Reducing Disaster Risks through Education: Exploring the Mechanisms in Southeast Asia Using a Dynamic Household Model

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Abstract

In the past decades, the world has witnessed a substantial increase in the number of natural disasters imposing severe threats to human livelihoods. Scholars and policy makers have emphasized the important role of education and learning to strengthen preparedness and mitigating disaster risks. Despite this, we lack a theoretical and empirical understanding of why and how education can have a positive impact on resilience. Based on the empirical literature, we propose a dynamic household model, which distinguishes direct and indirect theoretical channels through which education effects operate. We test the model predictions using original data from two countries in Southeast Asia, the Philippines and Thailand, which belong to one of the most disaster-prone regions in the world. As predicted by the model, education is found to substantially reduce disaster risks, mainly by improving access to financial resources and by raising household members' awareness. Based on representative data for the two countries, we run simulations to further illustrate the insights from our theoretical model and to highlight the implications of our findings on the role of education in disaster risk reduction. The simulations also showcase the applicability of the model in predicting household behavior in the future under different scenarios.

JEL Codes: C12, C15, C21, C6, Q54, Q56

Keywords: disaster risk reduction, disaster resilience, education, household model, mechanisms, Southeast Asia, simulations

1 Introduction

In the last decades, many parts of the world were faced with an increase in the number of extreme weather events and worsening climatic conditions with negative impacts for local populations and their livelihoods (Hoffmann & Muttarak 2017; Black et al. 2011; Intergovernmental Panel on Climate Change 2014). Households in low- and middle-income countries are particularly vulnerable as they often lack resources and capacities to adapt to and cope with environmental hazards and shocks. In line with recent efforts of the international community to reduce disaster risks and vulnerabilities, this study analyzes the role of human capital, specifically formal education, in influencing household vulnerability, which refers to the household's ability to adequately prepare against, respond to and cope with hazardous events. To the best of our knowledge, our study is the first attempt to combine quantitative theoretical modeling with actual empirical data to study household vulnerability and disaster resilience in low and middle-income settings.

While various studies both from high as well as low and middle-income countries have reported a positive effect of education on disaster preparedness and vulnerability (Chankrajang & Muttarak 2017; Meyer 2015; Hoffmann & Muttarak 2017; Adger et al. 2012a), we still lack a good understanding, especially from a theoretical perspective, of how education can support disaster prevention efforts. To this end, this study develops a household lifecycle model, in which households face different environmental risks and hazards, which can lead to a potentially existential loss of their wealth. To respond to the risk, households can either relocate to a safer area or undertake preventive measures to protect their assets. Both actions require material and immaterial resources, which constrain the household's decision.

In the model, education can influence vulnerability through four major channels, which have been identified as relevant in the empirical literature: (i) Education can increase income levels and hence financial resources, which can be used to undertake costly precautionary measures; (ii) it can provide households with access to cost-efficient prevention measures, for example through social capital/networks; (iii) it can directly affect information, knowledge and awareness of disaster risks; and (iv) it can alter time preferences and strengthen the future orientation of household members (Paton & Johnston 1999; Drabo & Mbaye 2015; Nawrotzki et al. 2015; Lutz et al. 2014)

Original survey data from the Philippines and Thailand is used to test the model predictions and to estimate key parameters for the model calibration. The data, which was collected by the authors in household surveys, is specifically tailored to the purpose of this study. With their diverse socio-economic background and high exposure to disaster risks, the two emerging lower-middle income countries represent well-suited empirical testing grounds for the model.

In a final step, we employ simulations and policy experiments to study the role of education in shaping household disaster risks in different contexts and help to understand drivers of household decision making, which can be used to predict household behavior under different future scenarios. The simulations rely on real world data on the wealth and education distribution from the two country cases, Thailand and the Philippines. They allow us to showcase the applicability of the model and to explore and test for the effectiveness of different policy interventions for disaster risk reduction efforts. In particular, in our hypothetical simulations, we consider the effect of five commonly used disaster risk reduction measures/interventions (Shreve & Kelman 2014; Kelman 2015): (i) raising universal education in a population (elevator effect scenario), of (ii) improving general awareness levels (e.g. through media campaigns), of (iii) enhancing disaster trainings and drills at school, of (iv) facilitating access to cost-efficient means of prevention, and (v) introducing a damage compensation fund or disaster insurance.

Our results are not only of relevance from an academic point of view, but can also inform public policy and global prevention and resilience building efforts. Furthermore, our model also provides interesting insights in related fields of the literature, such as on environmental migration (Hunter et al. 2015; Obokata et al. 2014; Abel et al. 2019), environmentally induced poverty traps (Sachs et al. 2004; Ikefuji & Horii 2007; Dasgupta 1998), and environmental management (Selin & Chevez 1995).

The remainder of the paper is structured as follows. Section 2 provides an overview of the literature on education and disaster vulnerability and risks. Section 3 motivates and introduces the basic model and presents the optimization problem for the households. Section 4 introduces the data sets used to test the predictions of the model (Section 5) and to derive numerical parameters, which we use for our simulations (Section 6). The project is currently ongoing. As of now, the theoretical and empirical analysis are completed and we are now working on the simulations and policy experiments, which we want to finalize within the next months.

2 Education and Disaster Risk Reduction: The Empirical Evidence

There is a growing empirical literature on the relationship between education and disaster risks and vulnerability. Commonly, households with a lower socio-economic status and an on average lower education level are found to be more likely to reside in areas with higher disaster risk. This makes them more exposed to natural disasters in the first place (Adger et al. 2012b; Fothergill & Peek 2004). Given an elevated risk level, preparing against disasters and the undertaking of precautionary measures is crucial. Numerous studies report that education, be it formal or informal, increases individual and household preparedness, including preparedness for earthquakes (Russell et al. 1995), hurricanes (Baker et al. 2011; Norris et al. 1999; Reininger et al. 2013), floods (Lave & Lave 1991; Thieken et al. 2007), tsunami (Muttarak & Pothisiri 2013), as well as general emergency preparedness (Al-Rousan et al. 2014; Smith & Notaro 2009).

Similar findings are reported not only on individual but also on aggregate level in country comparisons (Pichler & Striessnig 2013). At the same time, better educated households are found to respond faster and more effectively, once a disaster strikes, e.g. by taking warnings more seriously and by evacuating faster (Sharma et al. 2013; Wamsler et al. 2012; Muttarak & Lutz 2014). Also in the aftermath of a disaster, education has been shown to positively influence the ability to cope with and adapt to shocks, among others in Indonesia (Frankenberg et al. 2013; I. et al. 2010) and Thailand (Garbero & Muttarak 2013).

While there is convincing evidence that education positively affects preparedness, prevention, and the ability to cope with hazards, the exact mechanisms explaining its positive effects on disaster vulnerability are not fully understood. Education effects can be distinguished in direct and indirect effects. Direct effects concern any immediate effects education has on an individual, such as improving her knowledge, awareness and beliefs about natural hazards. Indirect effects, on the other hand, refer to positive influences on (material, informational, and social) individual and household resources, which allow a better preparation against and adaptation to natural hazards and harmful environmental conditions. Our theoretical model takes both direct and indirect channels into consideration, which play a role in explaining education effects on disaster vulnerability.

With regard to direct channels of influence, studies show that education equips learners' with knowledge, cognitive abilities, and skills that are useful when it comes to preparing for the possibility of a disaster (Blair et al. 2005; Ceci 1991; Lee 2010; Eslinger et al. 2009; Quartz & Sejnowski 1997). These can be particularly helpful with understanding disaster warnings and making informed decisions about how to react. At the same time, education has been found to raise the level of awareness, helping the better educated to better assess risks related to disaster threats and to find adequate responses (de Bruin et al. 2007; Peters et al. 2006). Time preferences are another channel through which education could affect disaster preparedness, which has received less attention in the literature. Recent evidence suggests that education can change time preferences as well as the capacity to plan for the future, allowing the more educated to act more goal-oriented and to better allocate resources and make investments in financial, health or education for their future (Chew et al. 2010; Oreopoulos & Salvanes 2011; Grossman 2006). This could influence the adoption of such precautionary measures which require long term investments as purchasing disaster insurance.

Indirectly, education can provide households with access to different forms of resources, which enable them to better prepare against or avoid natural hazards. On average, individuals with higher formal education earn higher incomes resulting in higher wealth levels, which enables them to invest in more costly preparedness actions or the relocation from risk areas (Card 1999; Heckman et al. 2018). Thanks to their educational background, they often also have better possibilities to diversify their income sources and have more money at their disposal to buffer negative shocks. Moreover, there is evidence showing that education improves access to informational and social resources, which can reduce vulnerability by providing households access to cost-efficient means of disaster prevention and adaptation. For example, studies have shown that education improves access to information and communication technologies (Xiao & McCright 2007; Rodriguez et al. 2007). At the same time, it was found that the better educated households can build on broader and more resourceful social networks that can support them in the preparation and aftermath of disasters (Kirschenbaum 2005; Solberg et al. 2010; Witvorapong et al. 2015).

3 A Dynamic Household Model

3.1 Conceptual Framework

Building on the literature, we propose a formal model, which allows understanding and modeling the origins of education effects and its complex pathways in a comprehensive way. We assume that households behavior is represented by a lifecycle model over three time periods, which reflect in a stylized way the past, presence and future. The household members possess an initial endowment of durable wealth and education, which they obtained in the past. At the same time, households face an initial risk level, which influences their likelihood of being exposed to a disaster. In the model, all of these factors constitute the past (subscript 0 in the formulation), which is exogenously given to the household. Decisions are assumed to be made cooperatively by the members of the households.

In the present period (subscript 1), households decide how much of their income they want to spend on consumption, how much to save, and how much to invest in disaster preparedness, which can either take the form of resettling from a hazardous environment/location or investment in in-situ precautionary measures. At the same time, the household can invest in durable goods, such as their house, furniture, or vehicles. In contrast to consumption goods, durable goods are not consumed in one use, but yield utility over time.

Investments in disaster preparedness pay off in the future period (subscript 2). If a disaster strikes, the level of preparedness determines the probability with which durable household wealth is destroyed during the event and hence the household utility in the future. The probability with which a household is exposed to a disaster depends on the exposure level of her neighborhood, which can be influenced in period 1 by resettling to a different area. If a household decides to move, a small constant share of household wealth is lost.

Figure 1 illustrates the main pathways how education may be related to household characteristics and decisions. We focus on two direct and two indirect channels of influence, which have been shown to be relevant in the literature. Firstly, education can indirectly affect the household decision by influencing household income as well as access to prevention and mitigation measures. Secondly, it can directly help raising the household's awareness, knowledge and skill level and change the future orientation of its members (time preference) (Picone et al. 2004; Camerer et al. 2004). All of these factors influence the possibilities and incentives to prepare against hazards and hence the vulnerability to environmental shocks, which may – in case a disaster strikes – directly affect the household's utility.

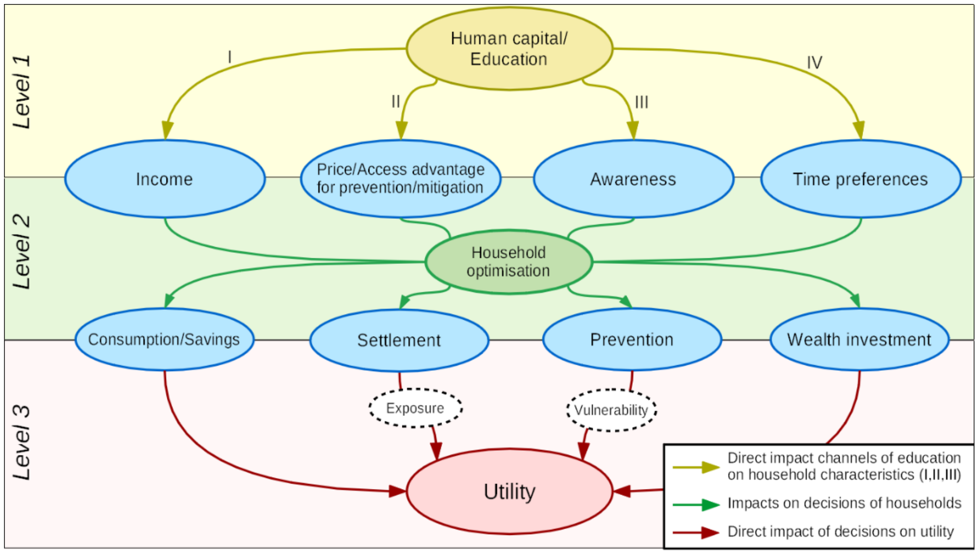

Figure 1 – Conceptual framework of the theoretical model

These four household characteristics (level 1 in figure 1) will have an impact on households decisions such as consumption, savings, settlement, prevention and wealth investment (level 2 in figure 1). Finally these household decisions will determine the households welfare (level 3 in figure 1). While the consumption and wealth investment decision are directly linked to the households utility, the decisions on settlement and prevention are related to the household's welfare via the level of exposure and vulnerability respectively. Conceptually, we distinguish between exposure and vulnerability. While the former reflects the probability that a household experiences a disaster event, vulnerability is the likelihood of a household being negatively affected, i.e. it captures the degree to which a household is negatively affected in a disaster event[1]. Both together constitute the aggregate disaster risk of a household, which affects its expected welfare/utility.

3.2 Household Utility

In our model, households aim to maximize their expected utility U The household discounts future utility at the rate $\rho(H_0)$, which depends on the exogenous given education level H_0 of the household. We assume that $\rho(H_0)$ is decreasing in H_0. The expected utility from period 1 and 2 can be formulated as follows:

[1] According to the IPCC's definition, vulnerability to environmental hazards is a function of a household's or community's susceptibility, sensitivity and adaptive capacity (IPCC 2014). Susceptibility refers to the presence of people in places that are at risk of being adversely affected, while sensitivity relates to the degree to which a population group is negatively affected once a shock occurs. Adaptive capacity is the ability to cope with and adapt to the consequences of a natural hazard.

$$U = u(c_1, W_1) + \frac{1}{1+\rho(H_0)}\left[E_1 a(H_0) u\left(c_{2,D}, W_{2,D}\right) + (1 - E_1 a(H_0)) u\left(c_{2,N}, W_{2,N}\right)\right] \quad (1)$$

In the present period, households derive utility from consumption c_1 and their accumulated wealth W_1, which is captured through the period utility function $u(c_1, W_1)$. Expected utility for the future is modeled by differentiating between two possible future scenarios that differ whether a disaster occurs or not: (i) the utility $u\left(c_{2,D}, W_{2,D}\right)$ denotes the welfare in case of a natural disaster (indicated with a second index D), and (ii) the utility $u\left(c_{2,N}, W_{2,N}\right)$ denotes the welfare in case no disaster occurs (indicated with a second index N). The respective utilities are weighted with the probability of occurrence of the two scenarios, which depend on the level of exposure E_1 after a potential relocation of the household has occurred.

Whether a household can correctly assess the risk associated with its exposure level depends on its awareness a. If the awareness level, which depends on the education level H_0, is low, households underestimate the probability of a disaster in their neighborhood, which we model by weighting the probabilities with the awareness level: $E_1 a(H_0)$ and $(1 - E_1 a(H_0))$. Both exposure and awareness range from zero to one. A household who is fully aware ($a(H_0) = 1$) of the risk of a disaster correctly estimates the risks associated with the level of exposure of the settlement.

3.3 The Present: Household Decision Problem and Constraints

When maximizing its expected utility, the household faces different inter- and intra-temporal budget constraints. First, households have an initial endowment of wealth, education, and disaster exposure, which they inherent from the past (see section 3.1). The initial level of exposure E_0 describes the probability with which the neighborhood, where the household is living, is affected by a disaster in the future. The initial wealth level W_0 captures all durable goods that were collected by the household in the past and the initial education level H_0 denotes the education inherited by the household members.

The key decision to be made by a household in period 1 is whether or not to relocate to a different neighborhood with a different exposure level. If a household decides to relocate, it loses a fixed share of its accumulated wealth, which makes it relatively more expensive for wealthier households to relocate. While locations with lower exposure levels makes it less likely to suffer from a natural disaster, they are typically also more expensive, creating an additional trade-off for the household. We capture this trade-off in our cost function $p_E(E_1)$ which describes the additional costs related to a decrease in the exposure level from E_0 to E_1. A stylized curve illustrating the functional relationship between exposure level and the costs is shown in Figure A1 in the Appendix.

Aside of deciding whether to relocate or not, the household can allocate resources to two utility generating channels. It can decide to use its budget either for direct consumption c_1 or investment

w_1 in the stock of wealth with investment cost of $p_w(w_1)$. The stock of wealth in period 1 is thereby denoted by equation (2)

$$W_1 = \widetilde{W_0} + w_1 \tag{2}$$

The wealth stock in period zero is denoted by $\widetilde{W_0}$ to reflect the location decision of the household in period zero: (i) if the household stays at the same settlement location the level for the wealth in period zero is equal to the initial level of wealth W_0, hence $\widetilde{W_0} = W_0$; (ii) if the household decides to relocate the settlement a share Δ^W of the initial wealth endowment is lost due to the moving costs, hence $\widetilde{W_0} = (1 - \Delta^W)W_0$.

Finally, the household decides which share P_1 of the accumulated wealth W_1 to use for prevention and the undertaking of precautionary measures against disasters. The costs p_P for these measures are increasing at an increasing rate in P_1 and in the level of exposure of the household, i.e. the riskier the neighborhood, the more expensive it is to prepare against disasters. This does not only reflect the fact that higher effort hasto be taken to achieve the same level of protection in higher exposed areas, but also accounts for increasing insurance costs in disaster prone areas.

The total expenditures of the household for relocation, consumption, wealth investment, disaster prevention is limited by the labor income $y_1(H_0)$ of the household, which increases in the education level. Out of the labour income, households can save a certain amount s_1 for the second period. The budget constraint for the present period can be formulated as follows:

$$c_1 + p_w(w_1) + p_P(P_1, E_1, H_0) + p_E(E_1) = y_1(H_0) - s_1 \tag{3}$$

3.4 The Future: Accounting for Potential Disaster Damages

For the second time period, two potential scenarios can be distinguished as already represented in the expected utility (equation 1). The probability of each scenario depends on the exposure level E_1 of the household. In case of a natural disaster the unprotected share $(1 - P_1)$ of the household wealth is destroyed. Additionally the remaining wealth depreciates at the rate δ, which implies the following wealth level in the second period:

$$W_{2,D} = (1 - \delta)W_1 P_1 + w_{2,D} \tag{4}$$

In case no disaster occurs, the household only loses wealth because of the depreciation and not because of any exogenous disaster shock. This results in the wealth level for the second period as follows:

$$W_{2,N} = (1 - \delta)W_1 + w_{2,N} \tag{5}$$

In contrast to the accumulated wealth, financial savings are not affected by natural disasters. They hence represent a risk-free possibility to transfer assets into the future, which additionally generates an interest at the rate r. In addition to the lost wealth, we assume that disasters reduce the labor income of the household, as the household members have to invest time and effort in coping with the shock. Summarizing the different consequences of the disaster (D) and no-disaster (N) scenarios for the household, we can obtain the following budget constraints for the second period:

$$c_{2,D} + p_w\left(w_{2,D}\right) + p_E(E_1) = y_2(H_0)(1 - \Delta^y) + (1 + r)s_1 \tag{6}$$

$$c_{2,N} + p_w\left(w_{2,N}\right) + p_E(E_1) = y_2(H_0) + (1 + r)s_1 \tag{7}$$

3.5 Household Optimization and First Order Optimality Conditions

To formulate the optimization problem of the household in a closed form, we introduce the indicator $I_1 \in \{0,1\}$, which indicates if a household stays at the same settlement location ($I_1 = 0$) or relocates to a different neighborhood level ($I_1 = 1$) with a different exposure level. The following two equations represent the relationship between the indicator I_1 and the exposure levels E_1und E_0.

$$(1 - I_1)(E_1 - E_0) = 0 \tag{8}$$

$$(1 - I_1)I_1 = 0 \tag{9}$$

The second equation forces I_1 to be either 0 or 1, while the first equation establishes that the chosen level of exposures E_1 is only allowed to be different to the initial level of exposure E_0, if the indicator for a relocation of the household is active. Using this indicator I_1 we can formulate the optimization problem of the household in the closed form (10.1-10.9):

$$\max_{c_1, W_1, s_1, P_1, E_1, I_1, c_{2,i}, w_{2,i}} u(c_1, W_1) + \frac{1}{1+\rho(H_0)}\left[E_1 a(H_0) u\left(c_{2,D}, W_{2,D}\right) + (1 - E_1 a(H_0)) u\left(c_{2,N}, W_{2,N}\right)\right] \tag{10.1}$$

$$W_1 = (1 - \Delta^W I_1)W_0 + w_1 \tag{10.2}$$

$$c_1 + p_w(w_1) + p_P(P_1, E_1, H_0) + p_E(E_1) = y_1(H_0) - s_1 \tag{10.3}$$

$$W_{2,D} = (1 - \delta)W_1 P_1 + w_{2,D} \tag{10.4}$$

$$c_{2,D} + p_w\left(w_{2,D}\right) + p_E(E_1) = y_2(H_0)(1 - \Delta^y) + (1 + r)s_1 \tag{10.5}$$

$$W_{2,N} = (1 - \delta)W_1 + w_{2,N} \tag{10.6}$$

$$c_{2,N} + p_w\left(w_{2,N}\right) + p_E(E_1) = y_2(H_0) + (1 + r)s_1 \tag{10.7}$$

$$(1 - I_1)(E_1 - E_0) = 0 \quad (10.8)$$

$$(1 - I_1)I_1 = 0 \quad (10.9)$$

$The\ baseline\ endowmend\ levels\ W_0, E_0, H_0\ are\ exogenously\ given$

Using the Lagrange-approach for constrained optimization problems, we derive first order optimality conditions, which have an intuitive interpretation. First we can characterize the decisions between consumption and wealth investment using equations (11) and (12).

$$u_W\left(c_{2,\sim}, W_{2,\sim}\right) = p'_w\left(w_{2,\sim}\right)u_c(c_{2,\sim}, W_{2,\sim}) \quad (11)$$

$$u_W(c_1, W_1) + \frac{(1-\delta)}{(1+\rho)}\left[E_1 a\, P_1 u_W\left(c_{2,D}, W_{2,D}\right) + (1 - E_1 a)u_W(c_{2,N}, W_{2,N})\right] = p'_W(w_1)u_c(c_1, D_1) \quad (12)$$

Equation (11) shows that in both scenarios for the second period (disaster and no disaster) the marginal utility of wealth has to be equal to the marginal utility of consumption weighted with the marginal costs of investments in wealth. In the first time period (equation 12) the expression of the marginal utility of wealth investment on the left side becomes slightly more complicated as investments in the first period also lead to higher wealth stocks and utility in the future. Hence the marginal utility of wealth investment consists of the marginal utility gain in the first preriod $u_W(c_1, W_1)$ and the expected marginal utility gain in the second period $\frac{(1-\delta)}{(1+\rho)}\left[E_1 a\, P_1 u_W\left(c_{2,D}, W_{2,D}\right) + (1 - E_1 a)u_W(c_{2,N}, W_{2,N})\right]$. Contrary, consumption in the present is a flow variable which does not affect the future. Both equations capture the well-known result from consumer decision theory that the ratio of marginal benefits equals the ratio of costs.

The household does not only have to make an intra-temporal decision between consumption and investment, but also an inter-temporal decision between consumption in the first and the second period. This trade-off can be represented as follows:

$$u_c(c, W_1) = \frac{(1+r)}{(1+\rho)}\left[E_1 a\, u_c\left(c_{2,D}, W_{2,D}\right) + (1 - E_1 a)u_c(c_{2,N}, W_{2,N})\right] \quad (13)$$

Similar to equations (11) and (12), we obtain the condition that the marginal utility of consumption in the first period has to equal the marginal utility of savings, which are consumed in the future after generating an interest. We can furthermore identify the first order conditions for the prevention and the settlement decisions:

$$p'_P(P_1, E_1, H_0)u_c(c_1, W_1) = \frac{(1-\delta)}{(1+\rho)} E_1 a\, W_1 u_W(c_{2,D}, W_{2,D}) \quad (14)$$

$$u_c(c_1, W_1)\left[\frac{(2+r)}{(1+r)}p'_E(E_1) + \frac{\partial p_P(P_1,E_1,H_0)}{\partial E_1}\right] = \frac{a}{(1+\rho)}\left[u\left(c_{2,D}, W_{2,D}\right) - u\left(c_{2,N}, W_{2,N}\right)\right] + \lambda_I(1 - I_1) \qquad (15)$$

Equation (14) illustrate the trade-off between consumption in the first preiod and investments in prevention. The right hand side of equation 14 shows that additional prevention measures only have an effect with a probability of $E_1 a$ and protect $(1 - \delta)\ W_1$ marginal units of wealth, which results in marginal utility gains of $\frac{u_W(c_{2,D},W_{2,D})}{(1+\rho)}$. The left hand side again shows the marginal utility of consuming the additional resources, if prevention is lowered by one marginal unit.

Lastly, equation (15) characterizes the settlement decision. On the left side, we can identify the marginal utility of consumption multiplied with the marginal total costs of changing the settlement location. These costs consist of the direct marginal costs $\frac{(2+r)}{(1+r)}p'_E(E_1)$ for the settlement itself, but also the indirect marginal costs due to the changing expenditures for prevention as less prevention might be needed after the relocation. On the right side, the first term shows that a marginal change in exposure, makes the disaster scenario with utility $u\left(c_{2,D}, W_{2,D}\right)$ more likely and the no disaster scenario with utility $u\left(c_{2,N}, W_{2,N}\right)$ less likely. Furthermore, we obtain an additional term, that shows, that in case of a household relocation $(I_1 = 1)$ the marginal costs and benefits have to be equal. If the household decides to stay at the same location $(I_1 = 0)$, the marginal costs on the left side may exceed the the marginal benefits.

4 Empirical Cases and Methods

4.1 Country Backgrounds

We focus on two Southeast Asian countries, the Philippines (PH) and Thailand (TH), to test whether our theoretical assumptions and derived predictions hold and to illustrate the implications of the model using real world data. With diverse socio-economic background of their populations and exposure to different disaster risks, the two countries represent well-suited empirical testing grounds for the model.

Both countries have on average a high level of formal schooling compared to other middle-income countries in the Southeast Asian region. At the same time, exposure to natural hazards is very high. For example, the Philippines are affected by more than 20 tropical storms every year. Aside of natural calamities, the populations of both countries are affected from slow evolving environmental hazards, such as drought, soil erosion, and desertification, which require adequate prevention and adaptation measures from households.

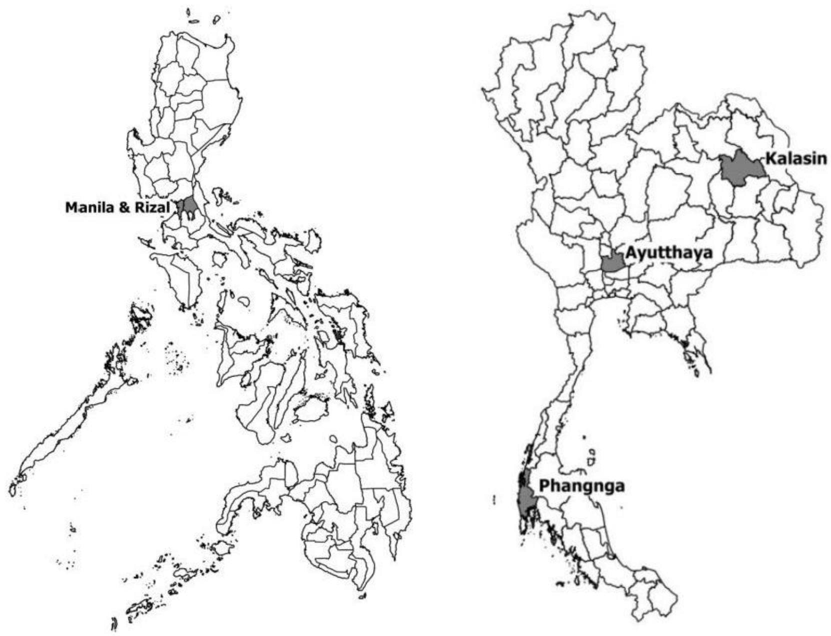

Figure 2 – Map of study areas in the Philippines and Thailand

4.2 Data and Measurement

The survey data for both countries were collected by the authors, which allowed us to tailor the research instruments to our research questions and to reach a high degree of comparability between the cases. The data for the Philippines were collected among low-income households in the wider area of Metro Manila, the capital (See Figure 2). A multi-stage cluster sampling was employed for the selection of the respondents. First, a sample of areas was randomly selected as primary sampling units. In the second step, respondents were randomly drawn from the community members in the selected areas. The data was collected using face-to-face interviews in February 2014. In total, 889 respondents (aged 20 to 75 years) were interviewed with standardized questionnaires. The three study areas have been frequently affected by natural calamities in the past with devastating consequences for the local communities. Primarily, these areas are exposed to risks of floods, landslides and storm damages caused by the numerous typhoons that hit the country with an average of 20 tropical storms per year (Brower et al. 2014).

The Thai data were obtained from a representative household survey of three provinces, namely, Phang Nga, Kalasin, and Ayutthaya (see Figure 2). The province of Phang Nga, located along the Indian Ocean coastline, was strongly affected by the 2004 Asian Tsunami with 4,224 deaths, accounting for 78% of the death toll from the 2004 tsunami in the country. The interior province of Ayutthaya is situated on the low-lying area in the central plains and is exposed to frequent flooding.

Kalasin as last location is located in the northeast and is particularly prone to drought, but floods and windstorms are also not uncommon. The survey was conducted based on a stratified two-stage sample design with villages and housing blocks as primary sampling units. In stage two, a random sample of 25% of districts in the selected provinces, 25% of villages in the selected districts and 25% of households in the selected villages was drawn for interview. Interviews were conducted face-to-face with one male or female member aged 15 or above from each household. The survey was carried out between May – August 2013 with 1,310 respondents who participated in the study.

As main outcome variable, we construct a vulnerability measure based on whether households have undertaken any precautionary measures and whether they have savings to cope with the consequences of a disaster. Education is measured in years of education for both countries. As mediating mechanisms we consider (i) the household's income level per capita; (ii) household's access to resources, which we measure by asking respondents whether they would have access to financial and other support if needed for example in case of an emergency; and (iii) awareness, which we proxy by asking respondents about their awareness of the risks of environmental hazards in their neighborhoods. In the Philippines, the latter measure was collected only for a subsample of respondents. All of the measures were normalized to a range from 0-1 to allow for comparisons across models and to obtain standardized coefficients, which can be used for the parametrization of the theoretical model needed to run the simulations (NOTE: we have not yet tested for the impact of education on time preferences, but we plan to do so using additional data, which we collected in the Philippines).

4.3 Simulations and Policy Experiments

To run our simulations, we use real world data from the two countries to determine our model variables and parameters. In a first step, we retrieve information for the endowment variables – durable wealth, education, and disaster exposure – using aggregate country level data. Importantly, we do not only retrieve information on country averages, but also on the distribution of the variables in the population allowing us to also account for inequalities, for instance in access to education or wealth levels.

Information on durable wealth is obtained from the World Bank wealth accounting data base, which provides global data on per capita wealth levels and allows distinguishing between durable and other capital stocks (Lange et al. 2018). The wealth distribution is approximated using information on income inequality from the World Development Indicator database (World Bank 2019). Information on educational attainment and inequalities is obtained from the Barro-Lee Educational Attainment Data, which provides detailed education statistics for different countries from 1950 to 2010 (Barro & Lee 2013). For the wealth and education data, we use 2010 as reference year to assess the current condition in the countries and to use it to analyze current household decisions.

Finally, we use the EM-DAT international disaster database to assess the country specific exposure levels (Centre for Research on the Epidemiology of Disasters 2019). The mean yearly number of affected individuals per country from 1990-2010 is divided by the total population to obtain an estimate for the likelihood of being exposed to a disaster. Since there is no information on the within country distribution of natural hazards, we assume a right-skewed beta distribution with the majority of the population facing a low to moderate and a smaller fraction facing a very high disaster exposure.

Apart from the central endowment variables, we retrieve information on some important modeling parameters. In particular, we focus on those parameters, which measure the relationship between education and the hypothesized mechanisms: income, awareness, access to effective prevention measures, and time preferences. Since comparable data on these relationships is hard to come by, we mostly rely on findings from the empirical literature, among others from some of our own work, and the estimations presented in Section 5. Since many of the findings rely on idiosyncratic cases, mostly representing correlations, the parameter estimates have to be interpreted with care. Nevertheless, they can provide a reasonable benchmark to model the relationships.

Information on income elasticities is obtained from different review articles on the returns to schooling around the world (Montenegro & Patrinos 2014; Patrinos 2016). National poverty lines are used as benchmark income for a hypothetical person without education. The increase in awareness (normalized from 0 to1) with an additional year of schooling is estimated to be 0.02 starting with an assumed mean baseline awareness level of 0.5 (see Table 1) (Hoffmann & Muttarak 2017). Education effects on access to cost-efficient prevention (normalized from 0 to 1) is estimated to be 0.01 with an assumed mean baseline access level of 0.5. Finally, education is expected to positively influence future orientation (normalized from 0 to 1) by a factor of 0.034 with every additional school year (Bauer & Chytilová 2010; Perez-Arce 2017).

Based on the country-specific distributions and estimated model parameters, we calculate the household behavior predicted by our theoretical model for a three dimensional grid of combinations of initial education H_0, initial wealth W_0 and initial exposure E_0 levels. Using this approach we are able to identify the impacts of any of the three variables at different levels of the other two (e.g. impact of education for different combinations of initial wealth and exposure). Using estimates for the distributions of education, wealth and exposure, we assign a probability of occurrence to every possible combination (H_0, W_0, E_0). Following this strategy, we are able to analyze disaster risks on an aggregated level for the three selected countries.

5 Empirical Results

5.1 Education and Disaster Risks

We test the predictions of the theoretical model in three steps. In a first step, as stylized facts, we consider differences in disaster exposure and vulnerability by educational level in both countries. If the predictions of the model hold, we expect, overall, higher levels of exposure and vulnerability for lower education groups. Figure 3 plots the relationships for both countries. Indeed, we observe a decrease in exposure and vulnerability with increasing education levels both in the Philippines and Thailand. Although there are clearly differences in the strength of the education effects, the overall pattern is similar for both of the considered cases.

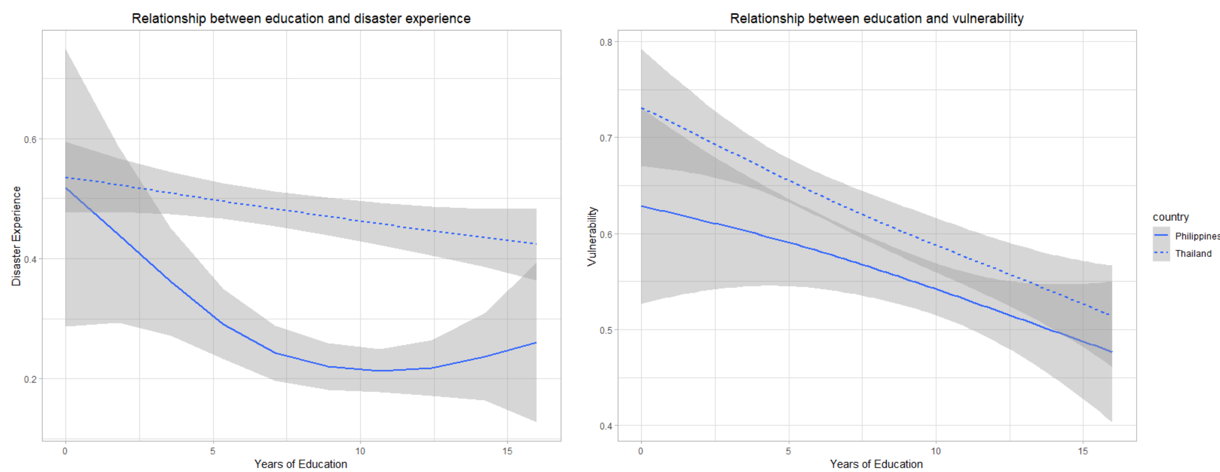

Figure 3 – Differences in disaster exposure and vulnerability by education level

5.2 Education Effects on Different Mechanisms

In the second step, of our empirical analysis, we test whether education has a positive effect on the mediating mechanisms, as predicted by the theoretical model. Table 1 shows the results of OLS models, which regress the mediating variables – income, access to resources, and awareness – on the respondents' education for both countries. Clustered standard errors and standardized beta effects are reported below the coefficients allowing to compare the estimates across the models. The derived estimates form the basis of the model simulations and policy experiments in Section 4, where they are complemented with further macro-level data.

All empirical models indicate a clear relationship between education and the mediating variables. For instance, an additional year of education raises the income on average by 0.4% in both countries, access to resources by 1.7% and 0.5%, and the awareness level by 2.7% and 1.1% in the Philippines and Thailand, respectively. Except for income, which is more strongly influenced by education in Thailand, the size of the standardized beta coefficients is highly similar in both countries. Whereas education has, among the considered variables, the strongest effect on awareness in the Philippines, it has the strongest effect on income levels in Thailand. Clearly, contextual factors matter in shaping the relationships in both settings.

Table 1 – OLS models: Education effects on mediating variables

	Philippines			Thailand		
	Income	Access to resources	Awareness	Income	Access to resources	Awareness
Years of education	0.004**	0.017*	0.027**	0.004***	0.005**	0.011***
	[0.001]	[0.007]	[0.009]	[0.001]	[0.002]	[0.003]
	0.119	0.094	0.156	0.308	0.082	0.115
Constant	0.093**	0.311*	0.848***	0.029**	0.851***	0.947***
	[0.028]	[0.147]	[0.192]	[0.010]	[0.051]	[0.087]
Observations	881	881	398	1263	1273	1279
Adjusted R^2	0.121	0.008	0.041	0.196	0.008	0.061
AIC	-1927.987	1281.080	524.012	-4175.195	226.707	1154.033

Notes: OLS regression coefficients in cells, standard errors in brackets. Standardized beta coefficients for education effects below the standard errors. Standard errors are clustered on center level (PH, m=70) and village/municipality level (TH, m=). All models control for fixed effects of the wider geographical area, health status, age, parental education, household size, and disaster experience. P-value: * p≤0.1, ** p≤0.05, *** p≤0.01

5.3 Explaining Education Effects

In the final step of our analysis, we are interested in how much the education effects on vulnerability are driven by differences in one of the considered mediating channels. For this, we regress our vulnerability outcome on years of education and extend the model in a stepwise manner. In each step, we add another of our mediating variables to the right-hand side of the equation and study how the total education effect changes after we control for the additional factor. If the factor represents an actual mechanism explaining the total education effect, we expect the education coefficient to be smaller than in the baseline model (1), because part of the variation in the outcome with education is explained through the mediator.

Table 2 reports the results of the ordinary least squares estimations. First, we observe a clear reduction in education effects across all models, which speaks for the mediation argument. The percentage changes in the size of the coefficient are also reported in the table (% change in coeff.). The reduction is strongest for the inclusion of the access to resources measure in the Philippines and the income measure in Thailand (potentially reflecting the closer link between education and income in Thailand). As theoretically expected, all mediators exert a consistent negative effect on the vulnerability outcome, except for the awareness measure in the Philippines. However, as information about this variable was collected only for a sub-sample (see reduced number of observations), the coefficient needs to be interpreted with care and may not be as informative as in the case of the Thai data.

Table 2 – OLS Models: Explaining education effects of disaster vulnerability

	Philippines				
	-1-	-2-	-3-	-4-	-5-
Years of education	-0.008*	-0.007	-0.005	-0.002	-0.005
	[0.004]	[0.005]	[0.005]	[0.008]	[0.004]
	-0.062	-0.054	-0.038	-0.011	-0.035
Income		-0.271+			-0.105
		[0.161]			[0.117]
		-0.060			-0.023
Access to resources			-0.197***		-0.194***
			[0.025]		[0.032]
			-0.255		-0.251
Awareness				0.022	
				[0.046]	
				0.026	
Constant	0.540***	0.565***	0.601***	0.375+	0.610***
	[0.115]	[0.109]	[0.105]	[0.192]	[0.113]
% change in coeff.		12.5%	37.5%	-	37.5%
Observations	880	880	880	397	880
Adjusted R^2	0.025	0.027	0.088	0.028	0.087
AIC	811.567	810.687	753.625	375.990	755.175
	Thailand				
	-1-	-2-	-3-	-4-	-5-
Years of education	-0.014**	-0.012**	-0.013**	-0.013**	-0.011**
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
	-0.153	-0.136	-0.143	-0.145	-0.121
Income		-0.392*			-0.337+
		[0.186]			[0.182]
		-0.055			-0.048
Access to resources			-0.121***		-0.119***
			[0.032]		[0.032]
			-0.088		-0.086
Awareness				-0.065*	-0.063*
				[0.024]	[0.024]
				-0.070	-0.068
Constant	0.904***	0.907***	1.005***	0.966***	1.064***
	[0.087]	[0.091]	[0.087]	[0.092]	[0.095]
% change in coeff.		14.3%	7.1%	7.1%	21.4%
Observations	1279	1263	1273	1279	1260
Adjusted R^2	0.121	0.126	0.130	0.125	0.138
AIC	898.427	881.810	880.617	893.735	862.069

Notes: OLS regression coefficients in cells, standard errors in brackets. Standardized beta coefficients for education effects and mediators below the standard errors. Standard errors are clustered on center level (PH, m=70) and village/municipality level (TH, m=35). P-value: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Overall, all considered mediators together explain about 37.5% of the education effects in the Philippines (excluding the awareness measure) and 21.4% in Thailand. While, our empirical model can explain large parts of the variation in the vulnerability outcome, some unexplained variation remains suggesting that other non-captured channels, such as differences in preferences, may be relevant for explaining education effects. Also, as becomes visible from the comparisons of the two countries, there are again differences, which reflect the country specific context and settings.

6 Results of Simulations and Policy Experiments (WORK IN PROGRESS)

[NOTE: We are currently still working on the simulation section. The presented findings here are from an earlier manuscript version, which considered three country cases, the Philippines, Bangladesh, and Mali. The final version will use similar simulation analyses, but focus only on the Philippines and Thailand].

6.1 Baseline Scenario

In a first step, we study the behavior of the model in a baseline scenario using real-world data. The section also allows to showcase some of the main features and properties of the model. Mainly, we focus on education effects on household prevention (P) and relocation decisions (E), which together determine the disaster risk level of a household ((1-P)*E). For the latter, we assume direct substitutability, i.e. households can compensate a higher exposure in their neighborhood with a higher level of prevention. Education effects play a role both within and across the three considered country cases: Bangladesh, Mali, and the Philippines.

Figure 4 shows the disaster risk distribution (from 0-1) for the three countries. Despite a high baseline exposure, the Philippines shows on average the lowest risk level. This is due to the country's high level of universal education, enabling the population to make greater investments in prevention and to relocate from disaster areas if they face a risk. Compared to the other countries, Mali's population faces the greatest disaster risks due to its limited wealth and educational resources. In contrast to the Philippines and Bangladesh, some 3% of the simulated households in Mali have a disaster risk greater 0.5, i.e. with at least 50% probability they are adversely affected by a disaster event.

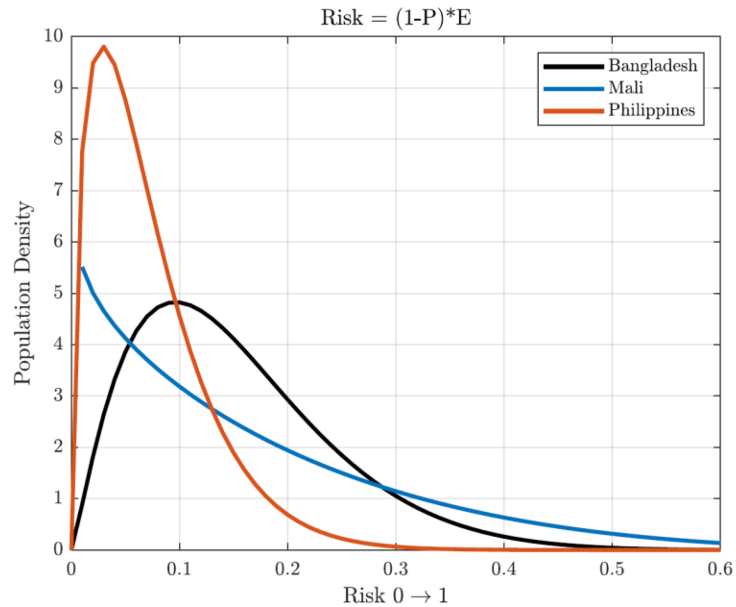

Figure 4 – Simulated Disaster Risk Distribution in Country Cases

The major burden of the alleviated disaster risk level in Mali is carried by households with a low socioeconomic status and low education levels (see also Figure 11 in the Appendix). **Figure 5**Figure **5** shows the level of household prevention (P) and exposure (E1) in period 1 after the household could decide whether to relocate from a disaster risk area or not. A clear pattern is observable with households with lower education and wealth being more likely to reside in higher risk neighborhoods. None of the poor, low educated households (straight blue line) reaches an exposure level below 0.35, i.e. the households face at least a probability of 35% to experience a disaster event.

Adequate prevention measures can be used to counterbalance the increased disaster exposure. As the graph shows, there is strong correlation between education, wealth and the level of household investments in prevention (range 0-1). Despite of facing the overall highest exposure levels, poor, low educated households do not invest a lot in prevention, because they lack the resources and awareness to do so. Importantly, with increasing levels of exposure (from 0.35 to 0.75), there is no corresponding increase in prevention, resulting in an exceptionally high vulnerability. For wealthy, high educated households, on the other hand, a clear correlation with disaster exposure and prevention efforts is visible. While most of these households decide to move away, if initial disaster levels (E0) are too high, the few households who decide to stay in an area with higher exposure invest a lot in prevention to protect themselves from the devastating consequences of disaster shocks.

Comparing the solid lines in **Figure 5** furthermore illustrates that being endowed with higher initial wealth serves as an incentive for households to invest more in prevention measures as they want to protect their wealth from the potential damages of a disaster. Independent of the level of exposure, households with the same education level thus choose a higher prevention if they are endowed with a higher initial wealth level. This pattern also holds for households with intermediate education (dashed lines) as well as highly educated households (dotted lines).

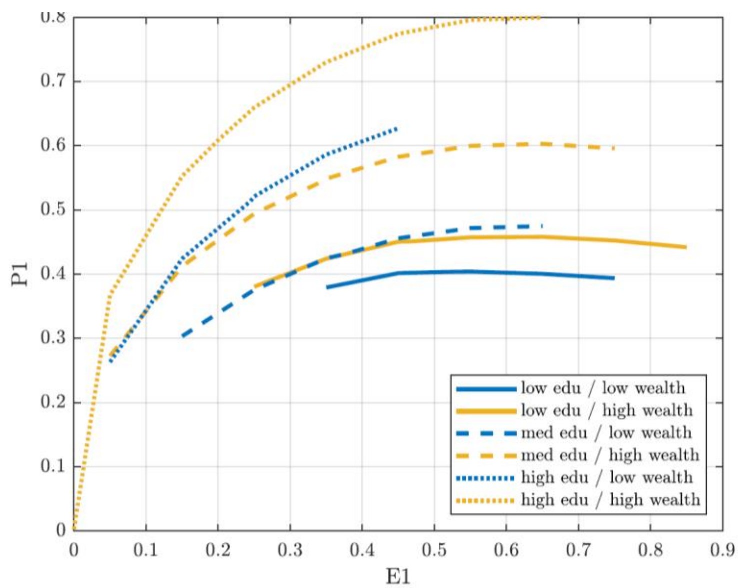

Figure 5 – Optimal relocation and prevention decisions of households in Mali by education and wealth

Using the case of Bangladesh, **Figure 6** highlights the relationship between education and the relocation decision for poor households with a low and rich households with a high initial wealth level. The x-axis shows the initial exposure level and the y-axis the exposure level after the household made the decision whether to relocate or not. As shown in the graphs, household are more likely to shoulder the additional moving and relocation costs, the higher the initial exposure level. Better educated households respond stronger to increases in the disaster exposure independent of their initial wealth level. Whereas almost all highly educated households with education above 12 years relocate once the probability of being exposed to a disaster is greater than 70%, this is the case for only few of the low educated households, who face more binding resource constraints. Interestingly, based on our model, households from the lowest education group decide to move to high risk areas to benefit of the lower living cost there. This simulation outcome reflects well findings in the literature, which show that areas with high disaster risks are often inhabited by poor households due to the lower living costs (Fothergill & Peek 2004; Bolin & Kurtz 2017).

Interestingly, when we compare the curves of the same colors between the two plots, we can observe that higher initial wealth imposes a slight disincentive to relocate. While households with greater wealth possess more resources, which they can use for relocations, they lose an absolute larger amount of their wealth as compared to poorer households. These can resettle more easily as they are less bound to their current location in terms of their durable assets and wealth[2]. However, unlike poorer households, more wealthy households are able to compensate for increased exposure levels with greater prevention, if they decide to stay in their neighborhood.

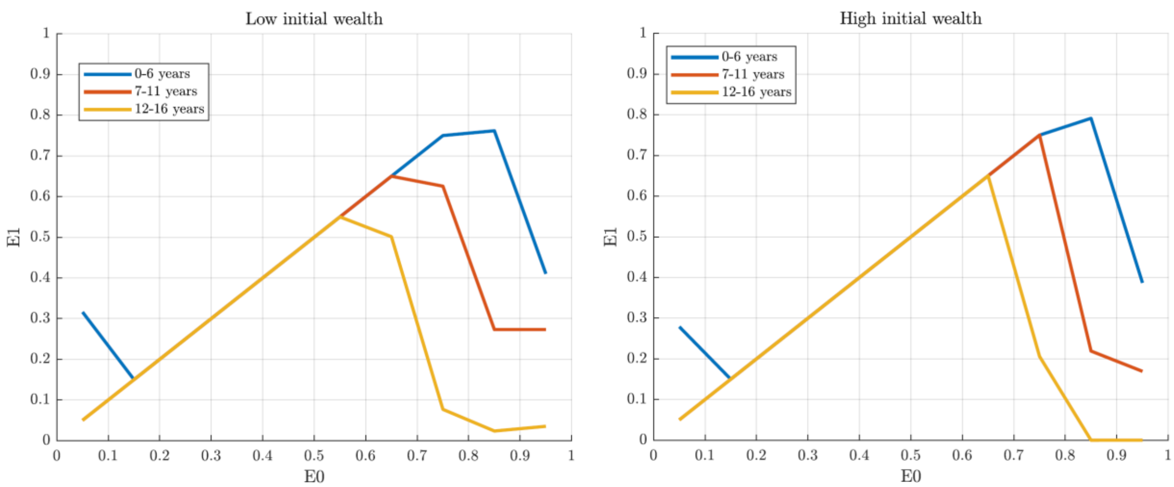

Figure 6 – Differences in relocation decisions by education and initial wealth level in Bangladesh

6.2 Policy Interventions and Evaluation

We are currently working on the simulations and policy experiment section. We can hence at this point only provide the reader with a teaser of our expected simulation outputs. Figure 4 shows a simulated vulnerability distribution for the population in the Philippines.

[2] This phenomenon occurs although in our simulations only a small share 5% of the wealth is assumed to be lost when a household decides to relocate

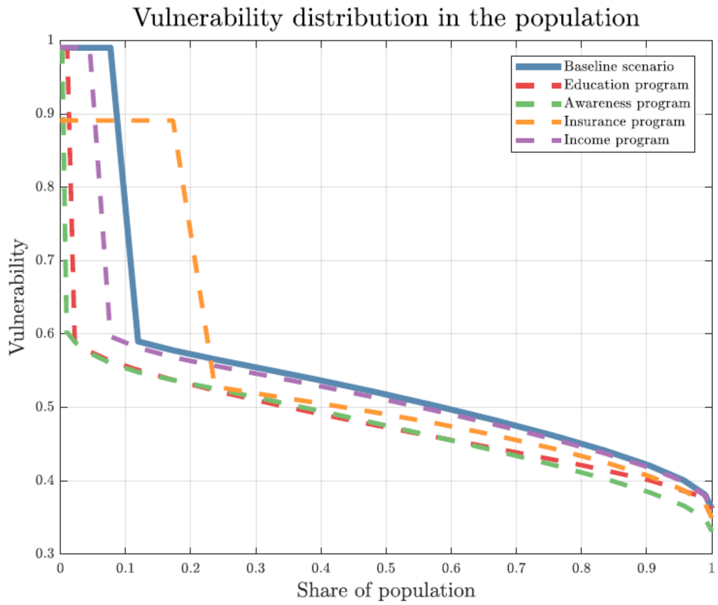

Figure 7 – Distribution of vulnerability and exemplary policy measures in the Philippines

Using simulation methods, we explore the effects of different commonly used policy measures and interventions, such as educational extension programs, awareness campaigns, insurance programs, and subsidy and income programs. Our preliminary findings suggest that while all of these interventions can help reducing vulnerabilities at the lower end of the population distribution, some of them may also generate undesired effects. For instance, providing subsidies for prevention measures ("low-income support program", orange curve), raises vulnerability in certain population groups by making them postpone the resettlement from hazardous areas. We hope that through our simulations we are able to derive more of such insights, which are of high relevance for public policy, in particular for public subsidization and resettlement programs. In the upcoming months we plan to (i) add additional simulations and policy experiment for the other country case studies, Bangladesh and Chad, (ii) explore and illustrate in additional simulation exercises why certain policy intervention prove to be more effective in certain contexts than in others, and (iii) extend our analysis by also considering the costs of the different interventions to determine their cost effectiveness.

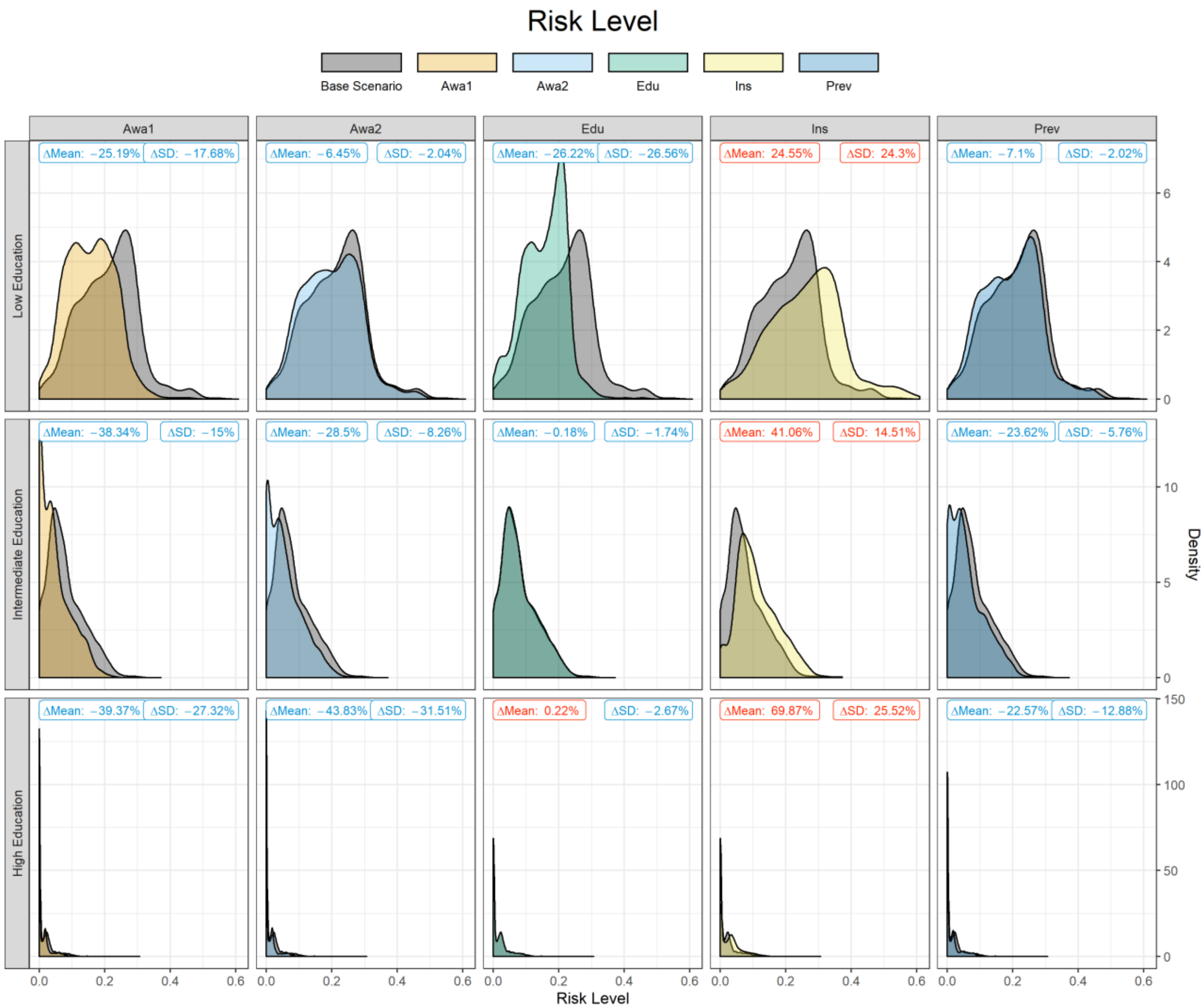

Figure 8 – Evaluating different policy interventions in the Philippines

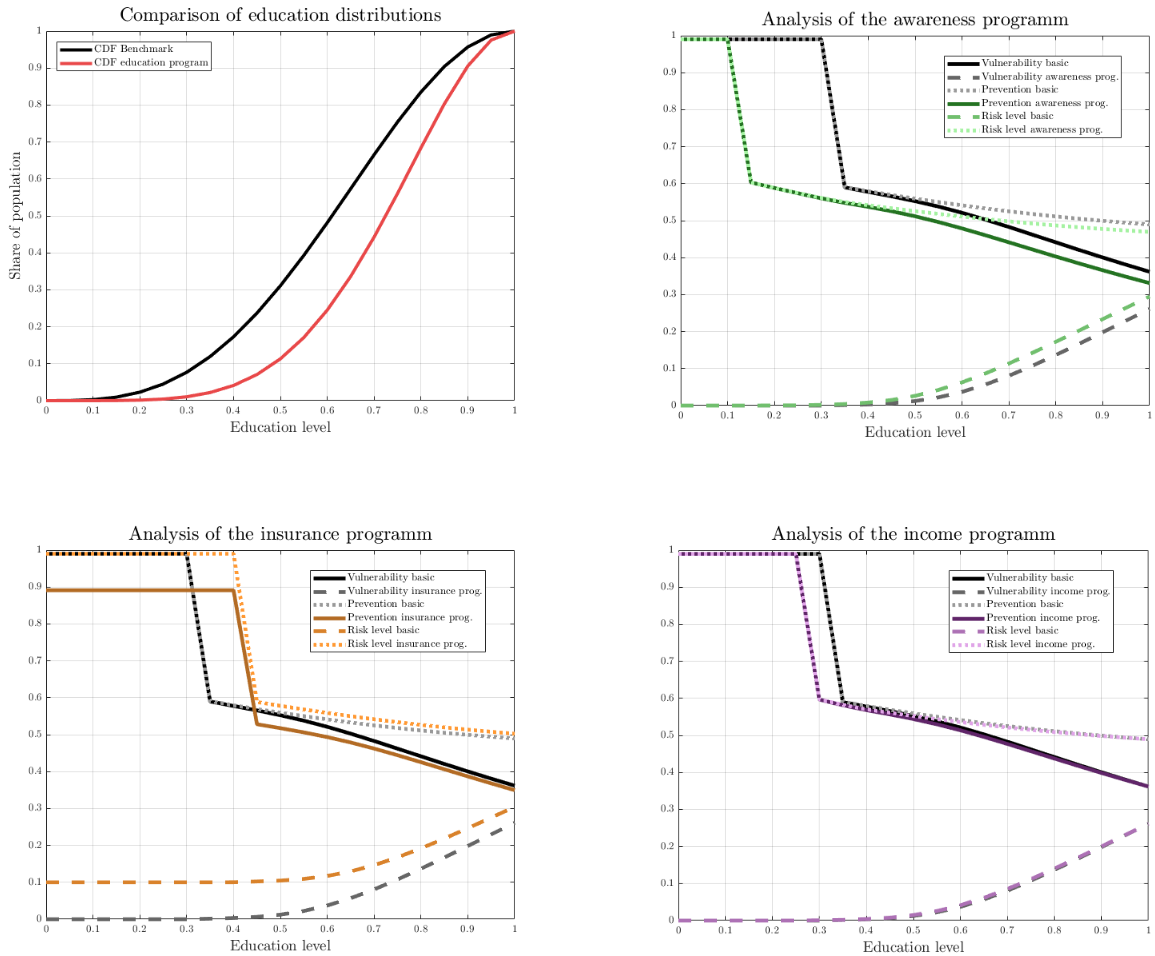

Figure 9 - Analyzing the impact of different disaster risk reduction policy interventions

Appendix

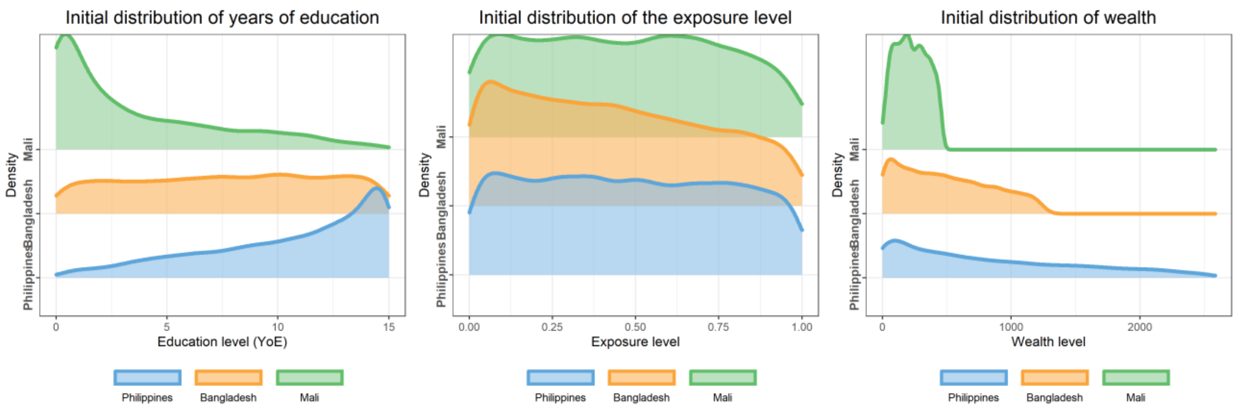

Figure 10 – Initial distribution of education, exposure levels, and wealth in the three countries

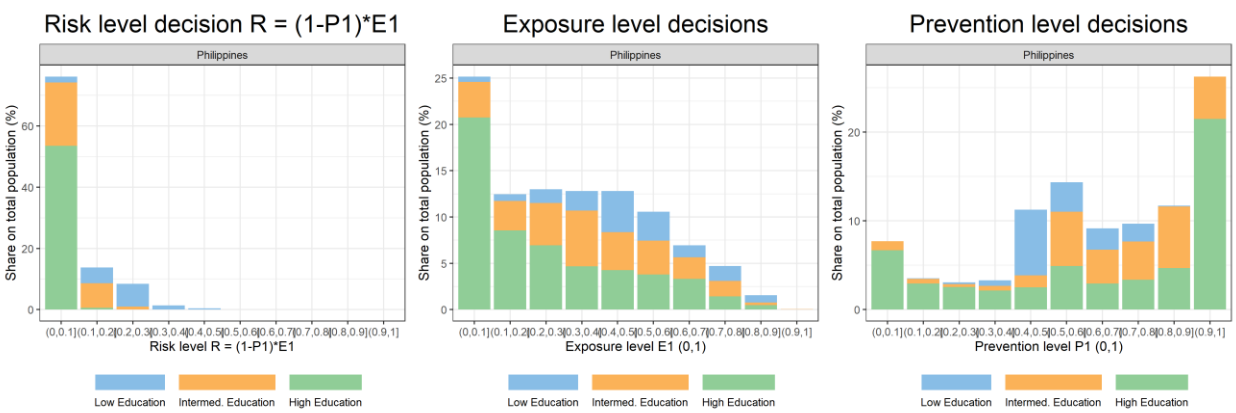

Figure 11 – Disaster risk reduction efforts by households in the Philippines

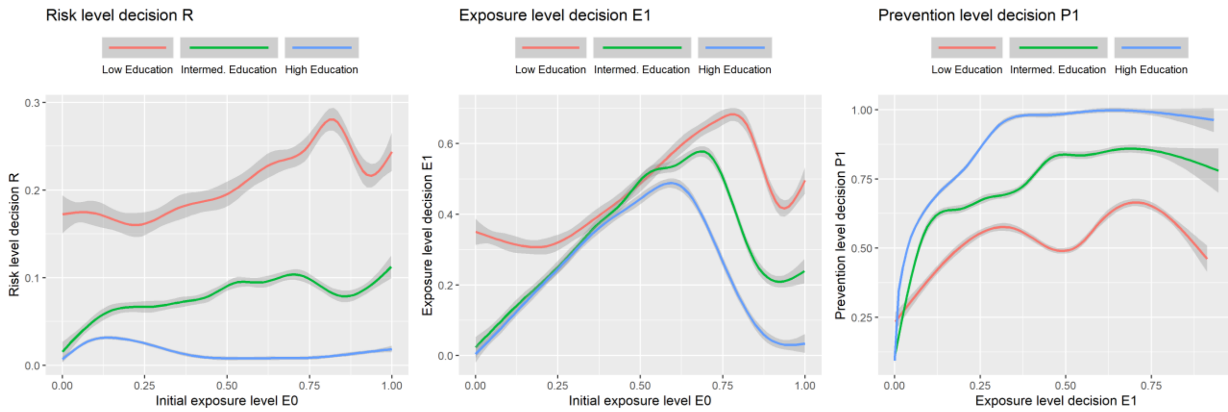

Figure 12 – Impact of education on disaster risks in the Philippines

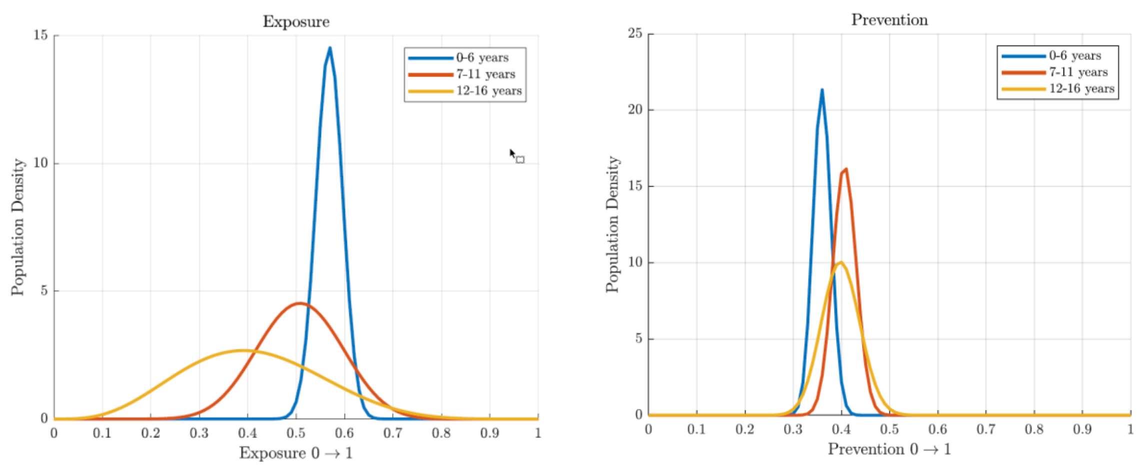

Figure 13 – Differences in exposure and prevention in Mali by different education levels

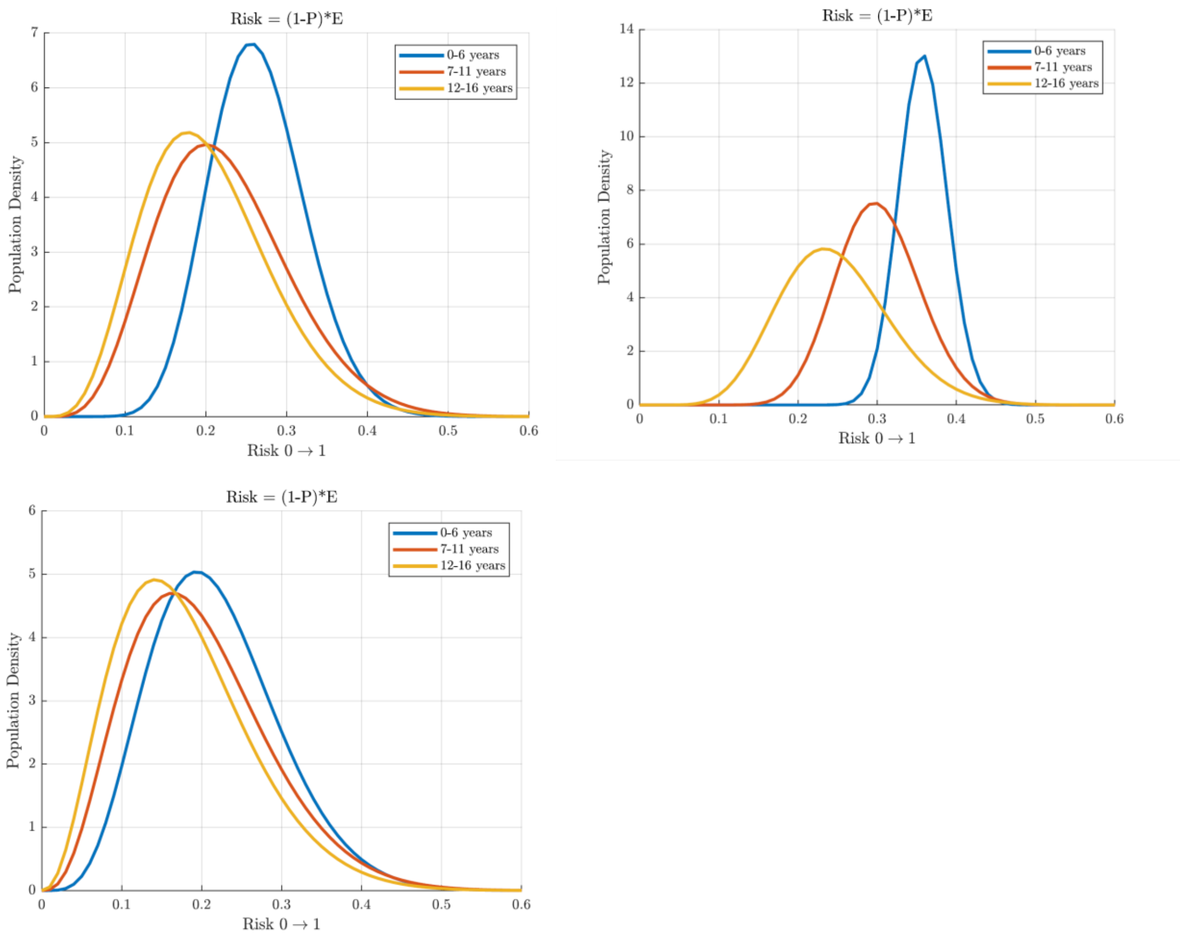

Figure 14 – Simulated disaster risk levels by education for the Philippines, Mali & Bangladesh

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