equivalent to 0.1 standard deviation).

Thus, Hypothesis 2 cannot be rejected. This study finds that natural disasters increase the likelihood that a disability prohibits an individual from working and increases unemployment in the long term.

5.4 Effects on Other Outcomes for the First Generation

Natural disasters cause shocks that can affect many dimensions of welfare apart from education, health and labor outcomes. For that reason, this paper hypothesizes the following:

Hypothesis 3a: Natural disasters affect physical assets accumulation.

Hypothesis 3b: Natural disasters disrupt fertility decisions.

Hypothesis 3c: Natural disasters generate incentives to migrate.

In order to capture the effect of natural disasters on wealth, this work generates an index using census information about assets such us rooms per capita, access to current water and ownership of the household. In Figure 6 results for the main specifications are shown using the wealth index as the explicative variable for the exposure of the head of household. The first column shows the effects of floods on wealth if the head of household has been affected. In terms of wealth, the shocks are relevant if the individual is affected at school age, including preschool, primary school and the first years of high school.

This study finds significant effects on wealth of earthquakes and volcanoes for almost all ages. The main difference between these shocks is that the impact in utero is larger for volcanoes, reducing wealth by 0.98 (equivalent to 0.9 standard deviations) if a head of household is affected in utero. This effect is economically relevant taking into account that the mean of the wealth index is -0.07. In the case of floods, a stronger effect is found if the individual is affected during school age.

Tropical cyclones and volcanoes affect the wealth of a household if the head of household was affected during his or her first four years of life, with the in utero effect larger for tropical cyclones. The main difference between these natural disasters is that tropical cyclones affect wealth if the shock affects the head of household during school age, while the effect of landslides during that period is not significant after the first eight years of life.

Table A.1 presents results for fertility, as measured by the number of children of the head of household. Although the estimations present several statistically significant results showing negative effects on the number of children, the effects are only economically significant for earthquakes occurring in the first four years of life, for floods during the gestation period, and for landslides during school age. The interpretation of this result may suggest that more deprived households have fewer resources to increase their family size, or it may indicate wealthier and more highly educated households. However, since this effect overlaps with the effects found for years of education, the first interpretation is more plausible. In either case, the evidence on fertility found by this study is economically negligible given the size of the coefficients found.

In addition, this study finds significant results for migration, 7% of exposed individuals would be misclassified in the absence of birth location information. In order to compute the advantage of using birth location instead of location at the time of the survey, this paper re-estimates all the analysis using current location as a measure of exposure. The results indicate that the bias produced as a consequence of this misclassification may lead to estimations up to 18% higher than the ones presented in the main tables of this paper[21].

To sum up, Hypothesis 3a cannot be rejected, while Hypothesis 3b and 3c are rejected. In particular, this paper finds relevant effects on the asset accumulation of affected individuals, and small effects on fertility and migration.

Finally, before analyzing the effects on the second generation, additional calculations are performed on the outcomes found to be affected. In order to compare the impact of natural disasters by outcomes, the results are expressed in standard deviations (SD) for the most affected cohort. In Table 5, the results for in utero exposure are shown. Floods and landslides mainly reduce years of education. On the other hand, tropical cyclones and earthquakes mainly affect the probability of being disabled. Volcanoes are shown to be more destructive for long-term wealth accumulation.

5.5 Effects on Education and Child Labor among the Second Generation

Exposure to natural disasters during childhood has long lasting effects that may also affect the descendants of those exposed as children. In particular, the performance of the children of exposed individuals in terms of years of education is analyzed, along with their disabilities and their participation in child labor. Therefore, the following hypotheses were formulated:

Hypothesis 4a: Natural disasters affect the human capital accumulation of descendants of those that have been exposed to such shocks.

Hypothesis 4b: Natural disasters increase the probability that the descendants of those who have been exposed to such shocks will be disabled.

Hypothesis 4c: The impact of natural disasters results in an increase in child labor among the descendants of those who have been exposed to such shocks.

Tables 6 and 7 present the estimation of the intergenerational transmission of shock

[21] In addition, any potential migration after birth may led to attenuation bias, where the effect of natural disasters may be even larger than those obtained in this study.

for affected mothers and fathers, respectively. Both tables present an estimation of the indirect effect model, coding as the treatment group those children with parents affected by the shock. This work finds significant negative effects of natural disasters on years of education for the children of affected parents. Although effects on the next generation are significant when either of the parents is affected, the effect of having an affected mother is significantly larger than the effect of having an affected father. These results are in line with previous literature that argues that the education of the mother is more relevant than the education of the father (Smith, 1989) when analyzing the effect on education for the next generation. [22]

The strongest intergenerational effect caused by floods occurs in the in utero period. The fact of having a mother affected by a flood while in utero reduces the education of that child by 0.478 in comparison with other children of the same age with non-affected mothers. The effect of having a father affected during his in utero period is to reduce the years of education of his child by 0.02.

In the case of earthquakes, this study finds statistically and economically relevant results for the education of the next generation when parents are affected before their first three years of life. According to the results, the effect of having an affected mother is ten times larger than the effect of having an affected father.

Column 3 of Tables 6 and 7 shows the effects of tropical cyclones on the education of the next generation. The effects are economically and statistically relevant if the mother was affected during school age (ages 5 to 12). Table 7 shows that the effects of having an affected father are statistically significant independent of his age when exposed, but the size of the effect is considerably less than the effect of having an affected mother.

The last two columns of Tables 6 and 7 show the effect of having a mother or a father affected by a landslide or volcano. Mothers in affected districts are found to reflect the larger effect. The results show that the fact of having a mother affected by any of these shocks reduces the years of education by 0.2. Smaller reductions in years of education for the next generation are found if mothers were exposed to the shock of either landslides or volcanoes during their school age. On the other hand, children with a father affected

[22] The results are robust both to the inclusion of the parents' education as controls and the inclusion of the predicted education of the parents in a 2-step estimation.

during school age suffer a significant but smaller reduction in the years of education.

Finally, Tables A.2 and A.3 analyze the effect of natural disasters on the child labor of the second generation. Comparable to the education results, the fact of having a father that was affected has no impact on the child labor of the second generation, but this is not the case when the mother is affected. The results suggest that those with mothers affected in utero by a flood, an earthquake, a landslide or a volcano have a larger probability of working before age 16. In addition, the impact of tropical cyclones and landslides (Columns 3 and 4) increases the child labor of the second generation when mothers are exposed during school age and pre-school age, respectively.[23]

This paper also observes no statistical difference in the probability of being disabled between those with affected parents and those with non-affected parents. Thus, Hypothesis 4b is rejected. However, the findings of this study do suggest that the second generation of individuals have less human capital accumulation and a larger probability of work before age 16. In this light, Hypotheses 4a and 4c cannot be rejected.

5.6 Discussion of the impact mechanisms of natural disasters

Proper understanding of the mechanisms by which natural disasters affect the outcomes studied in this paper is crucial for developing alleviation policies that protect people during and after this kind of event. Unfortunately, the information available in the censuses does not allow this study to answer the question entirely. Although this data is limited, the results presented do suggest which mechanisms operate to affect the outcomes studied in this work.

Because the intensity of each disaster differs, the intensity of the shocks should be taken into account before arriving at any conclusion about mechanisms. It is possible that, independent of the type of shock experienced, large shocks affect outcomes in a larger manner than small shocks do. In order to control for disaster size, a third model is estimated. The results presented in Table 8 show the differences in years of education across different types of natural disasters, controlling by the number of people affected by each disaster. Tables 9 and 10 control by the number of individuals killed and the damage

[23]The results for education and child labor are robust to estimate the regressions conditional on having both parents exposed.

provoked by each disaster respectively.

Controlling for the intensity of each disaster yields insights about the possible mechanisms of its effects. Naturally, the impact of a disaster in a highly populated area may be very different than its effect on a sparsely populated area. A disaster may also either extend across the country or be a localized event. When taking into account the number of individuals affected, the results show that the most relevant shock during gestation and the first two years of life is caused by earthquakes, while during school age the largest impact is caused by landslides. Both disasters generally affect all the population of the city exposed to them, highlighting the fact that earthquakes and landslides in very populated areas heavily affect young children. When controlling by the number of individuals killed and the damage to infrastructure, tropical cyclones appear to have a significant effect for children under five years old that was not significant before. This result indicates that even in presence of a predictable disaster, disasters that are very deadly and highly destructive of infrastructure can affect young children. The fact that the negative results increase with the level of damage produced suggests that damage to infrastructure is another relevant factor for investment in human capital for affected children. It also highlights the importance of having a resilient infrastructure to avoid negative welfare conditions. In particular, the effect of extreme events is shown to be greatest when individuals are exposed to the shock in utero, pointing out the importance of the health dimension and falling in line with the existing literature about health shocks during gestation (Almond et al., 2006).

Another relevant dimension is the effect on asset loss as a result of disaster. According to the results, floods and earthquakes are shocks that produce the greatest asset losses. If these results were driven only by a deterioration of the economic situation of the families of affected individuals, then the impact for those exposed in utero or in the first years of life should not be larger than the impact during school age. However, for both disasters, the greatest effects occur when the individual is exposed during the in utero period and early childhood. Given the existing literature about the effects of malnutrition on early childhood, this result suggests that poverty generated by asset loss would affect the nutrition of all children in the household, but would generate greater negative effects for those affected in early childhood. The results suggest that this mechanism might be relevant, since children affected in the first years of life and in utero are the most affected.

Related to the transmission of shocks to the next generation, there is a large body of literature arguing that the education of the mother is a more important determinant of the education of the children than that of the father. In fact, according to the results, the impact found on years of education for the first generation is mimicked by the effects found on years of education for the second generation. However, there may be a differential impact by gender that can explain why mothers transmit shocks in a stronger way than fathers. In order to test this, the results of the main outcomes by gender are presented in Table 11.[24]

According to the results, the impact of natural disasters on employment disabilities is larger for women, but the impact on years of education is similar for males and females (Table 11). These results suggest that the mechanism operating in the transmission of shocks may be the deprivation of the household. Since mothers are more deprived than fathers in terms of health, the scarcity of resources in households with affected mothers may explain the lower education level of the children.

5.7 Robustness checks

In addition to previous approaches that use an identification strategy to compare different cohorts in different birth districts, this study estimates the effects of natural disasters using the oldest census available as a control group. This allows to control for individual characteristics that may vary but are not related to the natural disasters. Such a check is relevant since it reveals that the results obtained by this study are not just casual. On the contrary, a different identification strategy also generates results in the same direction as the main specification. In this case, identification is driven by individuals born in the same district and of the same age, with some surveyed before and some surveyed after the natural disaster occurred. The results are consistent with the outcomes analyzed in the above sections using the same estimation strategy. This suggests that the identification strategy per se is not capturing spurious relationships.

A possible distortion of the size of the coefficients may have resulted in a potential reporting bias from disasters that occurred during the first years of the analyzed period. Since some of the natural disasters are from the early 1900s when records were not as

[24] All these results between males and females are statistically different at the 10% level.

accurate as nowadays, this paper estimates the main regressions using only natural disasters registered after 1970. The results are consistent with those results derived from all the disasters of the 20^{th} century. As expected, results using only a partial sample of disasters show smaller coefficients because of the inclusion of affected individuals in the control group.[25]

To reject the possibility that our findings are only the result of a spurious relationship picked up by the model, this paper generated false experiments expecting to find no results for simulated events. False experiments were performed by simulating false dates for different types of natural disasters in affected districts. Simulations of false locations for different types of natural disasters for the affected cohorts were also performed.[26] After several simulations, this study finds no effects of these false experiments that strengthen the reliability of the results.

Although this paper estimates the intergenerational impact of disasters by following the empirical strategy of Caruso and Miller (2015), one potential concern is that the results of the reduced form equation for the intergenerational regressions may be picking up the impact of lower educational attainment among affected parents. In order to test this issue, this paper estimates two alternative models. This study first estimated the main regressions controlling by the education of the parents, and second, controlling by the predicted education of the parents in a 2-step estimation. The results hold in both alternative estimations.

A final concern regarding the validity of the main estimates relates to the possibility that fertility and mortality patterns may differ in affected and non-affected districts. When the impact on fertility patterns was examined, the results showed relatively little evidence that affected individuals had a different number of children due to the natural disasters as discussed in the main results section. This study also uses information about household mortality to examine whether exposure to natural disasters resulted in systematically increased mortality. The results generally indicate no significant effect on mortality. This overall lack of relationship between disaster exposure and mortality should be understood

[25]The fact that smaller results are found for recent disasters may be interpreted as the impact of more adequate disaster risk management practices that have been implemented in recent years.

[26]These false experiments include placebos, coding as exposed those cohorts that were affected 1 to 15 years before the child was in utero.

in the context of an environment with high mortality until 1980 (Ahmad et al., 2000). Such a result would only lead to a downward bias in the main results reported in the paper.

5.8 Policy implications

Over the past 20 years, due to the increased number of people affected by natural disasters, an international effort in disaster risk reduction has emerged. Among them, the World Bank has arisen as a global leader in disaster risk management (DRM), supporting countries to assess exposure to disasters and address disaster risks. It provides technical and financial support for risk assessments, risk reduction, preparedness, financial protection, and resilient recovery and reconstruction. Disaster resilience research provides technical advice that contributes to the development of disaster risk policies.

In light of these results, this study focuses on a key set of policy implications that may mitigate the effects of natural disasters on education, health and labor outcomes. In particular, results point to four dimensions that may be improved to prevent and alleviate the negative impact of natural disasters.

First, every natural disaster is different. There is no recipe for alleviating the effects of all natural disasters. As shown in this work, different types of disasters affect different types of outcomes and have relevant effects at different stages of childhood. For this reason there is no unique contingency plan for natural disasters. Each prevention and alleviation plan should depend on the type and size of the disaster. Moreover, shocks in countries with different levels of development have different impacts, and taking this into account may benefit the planning of disaster risk management for each country.

Second, information plays an important role. The predictability of certain types of natural disasters allows policy makers to take preventive measures and avoid negative health impacts. Thus, the improvement of alert and information systems is recommended as an effective prevention policy. Improved predictability of these kinds of shocks will allow individuals the opportunity to evacuate affected areas.

Third, the cost-benefit evaluation of any alleviation policy should take into account the hidden cost of the intergenerational transmission of shocks. Natural disasters do not only affect the first generation of exposed individuals but also their children. The effect is transmitted to the next generation especially if it was the mother who had been exposed, highlighting the importance of targeting alleviation policies mainly for females.

Finally, the targeting of alleviation policies should be very specific. Based on the estimations, the main focus of alleviation policies should be pregnant women and children in their first years of life and school age, depending on the type of disaster.

6 Conclusion

This study has estimated the long-term effect of natural disasters on education, health, employment, fertility, and wealth, along with the intergenerational transmission of those effects. To conduct this research all the disasters occurring from 1900 to 2000 in Latin America were analyzed. As such, this is the first paper to measure the welfare impacts of all the natural disasters registered in one continent. In addition, by analyzing all disasters available, this work complements the existing extreme-case analyses by identifying relevant differences from the results obtained in those case studies.

This paper has found that natural disasters affect the education, health, labor outcomes and wealth of the individuals exposed. To identify these effects, this paper has exploited the exogenous variation in the location and timing of natural disasters, as well as the exposure of different cohorts to the shock. This study finds that the effect of natural disasters differs depending on the type and size of the disaster and the age of the affected individuals. The main results indicate that the most fragile period for any individual to receive this kind of shock is during the first years of life and school age. In particular, floods are found especially disastrous for education, fertility and employment, and tropical cyclones strongly affect the probability of suffering an employment disability. On the other hand, volcanoes are found to produce a large impact on wealth. Comparing results across different countries, this paper finds a non-linear relationship between the size of the impacts and the level of development of each country. In addition, the analysis of the intergenerational transmission of shocks shows that mothers exposed to shocks are more likely to affect their children's education than exposed fathers. Finally, the robustness check shows that the results described in this study are robust to the usage of the measures of intensity of natural disasters.

A critical reason for studying the impact of natural disasters on welfare outcomes is the lack of measures of their full impact. Such data is necessary in order to guide the elaboration, design and targeting of alleviation policies. Therefore, this study may be useful and worthy for governments and policy makers in a variety of ways. First, it identifies the individuals most vulnerable to natural disaster exposure. Based on the estimations, the main focus of alleviation policies should be pregnant women and children in their first years of life and school age. Additionally, according to the estimations, the cost of any intervention should take into account the hidden loss of human capital accumulation and the increase in child labor in the next generation.

Governments typically have few policies to prevent or alleviate the consequences of these types of shocks. This is probably because of a lack of evidence for the seriousness of the persistence of the effects produced by natural disasters. This paper does provide evidence of the long-term effects of natural disasters and argues that there is a great need to generate prevention and alleviation policies that focus on the mitigation of their long term effects. Estimating the effect of all the natural disasters and measuring them is of paramount importance for researchers and academics but mostly for policy makers and governments. A deep understanding of natural disasters and their effects is essential to designing new, effective and timely policies to preserve human welfare and to reduce the overall risk associated with these types of unfortunate events.

The results in this paper contribute to a growing literature that estimates the welfare impacts of natural disasters. This approach compares the impact of different types of disasters, strengthens confidence in the results and confirms that natural disasters negatively affect individuals in their childhood and extend those effects to their descendants. The findings in this study also benefit the knowledge of a broader issue, the long-term growth and development consequences of natural disasters. Since this paper has shown the long-term effects of shocks that occur during childhood, the effects of natural disasters may be able to be overcome with well-targeted and flexible social plans to support the exposed population.

References

Ahmad, O. B., Lopez, A. D., and Inoue, M. (2000). "The decline in child mortality: a reappraisal". *Bulletin of the World Health Organization, 78, 1175-1191.*

Akresh, R., Lucchetti, L., and Thirumurthy, H. (2012). "Wars and child health: Evidence from the EritreanEthiopian conflict". *Journal of development economics, 99(2), 330-340.*

Akresh, R., Bhalotra, S., Leone, M., and Osili, U. O. (2012). "War and Stature: Growing Up during the Nigerian Civil War". *The American Economic Review, 102(3), 273-277.*

Agüero, J. M. (2014). "Long-Term Effect of Climate Change on Health: Evidence from Heat Waves in Mexico" (No. IDB-WP-481). *Inter-American Development Bank, Research Department.*

Ahern, M., Kovats, R. S., Wilkinson, P., Few, R., and Matthies, F. (2005). "Global health impacts of floods: epidemiologic evidence". *Epidemiologic reviews, 27(1), 36-46.*

Ahlburg, D. (1998). "Intergenerational transmission of health. *American Economic Review, 88(2), 265-70.*

Alderman, H., Hoddinott, J., and Kinsey, B. (2006). "Long term consequences of early childhood malnutrition". *Oxford Economic Papers, 58(3), 450-474.*

Almond, D., Chay, K. Y., and Lee, D. S. (2005). "The costs of low birth weight". *The Quarterly Journal of Economics, 120(3), 1031-1083.*

Almond, D. and Mazumder, B. (2005). "The 1918 influenza pandemic and subsequent health outcomes: an analysis of SIPP data". *American Economic Review, 258-262.*

Annen, C., and Wagner, J. J. (2003). "The impact of volcanic eruptions during the 1990s". *Natural Hazards Review, 4(4), 169-175.*

Anger, S., and Heineck, G. (2010). "Do smart parents raise smart children? The intergenerational transmission of cognitive abilities". *Journal of Population Economics, 23(3), 1105-1132.*

Anttila-Hughes, J. K. and Hsiang, S. M. (2013). "Destruction, disinvestment, and death: Economic and human losses following environmental disaster". *Technical Report, National Bureau of Economic Research.*

Arouri, M., Nguyen, C., and Youssef, A. B. (2015). "Natural Disasters, Household Welfare, and Resilience: Evidence from Rural Vietnam". *World Development, 70, 59-77.*

Baez, J. E., de la Fuente, A., and Santos, I. (2010). “Do Natural Disasters Affect Human Capital? An Assessment Based on Existing Empirical Evidence” (No. 5164). *Institute for the Study of Labor (IZA).*

Baez, J. E., Lucchetti, L., Genoni, M. E., and Salazar, M. (2016). “Gone with the storm: rainfall shocks and household well-being in Guatemala”. *Forthcoming in Journal of Development Studies.*

Baez, J. E., and Santos, I. V. (2007). “Childrens vulnerability to weather shocks: A natural disaster as a natural experiment”. *Social Science Research Network*, New York.

Barker, D. (1998). “Mothers, Babies, and Health in Later Life”. Edinburgh, United Kingdom: Churchill Livingstone.

Barreca, A. I. (2010). “The long-term economic impact of in utero and postnatal exposure to malaria”. J*ournal of Human Resources*, 45(4), 865-892.

Barro, R. J. (2009). “Rare Disasters, Asset Prices, and Welfare Costs”. *American Economic Review, 99(1), 243-264.*

Behrman, J. and Taubman, P. (1976). “Intergenerational transmission of income and wealth”. *The American Economic Review, 66(2), 436-440.*

Belasen, A. R., and Polachek, S. (2008). “How Hurricanes Affect Wages and Employment in Local Labor Markets”. *American Economic Review 98(2): 49-53.*

Belasen, A. R., and Polachek, S. (2009). “How Disasters Affect Local Labor Markets: The Effects of Hurricanes in Florida”. *Journal of Human Resources 44(1).*

Black, S. E., Btikofer, A., Devereux, P. J., and Salvanes, K. G. (2014). “This Is Only a Test? Long-Run and Intergenerational Impacts of Prenatal Exposure to Radioactive Fallout”. *NBER Working Paper, 18987.*

Boustan, L. P., Kahn, M. E., and Rhode, P. W. (2012). “Moving to higher ground: migration response to natural disasters in the early twentieth century”. *American Economic Review, 102(3), 238-244.*

Bustelo, M. (2011). “Bearing the Burden of Natural Disasters: Child Labor and Schooling in the Aftermath of Tropical Storm Stan in Guatemala”. Unpublished manuscript. *Unpublished manuscript, Department of Economics, University of Illinois at Urbana-Champaign.*

Bustelo, M., Arends-Kuenning, M. P., and Lucchetti, L. (2012). “Persistent impact of natural disasters on child nutrition and schooling: Evidence from the 1999 Colombian earthquake" (No. 6354). *Institute for the Study of Labor (IZA).*

Caruso, G. (2017). "Intergenerational transmission of shocks in early life: Evidence from the Tanzania great flood of 1993" *Unpublished manuscript, Department of Economics, University of Illinois at Urbana-Champaign.*

Caruso, G. and Miller, S. J. (2015). "Long run effects and intergenerational transmission of natural disasters: A case study on the 1970 Ancash Earthquake". *Journal of Development Economics 117: 134-150.*

Charvriat, C. (2000). "Natural Disasters in Latin America and the Caribbean: An Overview of Risk" (No. 4233). *Inter-American Development Bank, Research Department.*

Coneus, K., and Spiess, C. K. (2012). "The intergenerational transmission of health in early childhoodEvidence from the German Socio-Economic Panel Study". *Economics & Human Biology, 10(1), 89-97.*

Currie, J. and Moretti, E. (2003). "Mother's education and the intergenerational transmission of human capital: Evidence from college openings". *The Quarterly Journal of Economics, 118(4), 1495-1532.*

Currie, J. and Moretti, E. (2007). "Biology as Destiny? Short-and Long-Run Determinants of Intergenerational Transmission of Birth Weight". *Journal of Labor Economics, 25(2).*

Currie, J. (2009). "Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development". *Journal of Economic Literature, 87-122.*

De la Fuente, A. (2010). "Natural disaster and poverty in Latin America: Welfare impacts and social protection solutions". *Well-Being and Social Policy, 6(1), 1-15.*

Dercon, S. (2004). "Growth and shocks: evidence from rural Ethiopia". *Journal of Development Economics, 74(2), 309-329.*

ECLAC (2003). "Handbook for Estimating the Socio-Economic and Environmental Effects of Disasters". *Santiago, Chile.*

Fabbri, A. G., Chung, C. J. F., Cendrero, A., and Remondo, J. (2003). "Is prediction of future landslides possible with a GIS?" *Natural Hazards, 30(3), 487-503.*

Fleming, R. W., and Taylor, F. A. (1980). "Estimating the costs of landslide damage in the United States" (No. 832). *Branch of Distribution, US Geological Survey.*

Floret, N., Viel, J. F., Mauny, F., Hoen, B., and Piarroux, R. (2006). "Negligible risk for epidemics after geophysical disasters". *Emerging Infectious Diseases, 12(4), 543-549.*

Geller, R. J., Jackson, D. D., Kagan, Y. Y., and Mulargia, F. (1997). “Earthquakes cannot be predicted”. *Science, 275(5306), 1616-1616.*

Gignoux, J., and Menndez, M. (2016). “Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia”. J*ournal of Development Economics, Vol. 118, pp. 26-44.*

Helmer, M and Hilhorst, D. (2006).“Natural disasters and climate change”. *Disasters, 30(1), 1-4.*

Hilker, N., Badoux, A., and Hegg, C. (2009). “The Swiss flood and landslide damage database 1972-2007”. *Nat. Hazards Earth Syst. Sci, 9(3), 913-925.*

Hornbeck, R. (2012). “The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe”. *The American Economic Review, 102(4), 1477-1507.*

Hornbeck, R., and Keskin, P. (2014). “The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought”. *American Economic Journal: Applied Economics, 6(1), 190-219.*

Hsiang, S. M. (2010). “Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America”. *Proceedings of the National Academy of Sciences, 107(35), 15367-15372.*

Hsiang, S. M., and Jina, A. S. (2014). “The causal effect of environmental catastrophe on long-run economic growth: evidence from 6,700 cyclones”. *National Bureau of Economic Research, w20352).*

Kahn, Matthew E. 2005. “The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions”. *The Review of Economics and Statistics 87(2): 271-284.*

Kirchberger, M. (2013). “Natural disasters and labor markets.” *Unpublished manuscript, Department of Economics, University of Oxford.*

Kurosaki, Takashi (2015). “Vulnerability of household consumption to floods and droughts in developing countries: evidence from Pakistan”. *Environment and Development Economics, 20, 209-235.*

Kwasinski, A., Weaver, W. W., Chapman, P. L., and Krein, P. T. (2009). “Telecommunications power plant damage assessment for hurricane katrina-site survey and follow-up results”. *IEEE Systems Journal, 3(3), 277-287.*

Leon, G. (2012). "Civil conflict and human capital accumulation the long-term effects of political violence in Peru". *Journal of Human Resources, 47(4), 991-1022.*

Longo, B. M., and Yang, W. (2008). "Acute bronchitis and volcanic air pollution: a community-based cohort study at Kilauea Volcano, Hawaii, USA". *Journal of Toxicology and Environmental Health, Part A, 71(24), 1565-1571.*

Maccini, S., and Yang, D. (2009). "Under the weather: Health, schooling, and economic consequences of early-life rainfall". *The American Economic Review, 1006-1026.*

Mardero, S., Schmook, B., Radel, C., Christman, Z., Lawrence, D., Millones, M., Nickl, E., Rogan, J. and Schneider, L. (2015). "Smallholders adaptations to droughts and climatic variability in southeastern Mexico". *Environmental Hazards, 14(4), 271-288.*

Maluccio, J. A., Hoddinott, J., Behrman, J. R., Martorell, R., Quisumbing, A. R., and Stein, A. D. (2009). "The Impact of Improving Nutrition During Early Childhood on Education among Guatemalan Adults". *The Economic Journal,119(537), 734-763.*

Martorell, Reynaldo and Habicht, Jean-Pierre, (1986). "Growth in early childhood in developing countries". In: Falkner, F., Tanner, J. (Eds.), *Human Growth: A Comprehensive Treatise. Plenum Press, New York.*

Mimura, N., Yasuhara, K., Kawagoe, S., Yokoki, H., and Kazama, S. (2011). "Damage from the Great East Japan Earthquake and Tsunami-a quick report". *Mitigation and Adaptation Strategies for Global Change, 16(7), 803-818.*

Moulton, Brent, (1986). "Random group effects and the precision of regression estimates". *Journal of Econometrics 32 (3), 385397.*

Nadal, N. C., Zapata, R. E., Pagan, I., Lopez, R., and Agudelo, J. (2009). "Building damage due to riverine and coastal floods". *Journal of Water Resources Planning and Management, 136(3), 327-336.*

Neild, J., O'Flaherty, P., Hedley, P., Underwood, R., Johnston, D., Christenson, B., and Brown, P. (1998). "Impact of a volcanic eruption on agriculture and forestry in New Zealand". M*AF policy technical paper, 99(2), 101.*

Neumayer, E., and Plmper, T. (2007). "The gendered nature of natural disasters: The impact of catastrophic events on the gender gap in life expectancy, 19812002". *Annals of the Association of American Geographers, 97(3), 551-566.*

Noji, E. K. (1997). "The public health consequences of disasters". *Oxford University Press.*

Noy, I. (2009). "The macroeconomic consequences of disasters". *Journal of Development Economics, 88(2), 221-231.*

Ohl, C. A., and Tapsell, S. (2000). "Flooding and human health: the dangers posed are not always obvious". *British Medical Journal, 321(7270), 1167-1167.*

Padgett, J., DesRoches, R., Nielson, B., Yashinsky, M., Kwon, O. S., Burdette, N., and Tavera, E. (2008). "Bridge damage and repair costs from Hurricane Katrina". *Journal of Bridge Engineering, 13(1), 6-14.*

Prestemon, J. P., and Holmes, T. P. (2000). "Timber price dynamics following a natural catastrophe". *American Journal of Agricultural Economics, 82(1), 145-160.*

Reed, D. A., Powell, M. D., and Westerman, J. M. (2010). "Energy infrastructure damage analysis for hurricane Rita". *Natural Hazards Review,11(3), 102-109.*

Rodriguez-Oreggia, E., de la Fuente, A., de la Torre, R., Moreno, H., and Rodriguez, C. (2013). "The impact of natural disasters on human development and poverty at the municipal level in Mexico". *Journal of Development Studies, 49(3), 442-455.*

Sahin, S. (2011). "Estimation of disasters economic impact in 1990-2007: global perspectives".*Washington DC: World Bank.*

Samadzadegan, F., and Zarrinpanjeh, N. (2008). "Earthquake destruction assessment of urban roads network using satellite imagery and fuzzy inference systems". *The international archives of the photogrammetry, remote sensing and spatial information sciences, 37(B8), 409-414.*

Santos, I. (2007). "Disentangling the effects of natural disasters on children: 2001 earthquakes in El Salvador". *Kennedy School of Government, Harvard University*

Shah, M., and Steinberg, B. M. (2016). "Drought of Opportunities: Contemporaneous and Long-Term Impacts of Rainfall Shocks on Human Capital". *Forthcoming in Journal of Political Economy.*

Smith, T. E. (1989). "Mother and Father Differences in Parental Influence on School Grades and Educational Goals". *Sociological Inquiry, 59(1), 88-98.*

Skidmore, M., and Toya, H. (2002) "Do Natural Disasters Promote Long-Run Growth?". *Economic Inquiry 40(4): 664-687.*

Skidmore, M., and Toya, H. (2007) "Economic development and the impacts of natural disasters". *Economics Letters 94(1): 20-25*

Skoufias, E., and Vinha, K. (2013). “The impacts of climate variability on household welfare in rural Mexico”. *Population and Environment, 34(3), 370-399.*

Soto-Martinez, M., and Sly, P. (2009). “Relationship between environmental exposures in children and adult lung disease: the case for outdoor exposures”. *Chronic respiratory disease.*

Stein, Z.; Susser, M.; Saenger, G. and Marolla, F. (1975). “Famine and Human Development: The Dutch Hunger Winter of 1944 1945”. *Oxford Press, New York.*

Stein, A. D., Barnhart, H. X., Hickey, M., Ramakrishnan, U., Schroeder, D. G., and Martorell, R. (2003). “Prospective study of protein-energy supplementation early in life and of growth in the subsequent generation in Guatemala”. *The American journal of clinical nutrition, 78(1), 162-167.*

Strauss, J. and, Thomas, D. (2008). “Health over the life course”. In: Schultz, Paul, Strauss, John (Eds.), *Handbook of Development Economics, Vol. 4. North-Holland, Amsterdam, pp. 33753474.*

Strobl, E. (2012). “The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean districts”. *Journal of Development Economics 97(1): 130-141.*

UNISDR (2009). “UNISDR Terminology for Disaster Risk Reduction”.United Nations International Strategy for Disaster Reduction (UNISDR). *Geneva, Switzerland.*

Ureta, M. (2005). “Hurricane Mitch, family budgets and schooling in Nicaragua”. *In InterAmerican Development Bank conference on remittances, February (Vol. 10).*

Van Aalst, M. K. (2006). “The impacts of climate change on the risk of natural disasters”. *Disasters, 30(1), 5-18.*

Walsh, R. P., Ellison, S., Los, S. O., Bidin, K., Sayer, A. M., and Tussin, A. M. (2013). “Changes in large rainstorm magnitudefrequency over the last century in Sabah, Malaysian Borneo and their geomorphological implications”. *The Holocene*, 23(12), 1824-1840.

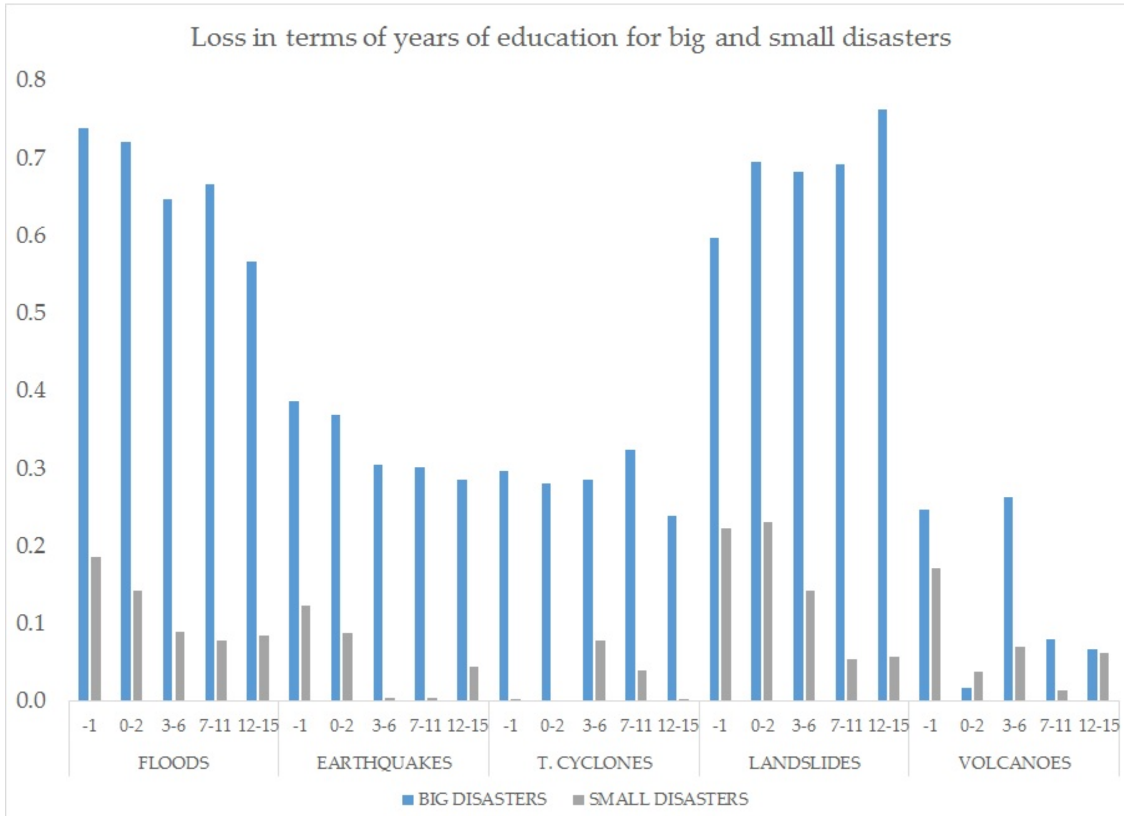
Watson, J. T., Gayer, M., and Connolly, M. A. (2007). “Epidemics after natural disasters”. *Emerging infectious diseases, 13(1), 1.*

Webster, P. J., Holland, G. J., Curry, J. A., and Chang, H. R. (2005). “Changes in tropical cyclone number, duration, and intensity in a warming environment”. *Science*, 309(5742), 1844-1846.

Wyss, M. (2001). “Why is earthquake prediction research not progressing faster?”. *Tectonophysics, 338(3), 217-223.*

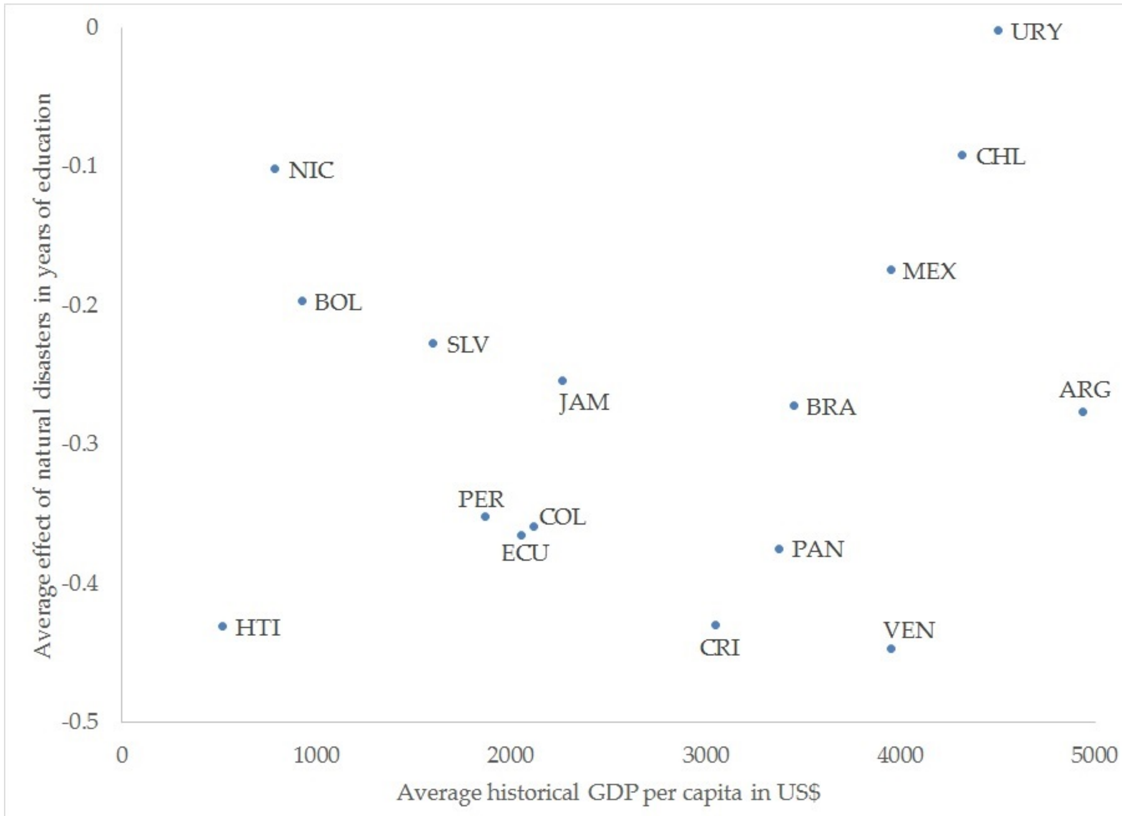
World Bank (2017). “Shaking Up Economic Progress”. *Washington, DC.*

Figure 1: Loss in years of education for each age range and disaster type - Big and Small Disasters



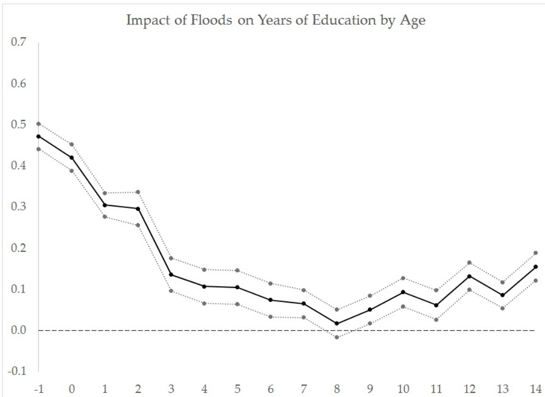
Notes: Author's calculations of the absolute value of the loss in terms of years of education are based on the estimation of the main model by the size of each natural disaster. Natural disasters above and below the mean number of affected individuals are classified as big and small natural disasters, respectively.

Figure 2: Average effect in years of education by Average GDP per capita

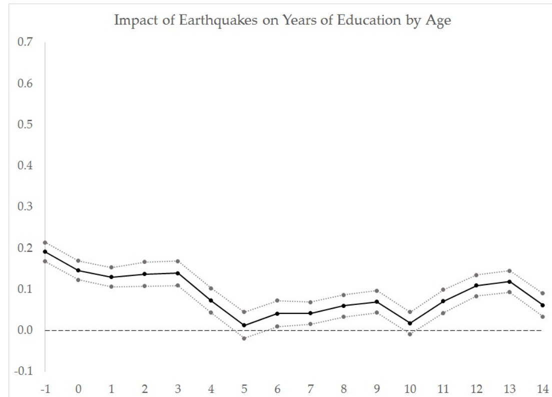


Notes: Author's calculations of the average effect in terms of years of education are based on the effect for individuals exposed between the in utero period and the first fifteen years of life. Average GDP per capita is calculated as the mean of the GDP per capita from 1960 to 2010 from World Development Indicators.

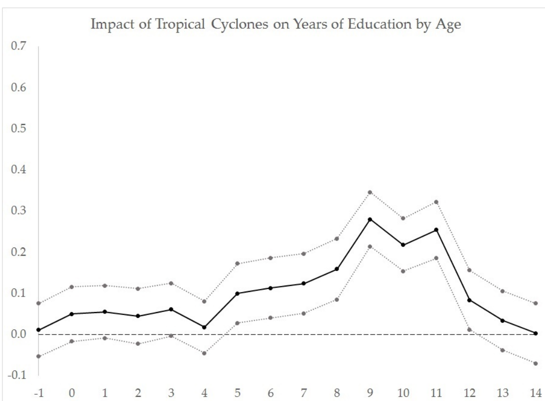
Figure 3: Negative Impact of Natural Disasters on Education



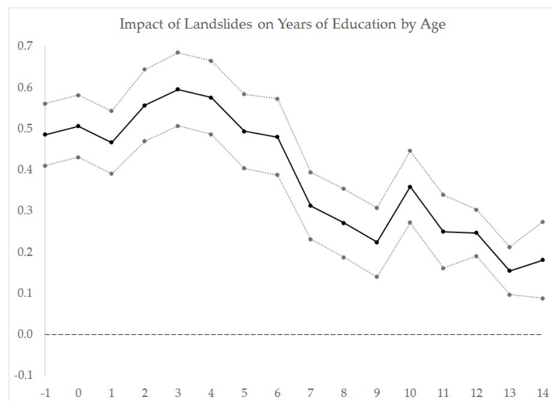
(a) Floods



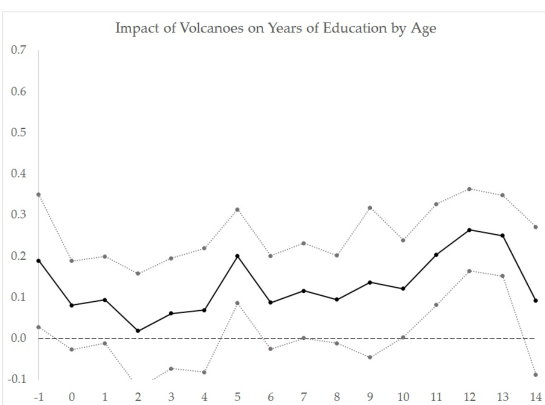
(b) Earthquakes



(c) T. Cyclones



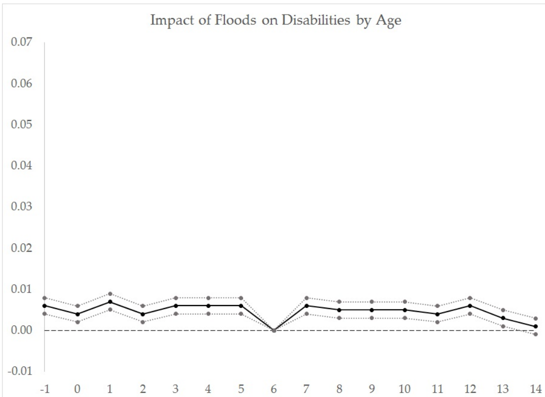
(d) Landslides



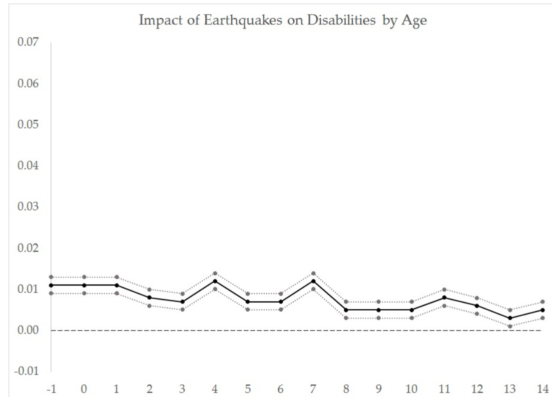
(e) Volcanoes

Notes: Author's estimations of the absolute value of the loss in terms of years of education. The solid line represents the estimated coefficients while the dotted line represents the confidence interval at 95% level.

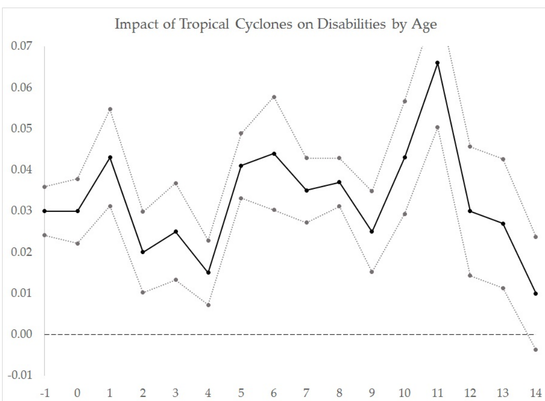
Figure 4: Negative Impact of Natural Disasters on Health



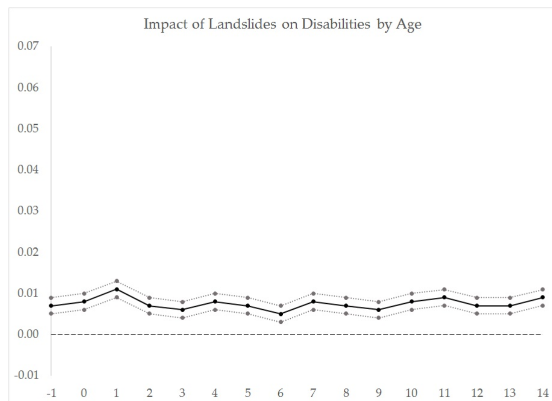
(a) Floods



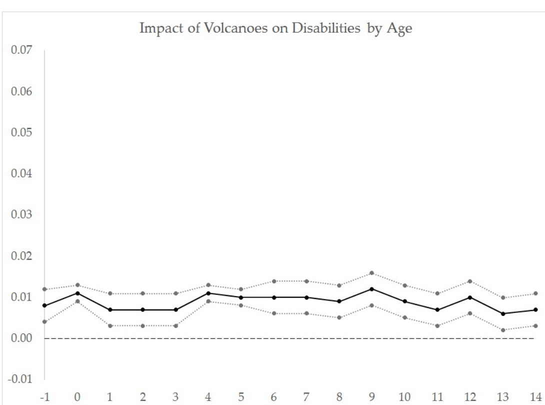
(b) Earthquakes



(c) T. Cyclones



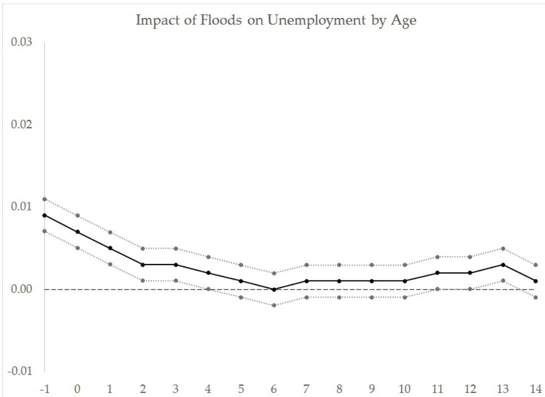
(d) Landslides



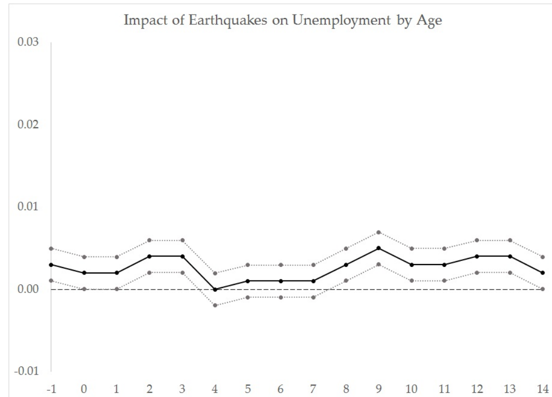
(e) Volcanoes

Notes: Author's estimations of the absolute value of the loss in terms of probability of being disabled. The solid line represents the estimated coefficients while the dotted line represents the confidence interval at 95% level.

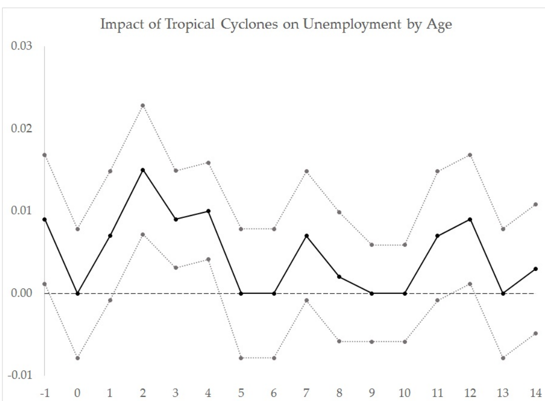
Figure 5: Negative Impact of Natural Disasters on Unemployment



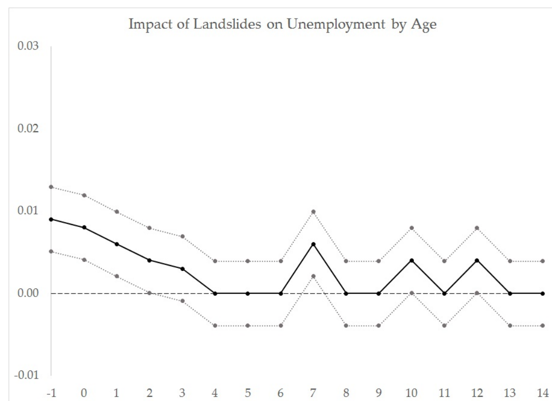
(a) Floods



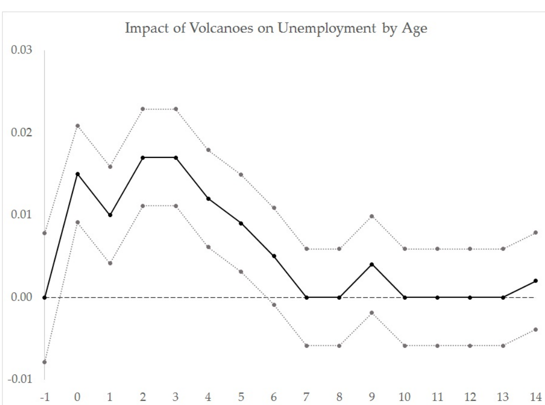
(b) Earthquakes



(c) T. Cyclones



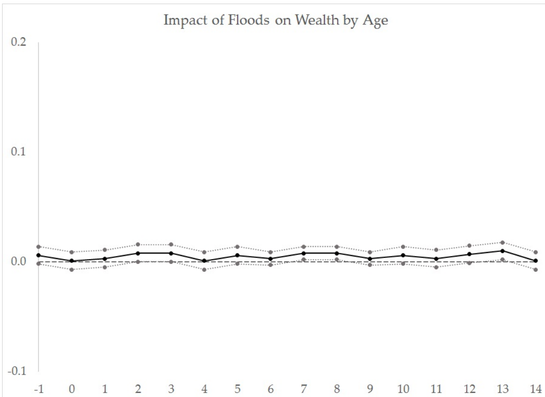
(d) Landslides



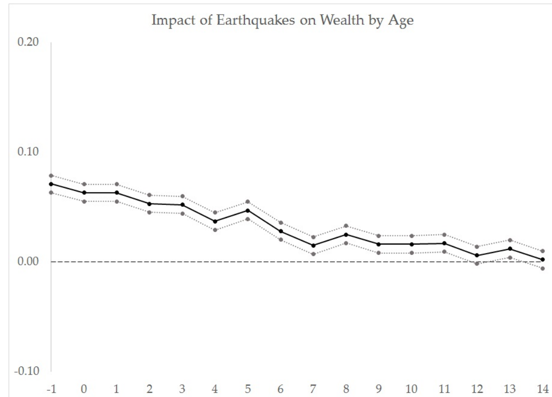
(e) Volcanoes

Notes: Author's estimations of the absolute value of the loss in terms of the probability of being unemployed. The solid line represents the estimated coefficients while the dotted line represents the confidence interval at 95% level.

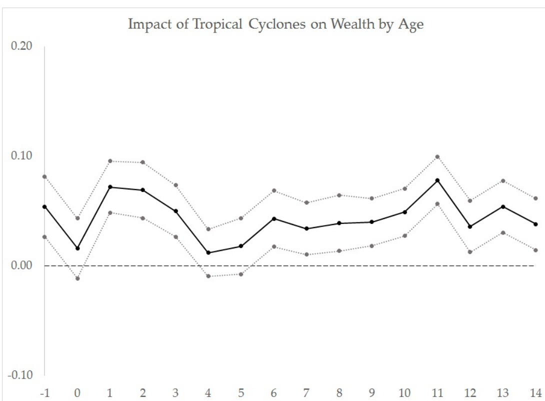
Figure 6: Negative Impact of Natural Disasters on Wealth



(a) Floods

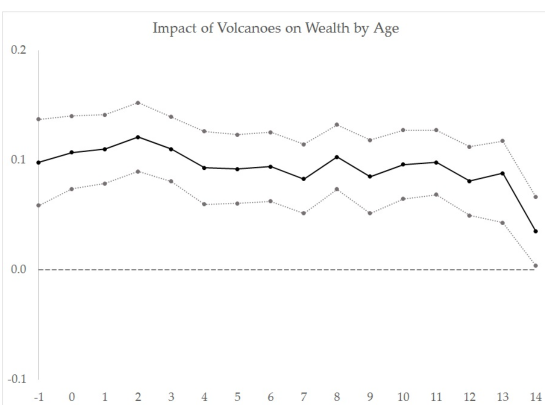


(b) Earthquakes



(c) T. Cyclones

(d) Landslides



(e) Volcanoes

Notes: Author's estimations of the absolute value of the loss in terms of the wealth index. The solid line represents the estimated coefficients while the dotted line represents the confidence interval at 95% level.

Table 1: Disasters Characteristics

Variables	Observations	1^{st} quartile	Mean	3^{rd} quartile	SD	CV	Skewness	Kurtosis
Floods	**419**							
Killed		9	158	54	1,701	11	17	305
Affected		2,235	127,160	54,116	546,226	4	8	71
Damage		2	168	100	442	3	5	29
Hurricanes	**190**							
Killed		4	158	60	550	3	6	47
Affected		1,110	113,129	72,000	286,959	3	4	20
Damage		3	243	180	657	3	5	35
Earthquakes	**177**							
Killed		6	1,231	185	6,313	5	8	82
Affected		468	149,431	38,708	485,488	3	4	21
Damage		5	265	165	631	2	4	22
Landslides	**124**							
Killed		22	144	100	496	3	8	80
Affected		117	92,600	6,000	535,355	6	7	52
Damage		1	212	400	330	2	1	4
Volcanos	**44**							
Killed		3	1,510	100	5,421	4	4	14
Affected		1,950	35,440	32,750	71,027	2	3	11
Damage		4	163	134	343	2	2	6
Total	**954**							
Killed		8	397	78	3,155	8	15	286
Affected		1,100	121,145	45,238	477,746	4	8	71
Damage		3	212	132	548	3	5	34

Notes: This table contains all the natural disasters included in this study. Variables "killed" and "affected" measure the number of people killed and affected by each natural disaster, respectively. Damage is measured in millions USD. More information on these variables can be found in the data section. In particular, this study includes all the natural disasters occurring during the 20^{th} century in Argentina, Bolivia, Brazil, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela. Data source: EM-DAT and DESINVENTAR.

Table 2: Balance Between Affected and Non-Affected Districts

Variables	Affected district (1)	Control district (2)	Mean Difference (3)
Panel A: Adult Characteristics			
Years of Education	7.126	6.588	0.538*
	(0.239)	(0.193)	(0.307)
Employment Disabilities	0.020	0.024	-0.004***
	(0.001)	(0.001)	(0.002)
Fertility (Number of children)	1.699	1.763	-0.063
	(0.035)	(0.044)	(0.057)
Unemployment	0.094	0.089	0.006
	(0.009)	(0.007)	(0.011)
Panel B: Household Characteristics			
Wealth index	0.041	-0.178	0.219**
	(0.074)	(0.056)	(0.093)
Asset Poverty	0.825	0.846	-0.022
	(0.018)	(0.015)	(0.024)
Land Ownership	0.751	0.735	0.016
	(0.011)	(0.014)	(0.018)
Access to Current Water	0.176	0.092	0.084***
	(0.035)	(0.034)	(0.049)
Access to Electricity	0.917	0.857	0.059***
	(0.008)	(0.017)	(0.019)
Panel C: Child Characteristics			
Years of Education for children 5 to 20	8.887	8.007	0.880***
	(0.176)	(0.240)	(0.297)
Years of Education for children 15 to 20	9.116	8.649	0.467
	(0.543)	(0.153)	(0.564)
Enrollment for children 5 to 20	0.294	0.311	-0.016
	(0.013)	(0.011)	(0.018)
Child Labor for children 5 to 15	0.203	0.198	0.005
	(0.024)	(0.026)	(0.036)

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The adult characteristics include all individuals older than 20 years while the child characteristics include all the individuals younger than 21 years. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 3: Long-term Effects of Big Natural Disasters on Years of Education

Dependent Variable: Years of education	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Exposed in utero	-0.590***	-0.336***	-0.191***	-0.534***	-0.247***
	(0.021)	(0.035)	(0.036)	(0.021)	(0.065)
Exposed at age 0-1	-0.578***	-0.309***	-0.162***	-0.589***	0.017
	(0.021)	(0.035)	(0.036)	(0.021)	(0.065)
Exposed at age 1-2	-0.504***	-0.259***	-0.131***	-0.581***	-0.263***
	(0.022)	(0.036)	(0.036)	(0.021)	(0.023)
Exposed at age 2-3	-0.476***	-0.236***	-0.182***	-0.588***	-0.079***
	(0.022)	(0.036)	(0.036)	(0.021)	(0.029)
Exposed at age 3-4	-0.372***	-0.213***	-0.203***	-1.534***	-0.067**
	(0.055)	(0.036)	(0.036)	(0.035)	(0.028)
Exposed at age 4-5	-0.261***	-0.170***	-0.120***	-1.239***	-0.082***
	(0.026)	(0.036)	(0.036)	(0.036)	(0.028)
Exposed at age 5-6	-0.116***	-0.040**	-0.095***	-1.486***	-0.357***
	(0.036)	(0.019)	(0.036)	(0.038)	(0.053)
Exposed at age 6-7	-0.095***	-0.112***	-0.226***	-0.627***	-0.140***
	(0.036)	(0.027)	(0.028)	(0.040)	(0.028)
Exposed at age 7-8	-0.072***	-0.139***	-0.164***	-0.401***	-0.118***
	(0.027)	(0.027)	(0.026)	(0.065)	(0.028)
Exposed at age 8-9	-0.068**	-0.163***	-0.183***	-0.355***	-0.112***
	(0.027)	(0.026)	(0.036)	(0.072)	(0.029)
Exposed at age 9-10	-0.058**	-0.176***	-0.299***	-0.314***	-0.141***
	(0.023)	(0.026)	(0.035)	(0.076)	(0.032)
Exposed at age 10-11	-0.096***	-0.199***	-0.278***	-0.421***	-0.123***
	(0.027)	(0.026)	(0.035)	(0.071)	(0.031)
Exposed at age 11-12	-0.041*	-0.176***	-0.286***	-0.391***	-0.297***
	(0.023)	(0.026)	(0.035)	(0.070)	(0.032)
Exposed at age 12-13	-0.110***	-0.250***	-0.085**	-0.346***	-0.282***
	(0.043)	(0.026)	(0.036)	(0.070)	(0.052)
Exposed at age 13-14	-0.077*	-0.214***	-0.044**	-0.205***	-0.241***
	(0.043)	(0.026)	(0.019)	0.0664766	(0.053)
Exposed at age 14-15	-0.100***	-0.142***	-0.097***	-0.209***	-0.127***
	(0.013)	(0.027)	(0.036)	0.0674766	(0.036)
Observations	24,079,057	24,079,057	24,079,057	24,079,057	24,079,057

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. The natural disasters included in these regressions are those that affect more individuals than the average number of affected individuals of each natural disaster type. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Natural disasters above and below the median number of affected individuals are classified as big and small natural disasters, respectively. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 4: Long-term Effects of Small Natural Disasters on Years of Education

Dependent Variable: Years of education	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Exposed in utero	-0.191***	-0.126***	-0.004	-0.224**	-0.176***
	(0.009)	(0.007)	(0.006)	(0.093)	(0.027)
Exposed at age 0-1	-0.149***	-0.096***	-0.003	-0.393***	-0.035
	(0.009)	(0.007)	(0.006)	(0.017)	(0.026)
Exposed at age 1-2	-0.145***	-0.104***	-0.002	-0.062	0.077
	(0.009)	(0.007)	(0.010)	(0.100)	(0.065)
Exposed at age 2-3	-0.141***	-0.069***	0.003	-0.241***	0.071
	(0.009)	(0.008)	(0.009)	(0.022)	(0.075)
Exposed at age 3-4	-0.133***	-0.038***	0.120	-0.078***	0.084
	(0.008)	(0.008)	(0.355)	(0.024)	(0.083)
Exposed at age 4-5	-0.101***	0.131	0.187	-0.211***	0.123
	(0.008)	(0.085)	(0.259)	(0.023)	(0.634)
Exposed at age 5-6	-0.099***	0.025	-0.009	-0.124***	-0.023
	(0.008)	(0.082)	(0.010)	(0.023)	(0.028)
Exposed at age 6-7	-0.040	-0.101	0.021	-0.171***	0.099
	(0.104)	(0.091)	(0.037)	(0.024)	(0.097)
Exposed at age 7-8	0.083	0.125	-0.042***	-0.097***	-0.068
	(0.104)	(0.085)	(0.010)	(0.018)	(0.065)
Exposed at age 8-9	0.142	0.017	-0.022*	-0.042**	0.042
	(0.104)	(0.082)	(0.011)	(0.018)	(0.067)
Exposed at age 9-10	0.009	-0.104	-0.045***	-0.087***	0.245
	(0.009)	(0.091)	(0.011)	(0.019)	(0.205)
Exposed at age 10-11	0.137	0.033	-0.036***	-0.012	-0.108***
	(0.085)	(0.082)	(0.011)	(0.019)	(0.049)
Exposed at age 11-12	0.028	-0.058***	-0.063***	-0.047**	-0.187***
	(0.082)	(0.008)	(0.011)	(0.020)	(0.030)
Exposed at age 12-13	-0.097***	-0.073***	0.012	-0.066***	-0.207***
	(0.009)	(0.008)	(0.011)	(0.014)	(0.031)
Exposed at age 13-14	-0.086***	-0.042***	-0.017	-0.058***	-0.142***
	(0.009)	(0.008)	(0.011)	(0.014)	(0.028)
Exposed at age 14-15	-0.078***	-0.024***	0.014	-0.059***	0.140
	(0.009)	(0.008)	(0.011)	(0.018)	(0.113)
Observations	24,079,057	24,079,057	24,079,057	24,079,057	24,079,057

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. The natural disasters included in these regressions are those that affect fewer individuals than the average number of affected individuals of each natural disaster type. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Natural disasters above and below the median number of affected individuals are classified as big and small natural disasters, respectively. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 5: Natural Disasters' Impacts in SD for in utero exposure

Outcome	(1) Floods	(2) Earthquakes	(3) T. Cyclones	(4) Landslides	(5) Volcanos
Years of education	-0.099***	-0.040***	-0.003	-0.102***	-0.040**
Employment disability	0.048***	0.088***	0.240***	0.056***	0.064***
Unemployment	0.031***	0.010***	0.031**	0.031***	-0.021
Wealth	-0.006	-0.065***	-0.049***	-0.033***	-0.089***

Notes: Impact expressed in standard deviations. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 6: Intergenerational Transmission of Exposure of Mothers to Natural Disasters on Children's Years of Education

Dependent Variable: Years of education	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Mother's Exposure in utero	-0.478***	-0.193***	-0.076	0.039	-0.086
	(0.017)	(0.013)	(0.047)	(0.057)	(0.154)
Mother's Exposure at age 0-1	-0.090***	-0.230***	-0.063***	-0.203***	-0.212**
	(0.005)	(0.010)	(0.005)	(0.018)	(0.094)
Mother's Exposure at age 1-2	-0.101***	-0.184***	-0.049***	-0.086**	-0.226
	(0.004)	(0.011)	(0.004)	(0.044)	(0.162)
Mother's Exposure at age 2-3	-0.094***	-0.139***	-0.044***	-0.093**	-0.024
	(0.004)	(0.011)	(0.004)	(0.044)	(0.206)
Mother's Exposure at age 3-4	-0.100***	-0.011**	-0.040***	-0.053*	-0.047
	(0.004)	(0.005)	(0.002)	(0.032)	(0.035)
Mother's Exposure at age 4-5	-0.048***	0.008	-0.108***	-0.158***	-0.096***
	(0.004)	(0.008)	(0.007)	(0.014)	(0.031)
Mother's Exposure at age 5-6	-0.105***	-0.064***	-0.295***	-0.100***	0.058
	(0.004)	(0.008)	(0.015)	(0.028)	(0.037)
Mother's Exposure at age 6-7	-0.022***	-0.012***	0.002	-0.123***	0.064
	(0.001)	(0.004)	(0.001)	(0.029)	(0.040)
Mother's Exposure at age 7-8	-0.077***	-0.014***	-0.178***	-0.024	0.013
	(0.004)	(0.004)	(0.015)	(0.023)	(0.040)
Mother's Exposure at age 8-9	-0.073***	-0.016***	-0.038***	-0.090***	-0.127***
	(0.004)	(0.004)	(0.013)	(0.013)	(0.026)
Mother's Exposure at age 9-10	-0.078***	0.005	-0.736***	-0.052**	-0.061
	(0.005)	(0.003)	(0.173)	(0.022)	(0.211)
Mother's Exposure at age 10-11	-0.028***	-0.016***	-0.120	-0.016	-0.110**
	(0.004)	(0.004)	(0.082)	(0.024)	(0.043)
Mother's Exposure at age 11-12	-0.007	-0.060***	-0.454***	-0.103***	0.183
	(0.004)	(0.004)	(0.087)	(0.025)	(0.355)
Mother's Exposure at age 12-13	-0.056***	-0.002***	-0.008	0.079***	-0.094***
	(0.004)	(0.000)	(0.011)	(0.013)	(0.029)
Mother's Exposure at age 13-14	-0.002	-0.002***	0.006	-0.029*	-0.021
	(0.004)	(0.000)	(0.008)	(0.016)	(0.025)
Mother's Exposure at age 14-15	-0.023**	-0.002***	-0.051*	-0.085***	0.174
	(0.009)	(0.000)	(0.030)	(0.026)	(0.239)
Observations	9,570,450	9,570,450	9,570,450	9,570,450	9,570,450

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 5 and younger than 20 years old. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 7: Intergenerational Transmission of Exposure of Fathers to Natural Disasters on Children's Years of Education

Dependent Variable: Years of education	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Father's Exposure in utero	-0.020***	-0.017***	-0.053***	-0.004**	-0.007*
	(0.001)	(0.001)	(0.003)	(0.001)	(0.004)
Father's Exposure at age 0-1	-0.019***	-0.014***	-0.053***	0.000	-0.009**
	(0.001)	(0.001)	(0.003)	(0.002)	(0.004)
Father's Exposure at age 1-2	-0.011***	-0.012***	-0.056***	-0.003**	0.004
	(0.001)	(0.001)	(0.003)	(0.001)	(0.004)
Father's Exposure at age 2-3	-0.010***	-0.007***	-0.057***	0.002	-0.005
	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)
Father's Exposure at age 3-4	-0.010***	-0.006***	-0.052***	-0.002*	-0.011***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)
Father's Exposure at age 4-5	-0.013***	-0.003***	-0.061***	-0.002	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 5-6	-0.009***	-0.003***	-0.041***	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 6-7	-0.012***	0.000	-0.036***	-0.004***	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 7-8	-0.004***	-0.002**	-0.033***	-0.006***	-0.017***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 8-9	-0.002***	-0.002***	-0.027***	-0.011***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 9-10	-0.009***	0.002***	-0.032***	-0.012***	-0.007**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 10-11	-0.008***	-0.001	-0.021***	-0.008***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 11-12	-0.006***	0.001	-0.023***	-0.009***	-0.014***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 12-13	-0.007***	0.002***	-0.022***	-0.012***	-0.008***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 13-14	-0.003***	0.005***	-0.016***	-0.004***	-0.010***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Father's Exposure at age 14-15	-0.006***	0.005***	-0.015***	-0.014***	-0.005*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Observations	9,570,450	9,570,450	9,570,450	9,570,450	9,570,450

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 5 and younger than 20 years old. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 8: Long-term Effects of Natural Disasters Exposure on Years of Education
Standardized by the Number of Affected Individuals

Dependent Variable: Years of Education	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Intensity of Exposure in utero	-0.044***	-0.072***	-0.005	-0.032***	-0.036
	(0.007)	(0.006)	(0.004)	(0.011)	(0.236)
Intensity of Exposure at age 0-1	-0.060***	-0.075***	-0.009**	-0.062***	-0.032
	(0.007)	(0.006)	(0.004)	(0.010)	(0.021)
Intensity of Exposure at age 1-2	-0.050***	-0.054***	-0.007	-0.067***	-0.081***
	(0.008)	(0.006)	(0.004)	(0.011)	(0.022)
Intensity of Exposure at age 2-3	-0.049***	-0.042***	-0.003	-0.089***	-0.025
	(0.008)	(0.006)	(0.004)	(0.011)	(0.021)
Intensity of Exposure at age 3-4	-0.028***	-0.045***	-0.007	-0.067***	-0.015
	(0.008)	(0.006)	(0.004)	(0.011)	(0.021)
Intensity of Exposure at age 4-5	-0.034***	-0.018***	-0.008**	-0.070***	-0.003
	(0.008)	(0.006)	(0.004)	(0.011)	(0.021)
Intensity of Exposure at age 5-6	-0.031***	-0.031***	-0.029***	-0.085***	-0.012
	(0.008)	(0.006)	(0.004)	(0.011)	(0.019)
Intensity of Exposure at age 6-7	-0.030***	-0.023***	-0.028***	-0.100***	-0.020
	(0.008)	(0.006)	(0.004)	(0.012)	(0.021)
Intensity of Exposure at age 7-8	-0.005***	-0.002	-0.019***	-0.115***	-0.091
	(0.001)	(0.007)	(0.004)	(0.012)	(0.191)
Intensity of Exposure at age 8-9	-0.006***	-0.022***	-0.018***	-0.140***	-0.051***
	(0.001)	(0.007)	(0.004)	(0.013)	(0.020)
Intensity of Exposure at age 9-10	-0.007***	-0.004	-0.037***	-0.165***	-0.072***
	(0.001)	(0.007)	(0.005)	(0.013)	(0.020)
Intensity of Exposure at age 10-11	-0.008***	-0.007	-0.029***	-0.170***	-0.068***
	(0.001)	(0.007)	(0.004)	(0.013)	(0.020)
Intensity of Exposure at age 11-12	-0.006***	-0.016**	-0.032***	-0.140***	-0.036*
	(0.001)	(0.007)	(0.005)	(0.014)	(0.020)
Intensity of Exposure at age 12-13	-0.050***	-0.034***	-0.007	-0.142***	-0.026
	(0.009)	(0.007)	(0.005)	(0.015)	(0.021)
Intensity of Exposure at age 13-14	-0.009***	-0.035***	-0.006	-0.153***	-0.081***
	(0.001)	(0.007)	(0.005)	(0.015)	(0.020)
Intensity of Exposure at age 14-15	-0.069***	-0.065***	-0.009*	-0.122***	-0.034
	(0.009)	(0.007)	(0.005)	(0.015)	(0.021)
Observations	24,079,057	24,079,057	24,079,057	24,079,057	24,079,057

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 9: Long-term Effects of Natural Disasters Exposure on Years of Education Standardized by the Number of Killed Individuals

Dependent Variable: Years of Education	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Intensity of Exposure in utero	-0.119***	-0.036***	-0.032***	-0.098*	-0.043
	(0.042)	(0.003)	(0.002)	(0.006)	(0.087)
Intensity of Exposure at age 0-1	-0.061	-0.039***	-0.020***	0.090	-0.007**
	(0.040)	(0.003)	(0.004)	(0.006)	(0.003)
Intensity of Exposure at age 1-2	-0.007	-0.027***	-0.023***	-0.111*	-0.011***
	(0.041)	(0.004)	(0.003)	(0.059)	(0.003)
Intensity of Exposure at age 2-3	-0.046	-0.028***	-0.022***	-0.034**	-0.011***
	(0.042)	(0.004)	(0.004)	(0.006)	(0.003)
Intensity of Exposure at age 3-4	0.043	-0.019***	-0.024***	0.037	-0.006*
	(0.041)	(0.004)	(0.004)	(0.006)	(0.003)
Intensity of Exposure at age 4-5	0.065	-0.015***	-0.033***	-0.031**	-0.004
	(0.042)	(0.004)	(0.003)	(0.006)	(0.003)
Intensity of Exposure at age 5-6	-0.072*	-0.017***	-0.036***	-0.016**	-0.008
	(0.043)	(0.004)	(0.003)	(0.006)	(0.003)
Intensity of Exposure at age 6-7	-0.050	-0.001	-0.031***	-0.032**	0.001
	(0.044)	(0.004)	(0.032)	(0.063)	(0.003)
Intensity of Exposure at age 7-8	-0.049	-0.004	-0.031***	-0.036**	0.000
	(0.045)	(0.004)	(0.003)	(0.006)	(0.003)
Intensity of Exposure at age 8-9	-0.125***	-0.004	-0.028***	-0.028**	0.003
	(0.043)	(0.004)	(0.004)	(0.006)	(0.003)
Intensity of Exposure at age 9-10	-0.061	-0.023***	-0.034***	-0.056**	0.000
	(0.046)	(0.004)	(0.002)	(0.007)	(0.003)
Intensity of Exposure at age 10-11	-0.274***	-0.026***	-0.028***	-0.054**	-0.006
	(0.047)	(0.004)	(0.004)	(0.008)	(0.003)
Intensity of Exposure at age 11-12	-0.119***	-0.038***	-0.021***	-0.047**	-0.014***
	(0.046)	(0.005)	(0.003)	(0.007)	(0.003)
Intensity of Exposure at age 12-13	-0.066	-0.062***	-0.020***	-0.050**	-0.017***
	(0.047)	(0.005)	(0.003)	(0.008)	(0.003)
Intensity of Exposure at age 13-14	-0.246***	-0.044***	-0.024***	-0.031**	-0.016***
	(0.047)	(0.005)	(0.003)	(0.008)	(0.003)
Intensity of Exposure at age 14-15	-0.186***	-0.080***	-0.021***	-0.065**	-0.016***
	(0.048)	(0.005)	(0.003)	(0.008)	(0.003)
Observations	24,079,057	24,079,057	24,079,057	24,079,057	24,079,057

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 10: Long-term Effects of Natural Disasters Exposure on Years of Education
Standardized by the Damage in USD

Dependent Variable: Years of Education	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Intensity of Exposure in utero	-0.108***	-0.081***	-0.031***	-0.031***	-0.131
	(0.002)	(0.006)	(0.004)	(0.008)	(0.248)
Intensity of Exposure at age 0-1	-0.111***	-0.079***	-0.026***	-0.033***	-0.001**
	(0.002)	(0.006)	(0.004)	(0.009)	(0.001)
Intensity of Exposure at age 1-2	-0.096***	-0.056***	-0.022***	-0.017**	-0.002***
	(0.002)	(0.006)	(0.004)	(0.009)	(0.001)
Intensity of Exposure at age 2-3	-0.091***	-0.063***	-0.023***	0.007	-0.002***
	(0.002)	(0.006)	(0.005)	(0.081)	(0.001)
Intensity of Exposure at age 3-4	-0.071***	-0.057***	-0.022***	-0.026***	-0.001*
	(0.003)	(0.006)	(0.005)	(0.009)	(0.001)
Intensity of Exposure at age 4-5	-0.066***	-0.020***	-0.042***	-0.004	-0.001
	(0.003)	(0.006)	(0.004)	(0.088)	(0.001)
Intensity of Exposure at age 5-6	-0.068***	-0.024***	-0.035***	-0.026	-0.002***
	(0.003)	(0.007)	(0.005)	(0.010)	(0.001)
Intensity of Exposure at age 6-7	-0.057***	-0.040***	-0.026***	-0.012	0.000
	(0.003)	(0.006)	(0.005)	(0.011)	(0.001)
Intensity of Exposure at age 7-8	-0.068***	-0.034***	-0.028***	-0.013	0.000
	(0.003)	(0.006)	(0.005)	(0.010)	(0.001)
Intensity of Exposure at age 8-9	-0.055***	-0.044***	-0.024***	-0.013	-0.001
	(0.003)	(0.006)	(0.005)	(0.011)	(0.001)
Intensity of Exposure at age 9-10	-0.058***	-0.014**	-0.040***	0.006	0.000
	(0.003)	(0.006)	(0.004)	(0.110)	(0.001)
Intensity of Exposure at age 10-11	-0.049***	-0.026***	-0.025***	-0.094	-0.001*
	(0.003)	(0.006)	(0.006)	(0.114)	(0.001)
Intensity of Exposure at age 11-12	-0.046***	-0.005	-0.020***	-0.033	-0.003***
	(0.003)	(0.006)	(0.005)	(0.115)	(0.001)
Intensity of Exposure at age 12-13	-0.037***	-0.008	-0.019***	-0.011	-0.004***
	(0.003)	(0.006)	(0.006)	(0.011)	(0.001)
Intensity of Exposure at age 13-14	-0.033***	-0.003	-0.017***	-0.022*	-0.003***
	(0.003)	(0.007)	(0.005)	(0.012)	(0.001)
Intensity of Exposure at age 14-15	-0.032***	-0.019***	-0.015***	-0.019	-0.003***
	(0.003)	(0.006)	(0.005)	(0.013)	(0.001)
Observations	24,079,057	24,079,057	24,079,057	24,079,057	24,079,057

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table 11: Long-term Effects of Natural Disasters Exposure on Education and Health by Gender

Dependent Variable:	Male	Female	Male	Female
	Years of Education		Probability of disability	
	(1)	(2)	(3)	(4)
Exposed in utero	-0.271***	-0.307***	0.005***	0.009***
	(0.011)	(0.011)	(0.001)	(0.001)
Exposed at age 0-1	-0.237***	-0.216***	0.007***	0.010***
	(0.011)	(0.011)	(0.001)	(0.001)
Exposed at age 1-2	-0.225***	-0.204***	0.007***	0.009***
	(0.011)	(0.011)	(0.001)	(0.001)
Exposed at age 2-3	-0.218***	-0.203***	0.004***	0.006***
	(0.015)	(0.014)	(0.001)	(0.001)
Exposed at age 3-4	-0.170***	-0.177***	0.005***	0.004***
	(0.015)	(0.015)	(0.001)	(0.001)
Exposed at age 4-5	-0.136***	-0.095***	0.006***	0.008***
	(0.016)	(0.015)	(0.001)	(0.001)
Exposed at age 5-6	-0.061***	-0.068***	0.004***	0.006***
	(0.016)	(0.015)	(0.001)	(0.001)
Exposed at age 6-7	-0.076***	-0.072***	0.005***	0.006***
	(0.016)	(0.015)	(0.001)	(0.001)
Exposed at age 7-8	-0.013	-0.075***	0.005***	0.009***
	(0.013)	(0.013)	(0.001)	(0.001)
Exposed at age 8-9	-0.040***	-0.061***	0.004***	0.005***
	(0.013)	(0.013)	(0.001)	(0.001)
Exposed at age 9-10	-0.071***	-0.097***	0.003***	0.006***
	(0.013)	(0.013)	(0.001)	(0.001)
Exposed at age 10-11	-0.049***	-0.074***	0.005***	0.005***
	(0.013)	(0.013)	(0.001)	(0.001)
Exposed at age 11-12	-0.096***	-0.098***	0.004***	0.006***
	(0.014)	(0.014)	(0.001)	(0.001)
Exposed at age 12-13	-0.139***	-0.131***	0.004***	0.008***
	(0.013)	(0.013)	(0.001)	(0.001)
Exposed at age 13-14	-0.113***	-0.079***	0.003***	0.004***
	(0.013)	(0.013)	(0.001)	(0.001)
Exposed at age 14-15	-0.082***	-0.095***	0.004***	0.003***
	(0.015)	(0.014)	(0.001)	(0.001)
Observations	11,586,810	12,492,247	7,270,242	7,866,115

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. In this table all natural disasters are combined in the estimations for presentation reasons. However, the results are consistent for each separate disaster type. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

A.1 Data Appendix

A.1.1 Variable definition

The variables used in this paper are assembled for all LAC countries on an annual basis for the last census public available, whenever available.

- Years of Education: accounts for the number of years of study, regardless of the track or kind of study (Only formal schooling is counted).
- Unemployment: is a binary variable that takes value equal to one if the individual is unemployed (seeking work and without one) and zero otherwise.
- Disability: is a binary variable that takes value equal to one if the person reported being economically inactive because of disabilities of any kind and zero otherwise.
- Wealth: is an index elaborated as a result of a principal component analysis that includes household assets such as access to electricity, access to current water and land ownership.

A.2 Disaster Risk Management Terminology

This paper sticks to the terminology used in the literature. This terminology was developed in Latin America by ECLAC and nowadays refined by UNISDR. The literature distinguishes between damages (direct impacts) and losses (indirect impacts), and between natural disasters and separate disasters (which are not natural even if they are triggered by natural disasters). Below, the main terms are defined based on ECLAC (2003), Sahin (2011) and UNISDR(2009).

- Damages: These are defined as the direct effects produced by disasters. Concrete examples of these effects are the impact on physical capital stock.
- Losses: This are defined as the indirect effects produced by disasters. Concrete examples of these effects are business interruptions, destruction of the means of production, lack of inputs and increased transport cost.
- Hazard: A dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage.

- Natural Hazard: Natural process or phenomenon that may cause loss of life, injury or other health impacts, property damage, loss of livelihood and services, social and economic disruption, or environmental damage. Natural hazards are a sub-set of all hazards. The term is used to describe actual hazard events as well as the latent hazard conditions that may give rise to future events. Natural hazard events can be characterized by their magnitude or intensity, speed of onset, duration, and area of extent. For example, earthquakes have short durations and usually affect a relatively small region, whereas droughts are slow to develop and fade away and often affect large regions. In some cases hazards may be coupled, as in the flood caused by a tropical cyclone or the tsunami that is created by an earthquake.

- Disasters: A serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts that exceed the ability of the affected community or society to cope using its own resources. Disasters are often described as the result of a combination of: exposure to a hazard; the conditions of vulnerability that are present; and insufficient capacity or measures to reduce or cope with the potential negative consequences. Disaster impacts may include loss of life, injury, disease and other negative effects on human physical, mental and social well-being, together with damage to property, destruction of assets, loss of services, social and economic disruption and environmental degradation.

Table A.1: Long-term Effects of Natural Disasters Exposure on Fertility of the Head of Household

Dependent Variable: Number of children	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Exposed in utero	-0.083***	-0.099***	0.011	-0.072***	0.025
	(0.005)	(0.006)	(0.020)	(0.011)	(0.026)
Exposed at age 0-1	-0.065***	-0.126***	-0.023	-0.047***	0.014
	(0.005)	(0.006)	(0.018)	(0.011)	(0.022)
Exposed at age 1-2	-0.048***	-0.103***	-0.035**	-0.068***	-0.043**
	(0.005)	(0.006)	(0.018)	(0.011)	(0.021)
Exposed at age 2-3	-0.049***	-0.103***	0.011	-0.057***	-0.061***
	(0.005)	(0.006)	(0.018)	(0.011)	(0.021)
Exposed at age 3-4	-0.041***	-0.105***	-0.028*	-0.076***	-0.033*
	(0.005)	(0.006)	(0.017)	(0.011)	(0.020)
Exposed at age 4-5	-0.054***	-0.080***	-0.014	-0.103***	-0.054**
	(0.005)	(0.006)	(0.017)	(0.011)	(0.021)
Exposed at age 5-6	-0.041***	-0.075***	-0.041**	-0.081***	-0.042**
	(0.005)	(0.006)	(0.020)	(0.011)	(0.021)
Exposed at age 6-7	-0.043***	-0.078***	-0.022	-0.101***	-0.077***
	(0.005)	(0.006)	(0.019)	(0.011)	(0.020)
Exposed at age 7-8	-0.031***	-0.114***	-0.043**	-0.093***	0.032
	(0.005)	(0.006)	(0.020)	(0.011)	(0.020)
Exposed at age 8-9	-0.034***	-0.074***	-0.014	-0.112***	0.028
	(0.005)	(0.006)	(0.020)	(0.011)	(0.018)
Exposed at age 9-10	-0.038***	-0.062***	-0.031*	-0.114***	-0.087***
	(0.005)	(0.006)	(0.017)	(0.011)	(0.022)
Exposed at age 10-11	-0.034***	-0.064***	0.007	-0.114***	0.016
	(0.006)	(0.006)	(0.017)	(0.012)	(0.020)
Exposed at age 11-12	-0.031***	-0.056***	-0.033*	-0.118***	-0.053***
	(0.006)	(0.006)	(0.018)	(0.012)	(0.021)
Exposed at age 12-13	-0.030***	-0.066***	0.025	-0.091***	0.012
	(0.006)	(0.006)	(0.019)	(0.012)	(0.021)
Exposed at age 13-14	-0.022***	-0.048***	0.013	-0.111***	-0.009
	(0.006)	(0.007)	(0.019)	(0.012)	(0.020)
Exposed at age 14-15	-0.033***	-0.069***	0.014	-0.146***	-0.052**
	(0.006)	(0.007)	(0.020)	(0.012)	(0.022)
Observations	10,543,282	10,543,282	10,543,282	10,543,282	10,543,282

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals older than 20 years. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table A.2: Intergenerational Transmission of Exposure of Mothers to Natural Disasters on Child Labor

Dependent Variable: Child Labor	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Mother's Exposure in utero	0.012***	0.009*	0.039	0.036*	0.076*
	(0.005)	(0.005)	(0.028)	(0.021)	(0.039)
Mother's Exposure at age 0-1	-0.004	0.004	0.042	0.008	0.014
	(0.005)	(0.007)	(0.042)	(0.012)	(0.024)
Mother's Exposure at age 1-2	0.005	0.000	0.008	-0.015	-0.019
	(0.005)	(0.007)	(0.034)	(0.011)	(0.024)
Mother's Exposure at age 2-3	-0.006	0.005	-0.010	0.018*	-0.009
	(0.005)	(0.007)	(0.029)	(0.011)	(0.024)
Mother's Exposure at age 3-4	-0.004	0.010	0.063**	0.006	0.026
	(0.004)	(0.007)	(0.028)	(0.010)	(0.025)
Mother's Exposure at age 4-5	-0.004	0.007	0.031	0.021**	0.015
	(0.004)	(0.007)	(0.020)	(0.009)	(0.024)
Mother's Exposure at age 5-6	-0.004	0.007	-0.009	-0.001	0.014
	(0.004)	(0.006)	(0.020)	(0.009)	(0.023)
Mother's Exposure at age 6-7	0.004	0.008	0.034*	0.024***	0.002
	(0.004)	(0.006)	(0.018)	(0.009)	(0.022)
Mother's Exposure at age 7-8	-0.007	-0.001	0.051***	0.010	0.011
	(0.005)	(0.006)	(0.016)	(0.008)	(0.023)
Mother's Exposure at age 8-9	0.002	-0.001	0.058***	-0.003	0.020
	(0.004)	(0.006)	(0.016)	(0.008)	(0.026)
Mother's Exposure at age 9-10	-0.008	0.010	0.062***	-0.006	0.012
	(0.005)	(0.006)	(0.014)	(0.008)	(0.022)
Mother's Exposure at age 10-11	-0.007	-0.005	0.016	0.003	-0.018
	(0.005)	(0.004)	(0.013)	(0.008)	(0.021)
Mother's Exposure at age 11-12	0.001	0.009	0.043***	0.012	0.008
	(0.004)	(0.006)	(0.014)	(0.007)	(0.021)
Mother's Exposure at age 12-13	-0.002	-0.005	0.024*	-0.009	0.006
	(0.004)	(0.006)	(0.013)	(0.007)	(0.020)
Mother's Exposure at age 13-14	-0.003	0.004	-0.001	0.004	0.005
	(0.004)	(0.006)	(0.013)	(0.007)	(0.019)
Mother's Exposure at age 14-15	-0.004	0.006	0.000	0.006	-0.003
	(0.004)	(0.007)	(0.013)	(0.007)	(0.019)
Observations	528,790	528,790	528,790	528,790	528,790

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals younger than 16 years where child labor is a binary variable that takes value equal to one if the child works and zero otherwise. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.

Table A.3: Intergenerational Transmission of Exposure of Fathers to Natural Disasters on Child Labor

Dependent Variable: Child Labor	Floods (1)	Earthquakes (2)	T. Cyclones (3)	Landslides (4)	Volcanoes (5)
Father's Exposure in utero	-0.003	0.004	-0.014	0.030	-0.011
	(0.008)	(0.010)	(0.034)	(0.026)	(0.046)
Father's Exposure at age 0-1	0.005	0.010	0.045	-0.021	0.054
	(0.007)	(0.009)	(0.045)	(0.025)	(0.045)
Father's Exposure at age 1-2	-0.008	0.011	-0.025	-0.023	-0.017
	(0.007)	(0.009)	(0.044)	(0.024)	(0.036)
Father's Exposure at age 2-3	0.001	0.003	0.015	-0.011	0.007
	(0.006)	(0.009)	(0.051)	(0.018)	(0.043)
Father's Exposure at age 3-4	-0.004	0.006	0.014	-0.001	-0.019
	(0.006)	(0.008)	(0.045)	(0.021)	(0.038)
Father's Exposure at age 4-5	0.007	-0.003	0.029	0.018	0.030
	(0.005)	(0.008)	(0.028)	(0.019)	(0.041)
Father's Exposure at age 5-6	0.000	0.007	-0.038	0.004	-0.055
	(0.005)	(0.008)	(0.046)	(0.018)	(0.039)
Father's Exposure at age 6-7	0.004	0.005	0.005	0.030	0.020
	(0.005)	(0.008)	(0.038)	(0.019)	(0.036)
Father's Exposure at age 7-8	-0.004	0.008	0.035	0.010	0.004
	(0.005)	(0.008)	(0.036)	(0.017)	(0.023)
Father's Exposure at age 8-9	-0.005	0.007	-0.039	0.025	0.024
	(0.005)	(0.007)	(0.037)	(0.016)	(0.038)
Father's Exposure at age 9-10	-0.003	0.003	0.021	-0.002	-0.026
	(0.005)	(0.005)	(0.030)	(0.015)	(0.035)
Father's Exposure at age 10-11	-0.006	0.006	-0.035	0.007	-0.017
	(0.005)	(0.007)	(0.029)	(0.015)	(0.042)
Father's Exposure at age 11-12	-0.000	0.006	0.005	0.005	0.045
	(0.005)	(0.007)	(0.030)	(0.009)	(0.037)
Father's Exposure at age 12-13	0.003	0.007	-0.043	-0.020	-0.029
	(0.005)	(0.007)	(0.033)	(0.014)	(0.034)
Father's Exposure at age 13-14	0.000	0.008	-0.033	-0.002	-0.042
	(0.004)	(0.007)	(0.031)	(0.014)	(0.033)
Father's Exposure at age 14-15	-0.000	0.007	0.003	0.005	-0.039
	(0.004)	(0.007)	(0.015)	(0.008)	(0.033)
Observations	528,790	528,790	528,790	528,790	528,790

Notes: Robust standard errors in parentheses, clustered at the district level. *Significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include district fixed effects, cohort fixed effects, gender fixed effects and regional trends. The regressions are based on individuals younger than 16 years where child labor is a binary variable that takes value equal to one if the child works and zero otherwise. Data source: Last available National Censuses of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Haiti, Jamaica, Mexico, Nicaragua, Panama, Peru, Uruguay and Venezuela.