Human Capital and Disaster Vulnerability: Exploring the Mechanisms in a Household Life Cycle Model

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Short Abstract

In many parts of the world, increasing numbers of natural disasters and worsening climatic conditions impose severe threats to local populations. Poor households in low and middle-income countries are particularly vulnerable, not only because of their greater exposure, but also because they lack resources to take precautionary measures and to cope with shocks to their livelihoods. Recent empirical evidence suggests an important role of education in raising household resilience. Yet, we still lack a sound theoretical understanding why and how education can have a positive impact. To this end, this study develops a household life cycle model, which explicitly accounts for and quantitatively models different (direct and indirect) education effects. The predictions of the model are empirically tested using original data from the Philippines and Thailand. In a final step, the empirical estimates are used to parametrize the model and to run simulations and policy experiments for selected country cases.

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Extended Abstract

1 Introduction

In the last decades, many parts of the world were faced with a substantial increase in the number of extreme weather events and worsening climatic conditions with severe 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 disaster as well as to respond 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. 2012), 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 disaster 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 three major channels, which have been identified as relevant in the empirical literature: (i) Education increases income levels and hence financial resources, which can be used to undertake costly precautionary measures; (ii) it gives improved access to resources, for example through social capital/networks; and (iii) it directly affects information, knowledge and awareness of disaster risks (Paton & Johnston 1999; Drabo & Mbaye 2015; Nawrotzki et al. 2015; Lutz et al. 2014)

Original survey data from the Philippines and Thailand are used to (i) test the model predictions and to (ii) estimate key parameters of the model, which are used in the final part of the paper to run simulations and policy experiments. The simulations rely on real world data on the wealth and education distribution from different countries. To illustrate the key findings of the model and to highlight its policy implications, we have chosen three country-cases, the Philippines, Bangladesh, and Chad. All three cases are all highly prone to different forms of disasters and other environmental hazards, but different in terms of their educational and wealth endowment as well as their existing infrastructure.

This heterogeneity allows us to test for the effectiveness of different policy interventions – awareness campaigns, educational reforms, state subsidies, and insurance programs, among others – in increasing household resilience for each of the specific case settings. Our results are hence 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), environmentally induced poverty traps (Sachs et al. 2004; Ikefuji & Horii 2007; Dasgupta 1998), and environmental management (Selin & Chevez 1995).

The remainder of the extended abstract is structured as follows. Section 2 briefly introduces the basic model formulation on the micro level and formulates the optimization problem for the households. For this extended abstract, we transferred the main part of the model description and the solutions of the optimization problem to the Appendix. Section 3 introduces the data sets used to test the predictions of the model and to derive numerical parameters, which we use in Section 4 for our simulations. 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 hope to finalize by the end of this year.

2 Theoretical Model

We propose a stylized household lifecycle model with two time periods. In the first period, households decide how much of their endowments 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. The available endowment depends on the highest education level within the household as decisions of the households are made cooperatively between their members.

Figure 1 illustrates the main expected pathways explaining possible education effects. Education can affect the household allocation decision by influencing household income, access to prevention and mitigation measures, as well as the household's awareness. 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. In the Figure, we have included another potential channel through which education may affect household prevention: time preferences and future orientation (Picone et al. 2004; Camerer et al. 2004). As we are currently still in the process of including this additional factor into our theoretical and empirical modeling, it will not be discussed in more detail here in this extended abstract.

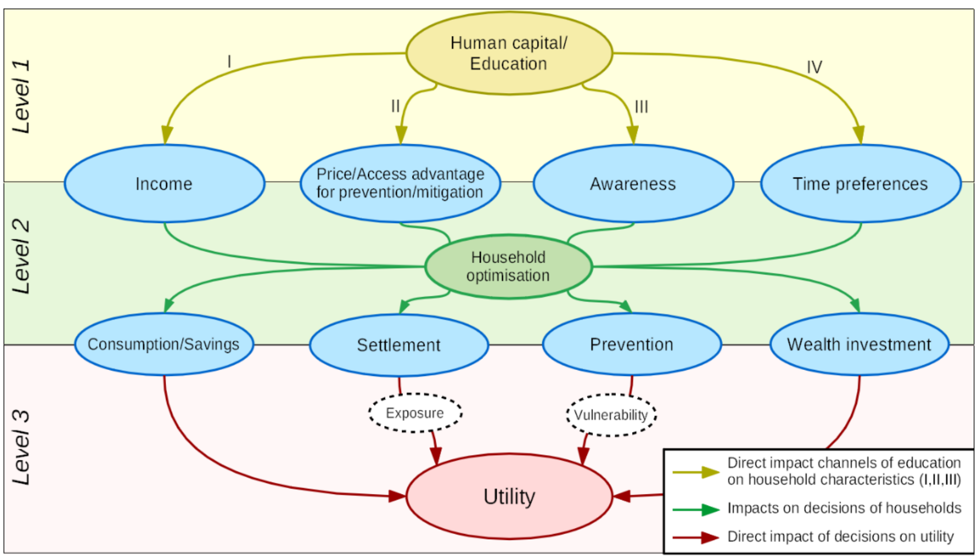

Figure 1 – Conceptual framework of the theoretical model

3 Research Design and Empirical Data

Data from two Southeast Asian Countries, the Philippines (PH) and Thailand (TH) are employed for the analysis. With diverse socio-economic background of the populations and different exposure to disaster risk, the two countries represent well-suited empirical cases for testing our theoretical model. 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.

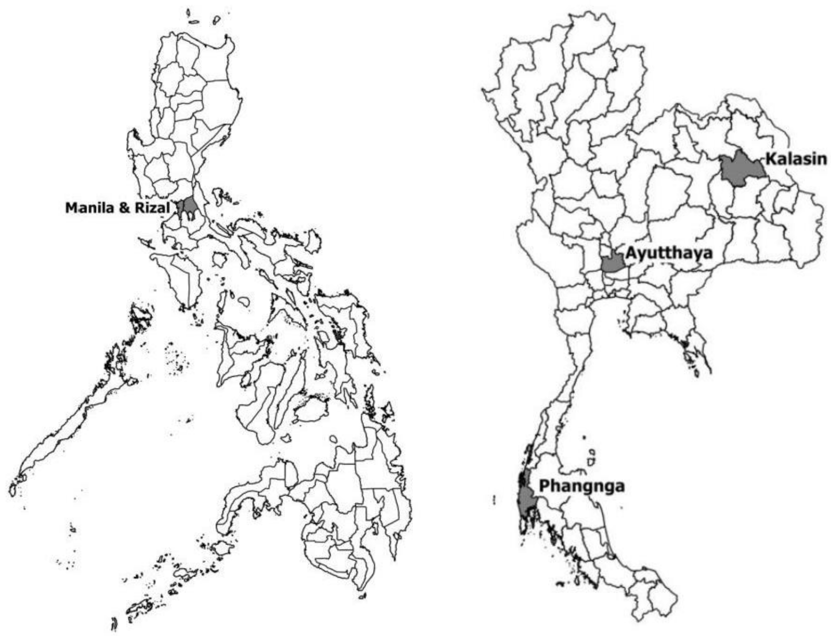

Figure 2 – Map of study areas in the Philippines and Thailand

The data for the Philippines were collected among low-income households in the wider area of Metro Manila, the capital. A multi-stage cluster sampling was employed . First, a sample of three wider neighborhoods 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. 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 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.

4 Empirical Results

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.

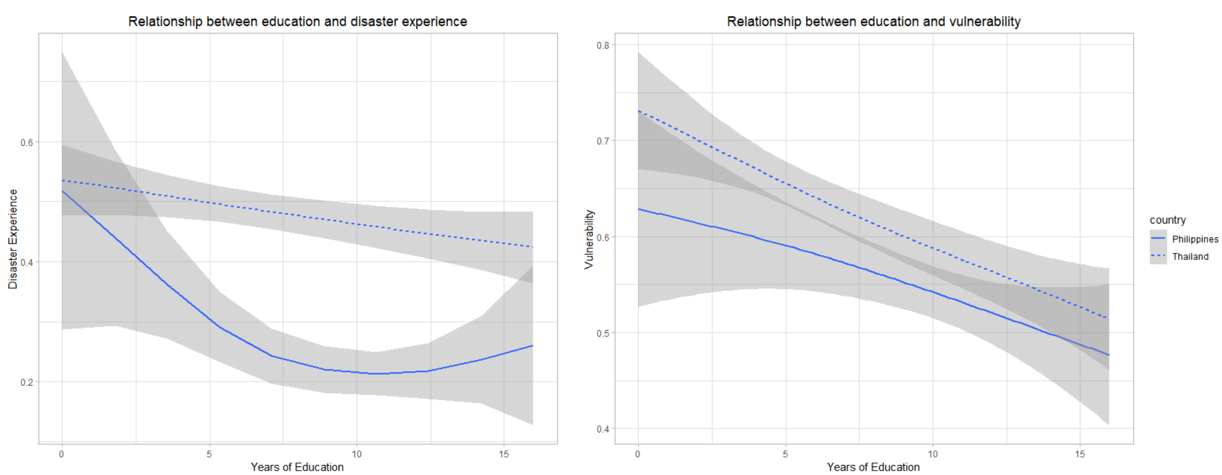

Figure 3 – Differences in disaster exposure and vulnerability by education level

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. The derived estimates form the basis of the model simulations and policy experiments in Section 4, where they are complemented with official administrative statistics from the selected country cases.

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	Aware-ness	Income	Access to resources	Aware-ness
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: * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

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 – 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]
% vhange 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]
% vhange 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≤0.1, ** p≤0.05, *** p≤0.01

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.

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.

5 Simulations and Policy Experiments

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. We use data from the Wittgenstein Human Capital Database as well as census information to model the country's specific education and wealth distribution. Based on our estimates, it becomes clear that parts of the population face a considerable disaster vulnerability.

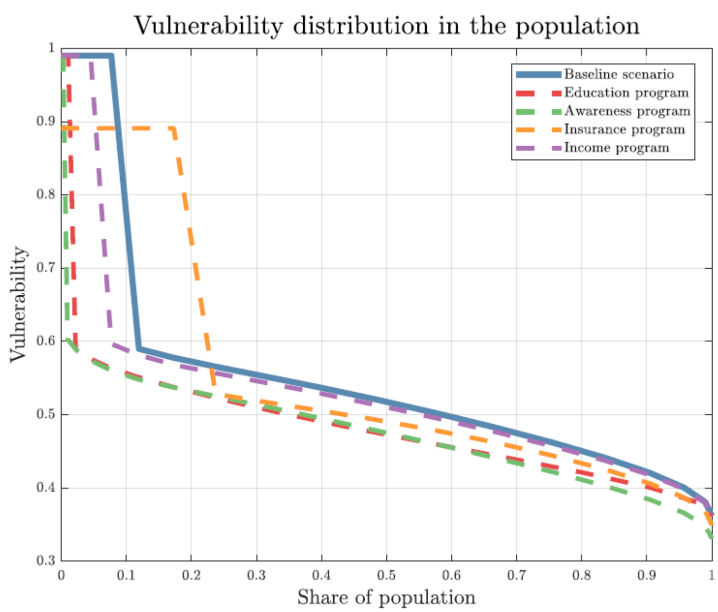

Figure 4 – Distribution of vulnerability and exemplary policy measures in the Philippines

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.

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Appendix

A1. Household Problem and Optimization

In our proposed model households maximize their expected lifetime-utility UU over the two time periods. Households gain utility in both periods from two different consumption goods (durable and non-durable). In the following we will refer to the durable consumption goods (e.g. housing) as wealth W and to the non-durable as consumption C. Furthermore households are assumed to show preference for consumption in the present leading to future consumption in the second period being discounted with a factor $\frac{1}{1+\rho}$. Utility in the first period is certain; in the second we impose utility to be stochastic due to the household potentially being exposed to a flood. For their objective, households consider their aggregated expected utility over the two time periods. This contains the deterministic utility in the first period and the expected discounted expected utility from the second period.

For the expected utility in the second period the household considers to different scenarios. In the first she is affected by a flood and a share of the wealth is destroyed. Additionally less household income can be generated in this case. The other possible scenarios contains no occurrence of floods and hence no damages or limitations for the households arise. The optimal utilities in both scenarios are then weighted with the subjective probabilities of the household ($R(D,a)$ and $(1-R(D,a))$), which depend on the settlement location D and her awareness a. A larger distance D to the riverside leads to a smaller probability of being affected by a flood. On the other hand higher awareness a about flood risk enables households to better estimate the true flood risk. Low awareness is likely to cause an underestimation of the flood risk given a settlement location D, what can have crucial impacts on the decisions made by the household.

Concluding the objective value UU takes the form below with $\sim_2^F$ describing the decision variables in the case of a flood and $\sim_2^{NF}$ analogous for the no flood scenario.

$$U(C_1, W_1) + \frac{1}{1+\rho}\left[R(D,a)U(C_2^F, W_2^F) + \big(1 - R(D,a)\big)U(C_2^{NF}, W_2^{NF})\right]$$

Risk coping strategies for the household consist of taking prevention measures P_1 to protect the wealth accumulated in the first period, resettling the household position D to change its risk exposure R, and lastly generate savings S_1 to cope for losses in case of flood damages. However all these different measures lead to direct and indirect costs. If the household decides to relocate, she looses a share L^W of her inherited wealth W_0. Furthermore increasing the distance D to the hazard origin decreases the exposure R, but on the other hand settlement locations with a lower risk are likely to be more expensive what is summarized in the cost function $p_D(D)$. [1]

We also obtain costs for the prevention measures taken to protect a share of P_1 of the accumulated wealth W_1 in the first period against flood damages. These costs additionally also depend on the distance to the risk origin and decrease with increasing D.[2] Furthermore we assume a convex functional structure for the costs of investment in wealth (I_1, I_2^F, I_2^{NF}). As a last part savings S_1 can be used to transfer income risk-free into the second stage with additional interest gains. This might be necessary, as we can assume lower income in second period due to decreasing productivity in old age. Additionally working income drops in case of flood occurrence, as time and efforts have to be spent to counter flood damages.

A2. Modeling Education Effects on Vulnerability

The education level h within a household now has four potential impact channels. First we propose that a higher education leads to higher income for the household. In our model this leads to the income ($y_1(h)$ and $y_2(h)$) in both time periods depending positively on h. Furthermore to incorporate that higher educated households are more forward looking compared to lower educated households we assume the time preference rate $\rho(h)$ to be decreasing in h. This lead to a higher weight for the second period utility within the optimization of higher educated households. As a third impact we identified a heterogeneity with respect to awareness a between household with differing education levels. In this case however we do not a-priori assume a positive effect of education, as other aspects like previous flood experience play a crucial role, and keep the functional form of $a(h)$ unspecified.

Lastly our model tries to reflect the better access to institutional assistance and the broader social networks of higher educated households. We decided to incorporate this fact through a price advantage for prevention measures with increasing educational level. Formally this means that $p_P = p_P(P_1, D, h)$ and $\frac{\partial p_P(P_1,D,h)}{\partial h} < 0$ and can also be interpreted that higher educated households need less effort (time and assets) to obtain the same level of prevention given a settlement location.

The complete model can thus be summarized as follows:

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[1] $p_D(D)$ can also be assumed to cover the opportunity cost of living further away from the river (and therefore commonly also the city center) regarding income losses.

[2] E.g. insurance is less expensive in areas with low risk of flood occurrence then in high risk areas.

$$\max_{C_1,I_1,S_1,P_1,D,\chi,C_2^i,I_2^i} U(C_1,W_1) + \frac{1}{1+\rho(h)}\Big[R\big(D,a(h)\big)U(C_2^F,W_2^F) + \Big(1-R\big(D,a(h)\big)\Big)U(C_2^{NF},W_2^{NF})\Big] \quad (1)$$

$$W_1 = (1-L^W * \chi)W_0 + I_1 \quad (1)$$

$$C_1 + p_W(I_1) + p_P(P_1,D,h) + p_D(D) = y_1(h) - S_1 \quad (2)$$

$$W_2^F = (1-\delta)W_1P_1 + I_2^F \quad (3)$$

$$C_2^F + p_W(I_2^F) + p_D(D) = y_2(h)(1-L^y) + (1+r)S_1 \quad (4)$$

$$W_2^{NF} = (1-\delta)W_1 + I_2^{NF} \quad (5)$$

$$C_2^{NF} + p_W(I_2^{NF}) + p_D(D) = y_2(h) + (1+r)S_1 \quad (6)$$

$$(1-\chi)\big(D-\overline{D}\big) = 0 \quad (8)$$

$$(1-\chi)\chi = 0 \quad (9)$$

$$W_0, \overline{D}, h \textit{ are exogenously given} \quad (10)$$

A3. Optimality Conditions

We can derive several optimality conditions with economic intuitions describing the behaviour of the households. First we obtain intratemporal optimality conditions, illustrating the decision between consumption and investment in wealth.

$$U_W(C_2^{\sim},W_2^{\sim}) = p_W'(I_2^{\sim})U_C(C_2^{\sim},W_2^{\sim}) \quad (11)$$

$$U_W(C_1,W_1) + \frac{(1-\delta)}{(1+\rho)}\big[U_W(C_2^{NF},W_2^{NF}) + R(D,a)[P_1U_W(C_2^F,W_2^F) - U_W(C_2^{NF},W_2^{NF})]\big] = p_W'(I_1)U_C(C_1,W_1) \quad (12)$$

Furthermore we can also characterize the intertemporal decision making.

$$U_C(C_1,W_1) = \frac{(1+r)}{(1+\rho)}\big[R(D,a)U_C(C_2^F,W_2^F) + \big(1-R(D,a)\big)U_C(C_2^{NF},W_2^{NF})\big] \quad (13)$$

We can also obtain a condition describing the decisions between prevention and the other variables. (We define $\frac{\partial p_P(P_1,D,h)}{\partial P_1} =: p_P'(P_1,D,h)$)

$$p'_P(P_1, D, h)U_C(C_1, W_1) = \frac{(1-\delta)}{(1+\rho)} R(D, a)U_C(C_2^F, W_2^F)p'_W(I_2^F)W_1 \tag{14}$$

$$\begin{aligned} U_W(C_1, W_1) + \frac{(1-\delta)}{(1+\rho)}\left[\big(1 - R(D, a)\big)U_W(C_2^{NF}, W_2^{NF}) + R(D, a)U_W(C_2^F, W_2^F)P_1\right] \\ = \frac{(1-\delta)}{(1+\rho)} R(D, a)U_W(C_2^F, W_2^F)\frac{p'_W(I_1)W_1}{p'_P(P_1, D, h)} \end{aligned} \tag{15}$$