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Should I stay or should I go: Modelling disaster risk behaviour using a dynamic household level approach

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Abstract

In the last decades, many parts of the world faced an increase in the number of extreme weather events and worsening climate conditions endangering the livelihood of households in developing countries that rely on their local environment. While various empirical studies have identified key factors of exposure and vulnerability to disaster risk, we still lack a conceptual understanding of how these forces interact and how they impact household decision making. To gain insight into these mechanisms we set up a dynamic household model where households face environmental hazards. To respond to the risk, households can either relocate to a safer area or undertake preventive measures. Both actions require material and immaterial resources, which constrain the household's decision. Households are assumed to be heterogeneous with respect to key empirically identified factors for individual disaster risk: education, income, risk awareness, time preference and their access to preventive measures.

This paper provides analytical insights into the short-run decision making of households derived from the theoretical framework as well as an extensive numerical investigation. To parameterize and calibrate the model we use data from Thailand and Vietnam. The roles of household characteristics on the short-term decision-making and long-run outcomes of households' well-being and disaster risk is discussed. We conclude the paper with an extensive evaluation of different policy interventions including housing and prevention cost subsidies as well as income transfers with respect to their heterogeneous effects on different sub-populations.

1. Introduction

Disaster risks are increasing on a global scale. Since the 1980s, the number of persons affected by weather- and climate-related hazards has increased by 43%. In 2021 more than 100 million people were directly affected by disasters that were causing damages of $230 billion (Centre for Research on the Epidemiology of Disasters (CRED), 2022). Climate change will lead to a further increase in the frequency and intensity of disaster events, while at the same time undermining communities' capabilities to adequately prepare against environmental hazards and cope with their consequences, leading to an increase in vulnerability in many regions of the world (IPCC, 2022; Hoffmann and Muttarak, 2017; Black et al., 2011).

Although human behavior has long been recognized as central for disaster risk management and planning (Aerts et al., 2018) as well as in mitigating disaster risks (Hoffmann and Blecha, 2020; Kohn et al., 2012), the influence of the social environment and behavioral drivers is often not fully taken into account in modelling disaster risk management (Kuhlicke et al., 2020; Lechowska, 2018). For example, undertaking precautionary measures, such as stockpiling of food, enhancing physical structures of houses, buying an insurance policy, or increasing precautionary savings, can be critical (Wisner et al., 2014). Also, the relocation from hazardous areas, if circumstances allow and if households are able and willing to move, can represent an effective strategy to reduce risks (Siders et al., 2019). Despite the importance of these factors in disaster risk reduction, a comprehensive and integrative understanding of the underlying behavioral and social drivers of disaster risk management at the household level as well as constraints and challenges faced by households is missing (Ejeta et al., 2015; Paton, 2019).

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. Their ability to adequately prepare against, respond to and cope with hazardous events is often limited. At the same time households are quite heterogeneous in their characteristics that shape their exposure and vulnerability to disaster risk. For instance, there is growing evidence that higher educational attainment constitutes an important channel to increase disaster preparedness and decrease vulnerability of households (Muttarak and Pothisiri, 2013; Meyer, 2015; Muttarak and Lutz, 2014; Hoffmann and Muttarak, 2017; Adger et al., 2005). However, the mechanisms through which household characteristics and particularly also human capital determine the vulnerability and exposure of households are not yet fully explored. The aim of our paper is to introduce a conceptual framework that links household characteristics to observed exposure and vulnerability of disaster risk and confront it with empirical data from developing countries. A specific focus of our framework is to differentiate household characteristics by educational level accounting for a key heterogeneity in our empirical data. Furthermore we will assess the effect of different policy interventions with respect to their effectivity in reducing risk and enhancing well-being and highlight the heterogeneous impact they have on households with different characteristics.

Formally, we develop a dynamic household model populated by households that differ in their human capital. To account for the heterogeneity of households by education we model four different channels, based on empirical findings, through which education can influence the exposure and vulnerability of households: (i) education is positively correlated with income levels and hence financial resources rendering costly precautionary measures possible; (ii) education can provide households with access to cost-efficient prevention measures, for example through social capital/networks; (iii) information, knowledge and awareness of disaster risks are positively correlated with education; and (iv) education is related to time preferences fostering far-sighted decisions (Paton and Johnston, 2001; Drabo and Mbaye, 2015; Nawrotzki et al., 2015; Lutz et al., 2014).

Households face environmental risks that expose them to the hazard of a potentially existential loss of their wealth. To reduce the risk, households can either relocate to a safer area or undertake preventive measures to protect their durable consumption goods. Both actions require material and immaterial resources, which constrain the household's decision. Their overall objective is to maximize welfare over an infinite time horizon. Thereby households optimize their behaviour while being constrained by their available wealth and being subject to the risk of natural disasters as well as to idiosyncratic shock on their income stream.

Data from the Thailand and Vietnam Socio-Economic Panel (TVSEP)[1], that cover a broad range of disaster risk behaviour of households, is used to parameterize the model and assess its predictive quality. With their diverse socio-economic background and high exposure to disaster risks, these two emerging lower-middle income countries represent ideal empirical case studies for our proposed model.

By solving the dynamic household model we obtain a set of optimal decision functions that allow us to predict the behaviour of households across, for instance, different settings of household wealth and exposure to disaster risk. Based on these decision functions and applying Monte-Carlo-Simulations we study the long-run behaviour of a synthetic population with respect to heterogeneity in education, prevention access, awareness and time preference as given in the TVSEP panel survey. These simulations allow us then to identify household types most prone to disaster risk. Moreover, our dynamic set up allows to differentiate between short and long term effects of disaster risks, i.e. whether households are persistently trapped into a vulnerable situation or only temporarily experience welfare losses after being hit by a disaster.

This novel framework consequently allows us to test the effectiveness of different policy intervention in reducing household risk to disaster shocks, since we are able to predict changes in the household behaviour and decision making. Basing the behaviour on household preferences enables us to identify unintended (and undesired) short- and long-term outcomes of interventions. These behavioural changes can not be predicted using empirical data alone, as correlations found in data are always dependent on the surrounding economic structure the households are facing.

The remainder of the paper is structured as follows. Section 2 provides an overview of the literature on education and its correlation to household characteristics that in the end determine the exposure and vulnerability of the household. Section 3 presents the conceptual framework of the mathematical model and summarizes analytical insights on the decision making process of the household. Section 4 introduces the TVSEP as the main data source for the calibration in the numerical analysis, which is also used for the assessment of the predictive quality of the model. Finally, Section 5 presents the results of the numerical calibration exercise. These consist of a discussion on the optimal household decision rules (Section 5.1), the presentation of the long-run equilibrium distribution and their evaluation against the empirical data from the TVSEP (Section 5.2), a discussion on the impacts of the different household characteristics (Section 5.3), and the assessment of different policy interventions (Section 5.4). Section 6 concludes.

2. Education and Disaster Risk Reduction: Empirical Evidence

There is a growing empirical literature on the relationship between the socio-economic status (including edcuation) and the exposure and vulnerability to disaster risk. Households with a lower socio-economic

[1] See `www.tvsep.de`

status and lower education level are found to be more likely to reside in areas with higher exposure to natural disasters in the first place (Adger et al., 2005; Fothergill and Peek, 2004). Given an elevated risk level, preparing against disasters and the undertaking of preventive measures is crucial. Numerous studies report that education, be it formal or informal, increases preparedness at the individual and household level, including preparedness for earthquakes (Russell et al., 1995), hurricanes (Baker et al., 2011; Norris et al., 1999; Reininger et al., 2013), floods (Lave and Lave, 1991; Thieken et al., 2007), tsunami (Muttarak and Pothisiri, 2013), as well as general emergency preparedness (Al-Rousan et al., 2014; Smith and Notaro, 2009).

Similar findings are reported not only at the individual and household level but also at the aggregate level in country comparisons (Pichler and 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 and 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. Case studies include among others Indonesia (Frankenberg et al., 2013; Irmansyah et al., 2010) and Thailand (Garbero and Muttarak, 2013).

While there is convincing evidence that education positively affects preparedness, prevention, and the ability to cope with disaster risk, the specific mechanisms underlying these positive effects on the exposure and vulnerability of disaster risk are not yet completely known. Moreover, these effects of education on exposure and vulnerability can be direct or indirect. 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 correlations with material, informational, and social resources at the individual and household level, which allow better preparation against and adaptation to natural hazards and harmful environmental conditions. Our model framework takes both of those channels, direct and indirect, into account.

With regard to direct channels of influence, studies show that education equips one 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 and 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 assess risks related to disaster threats and to find adequate responses (Bruine de Bruin et al., 2007; Peters et al., 2006). Time preferences are another channel through which education could affect disaster preparedness, though this channel has received less attention in the literature so far. 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 and 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, these individuals 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 and McCright, 2007). At the same time, it is found that better educated households can build on broader and more resourceful social networks that can support them in the preparation and aftermath of disasters (Kirschenbaum, 2006; Solberg et al., 2010; Witvorapong et al., 2015).

3. Conceptual framework

Disaster risk for a household can be decomposed into three components: hazard, exposure and vulnerability. The hazard of a natural disaster captures the likelihood of a disaster occurring. While changing climate conditions lead to increasing hazards of natural disasters raising disaster risk all around the world, households perceive this development to be unconnected to their individual decisions. We therefore assume the hazard of a disaster to be an exogenous parameter in our model framework. However, we assume exposure and vulnerability to be endogenous and determined by household characteristics and household decisions.

A households exposure captures the probability that a household is affected by a hazard once it occurs. The level of exposure is mainly determined by the location of the households settlement as different areas (e.g. close to a river or in a region with higher seismic activity) exhibit varying degrees of likelihood of being affected by a disaster (e.g. flood or earthquake). To assess the influence of different household characteristics on exposure and thereby replicate the differential exposure levels within countries we introduce the settlement location as a state variable of the household's decision problem. Vulnerability on the other hand captures the impact of a hazard on the households well-being. This includes in a holistic way the loss of durable consumption goods and/or income, the need to restore durable goods, emotional, psychological and health impacts, etc. How far a disaster destroys these material and immaterial assets is related to the households decisions on preventive and adaptive measures together with the inherent characteristics of households.

Besides the settlement location (which defines the exposure level) we assume that the household faces two more dynamic constraints represented by the financial assets and durable consumption goods acting as state variables. The financial assets cover all assets and liabilities in non-physical form, such as debt claims towards other households or savings accounts, but also outstanding credits, at financial institutions. Physical wealth items, such as cash and other valuables like gold, are summarized in the durable consumption goods together with other physical items like housing, appliances and cars. In the conceptual flow diagram in Figure 1 the three state variables are presented at the top.

Furthermore, we assume that households not only differ with respect to the realisations of the state variables, but can also be distinguished along four key characteristics: their education level, their access to disaster prevention measures, their awareness with regard to natural disasters and their time preference rate. The level of education thereby has a special role, as it does not directly affect the preferences or constraints of a household (unlike the other characteristics), but acts through indirect channels by being an influencing factor on the other three characteristics. Additionally the education level determines the household's working income via two channels. Higher education is associated with higher average working income and shapes the idiosyncratic income shocks.

The objective of the household is to maximize the sum of present value discounted expected period utilities which depend on consumption and durable consumption goods. In his optimal decision the household has to take into account the dynamic constraints on financial assets, durable consumption goods and the settlement location. The specific stochastic processes the household faces are: (i) the occurrence of a hazard (which is exogenous to the household), (ii) whether the household is affected by the hazard or not (i.e., the households exposure to the hazard) and (iii) the stochastic (positive and negative) shocks to working income.

In each time period the household decides on (i) whether to relocate (ii) the new settlement location (in case of deciding for relocation), (iii) financial savings, (iv) final good consumption, (v) investment in durable consumption goods and (vi) prevention efforts.[2] These decisions are based on the previous period's state variables and are shaped by the characteristics of the household (as illustrated in Figure 1). While the settlement decision directly determines the households exposure level, the latter four decision

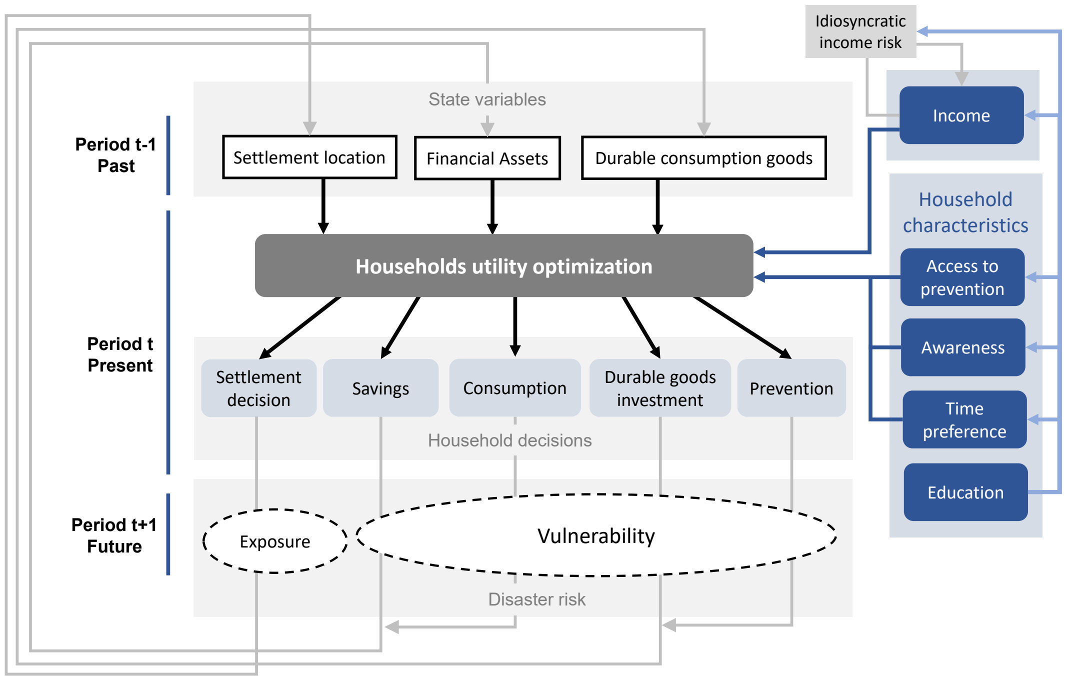

Figure 1: Conceptual framework

variables (savings, consumption, investment in durable consumption goods, and prevention) define the household's vulnerability. The household's decisions made in period t will determine the initial state variables and constraints in the next period $t+1$ (indicated by arrows going from the bottom back to the top in Figure 1).

In the following sections we introduce the mathematical specifications of our framework. Based on the dynamic optimisation problem at the household level we derive key analytical results of the households optimal dynamic strategies. We then calibrate the model to data from Thailand and Vietnam based on which we then present various numerical results.

[2]As described in Courbage et al. (2013) the term prevention generally describes two types of efforts in the literature of risk behaviour: (i) actions to reduce the probability of conceding losses (loss prevention) and (ii) actions to reduce the size of the losses (self-insurance or loss reduction). However since we consider preventive efforts of the first kind explicitly through settlement location (resp. exposure level), we explicitly only consider loss reduction efforts, when we refer to "prevention measures" or "prevention".

3.1. Dynamics of Exposure and Assets

The risk of a household being hit by a natural disaster depends on two stochastic processes: $\mathcal{N} = \{N_t \mid t = 0, 1, 2, \ldots\} \in \{0,1\}^{\mathbb{N}}$ and $\mathcal{D} = \{D_t \mid t = 0, 1, 2, \ldots\} \in \{0,1\}^{\mathbb{N}}$. N_t captures the occurrence ($N_t = 1$) or absence ($N_t = 0$) of a natural disaster between time periods $t-1$ and t. D_t on the other hand indicates whether a household is affected ($D_t = 1$) by a natural disaster or not ($D_t = 0$) between time period $t-1$ and t conditional on a natural disaster occurring ($N_t = 1$). While the stochastic process $\mathcal{N}$ is completely exogenous to the household, the probability of being hit by a disaster $\mathcal{D}$ (i.e. the probabilities of $D_t = 0$ or $D_t = 1$) is shaped by the household behaviour.

(i) By relocating their settlement households can alter the probability of being hit by a natural disaster in the future, i.e. they can adjust their exposure $E_{t+1} = \mathbb{P}[D_{t+1} = 1 | N_{t+1} = 1]$ at each point in time t by changing their household location.[3]

(ii) A natural disaster threatens the household to loose all its durable consumption goods W_{t+1}.[4] To prevent such damage, the household can undertake protective measures such as insuring their durable consumption goods against natural disasters or installing physical protection measures. These efforts will determine the share P_{t+1} of durable consumption goods protected against a disaster while the remaining amount, $(1 - P_{t+1})W_{t+1}$, is assumed to be destroyed in case of a disaster.[5]

(iii) Alternatively through savings households can build up a stock of financial assets S_{t+1}, which are in no danger of being destroyed and furthermore generate interest at rate r_t. These assets not only allow the households to smooth the impact of uncertain labor income, but also enable them to reinvest into durable consumption goods W especially after losses during a natural disaster. As a result financial assets enhance the households abilities to mitigate potential damages ex-post, i.e. after a disaster has occurred. Although not contributing directly to the period utility (in contrast to durable consumption goods W), savings are important to smooth consumption. Labor activity and hence labor income may be reduced after a disaster when households have to invest time to deal with damages caused by natural disasters. To implement such income losses we assume that the working income is reduced by a share Δ^y, if the household was hit by a disaster in the previous time period.

These three mechanisms (how households are affected and react to a disaster) will shape the evolution of the dynamic state constraints at the household level. The decision on the settlement relocation is represented by an indicator variable I_t ($I_t = 1$ if the households relocates and respectively $I_t = 0$ if the household remains at the same settlement location). The location decision determines the level of

[3] In this model we assume that the exposure level is the distinctive trait of different settlement locations. In general we could still allow households to choose the place to relocate by its position L_t out of a general geographic set $\mathcal{L}$. However, as the location enters the household problem only through the induced exposure to natural hazards, it significantly simplifies the model to use the exposure level E_t directly as the decision variable. This allows to omit a functional transformation $L_t \to E_t$ and hence implies a simpler feasible domain for the relocation decision, since $E_t \in [0, 1]$.

[4] Durable consumption goods W_{t+1} cover all durable consumption goods of the household.

[5] The literature on disaster risk behavior (Bensalem et al., 2020; Ehrlich and Becker, 1972) often distinguishes between physical protection measures and investments in insurance. However, within our framework the impact of both types of intervention on the transfer of durable consumption goods across time are actually identical. So to simplify the model, we unify both approaches into the prevention decision.

exposure in the next period as represented by equation (1).

$$\begin{cases} E_{t+1} = E_t & \text{if } I_t = 0 \\ E_{t+1} \in [0,1] & \text{if } I_t = 1 \end{cases} \iff \qquad 0 = (E_{t+1} - E_t) \cdot (1 - I_t) \qquad \text{with } E_{t+1} \in [0,1] \tag{1}$$

Note, that in (1) we have applied the fact that the case distinction can also be written as a single constraint on the two variables E_{t+1} and I_t.

Nevertheless, relocating to a new settlement location is costly by itself and not all durable consumption goods can be transferred to the new settlement location. We implement these losses by assuming that only a share $1 - \Delta^W$ of the households durable consumption goods remain in their possession in case of a settlement relocation.[6] Accounting for general depreciation of durable consumption goods at rate δ, we assume that the accumulation follows equation (2)

$$W_{t+1} = (1-\delta)(1-\Delta^W I_t)W_t \cdot (1-(1-P_t)D_t) + w_t \tag{2}$$

with w_t being the investments into durable consumption goods. Thereby we allow w_t to also be negative modeling the option for households to dissolve some of their durable consumption goods into financial assets. We account for potential sales at a lower value as stated in equation (4) below.[7] Note that the durable consumption good of the last period W_t needs to be adjusted depending on whether the household was affected by a natural disaster or not. This is covered by the term $(1-(1-P_t)D_t)$, as it holds that

$$W_t \cdot (1-(1-P_t)D_t) = \begin{cases} W_t & \text{if } D_t = 0 \\ W_t P_t & \text{if } D_t = 1 \end{cases}.$$

The dynamics of financial assets S_t are determined by the difference of total income and total expenditures as summarized in equation (3).

$$S_{t+1} = y_t \cdot (1-\Delta^y D_t) + (1+r_t(S_t))S_t - c_t - p^w(w_t) - p^P(E_{t+1}, W_{t+1}, P_{t+1}) - p^E(E_{t+1}) \tag{3}$$

$$p^w(w_t) = \begin{cases} w_t & \text{if } w_t \geq 0 \\ \kappa w_t & \text{if } w_t < 0 \end{cases} \tag{4}$$

Total income is composed of labor income y_t, which is diminished by the share Δ^y in case of a disaster, and the gross interest generated by financial assets $(1+r_t(S_t))S_t$.[8] Labor income is a stochastic process itself, representing the idiosyncratic income risk, summarized in $\mathcal{Y} = \{y_t \,|\, t = 1,2,\ldots\}$. The stochastic properties (e.g. the range of income realizations and transition probabilities between them) depend on the educational level of the household. We implement this assumption in the numerical calibration.

Total expenditure can be split up into (i) consumption expenditure c_t, (ii) investment in durable consumption goods $p^w(w_t)$ (which could also be negative), (iii) expenditures on prevention effort $p^P(E_{t+1}, W_{t+1}, P_{t+1})$

[6] This formulation in a stylistic way also tries to capture, that people get attached to their surroundings and living environments over time leading to a disincentive to relocate from even highly exposed areas. Also social ties and other emotional connections can be assumed to impact the decision making in a similar way.

[7] This specification is not only intuitive but also generates a disincentive for potential counter-intuitive behavior of households constantly buying and reselling durable consumption goods in different periods of time.

[8] As the empirical data used for parametrisation and calibration shows a significant difference between the interest rates on positive and negative savings, we decided to introduce a state-dependent interest rate.

and (iv) living costs $p^E(E_{t+1})$ depending on the settlement location/exposure level. We generally allow households to go into debt, i.e. $S_{t+1} < 0$, with a lower bound $\underline{S}$. $\underline{S}$ thereby corresponds to the level of financial debt at which the households are still able to pay the interest $-r_t(\underline{S})\underline{S}$ without going into further debt, when facing the lowest possible income realization, by reducing all other expenditures to the lowest possible level. Hence $\underline{S}$ can be implicitly defined by

$$-\underline{S}r_t(\underline{S}) = \max\left\{0, \min_{y_t\in\Omega}\{y_t\}\cdot(1-\Delta_y) - p^E(1)\right\} \tag{5}$$

with Ω being the domain of the stochastic income process $\mathcal{Y}$.

The costs for prevention efforts depend on the amount of durable consumption goods and the level of protection the household aims for, but also on the exposure level of the settlement location.[9] We assume living costs at different locations to depend on the exposure level that characterizes each location. The functional form $p^E(E_t)$ should not only reflect, that safer/less exposed areas often exhibit higher (induced) rents, but might also imply higher opportunity costs.[10]

To determine the optimal level of expenditures, households maximize their expected utility $\mathcal{U}$ as represented by the sum of discounted (at rate ρ) expected future period utilities $u(c_t, W_{t+1})$ that depend on consumption c_t and durable consumption goods W_{t+1}. We propose an additive separable dynastic utility function.[11] As indicated in equation (6) the expected value is built with regard to the stochastic processes of the occurrence of a disaster $\mathcal{N}$, the household affectedness $\mathcal{D}$ and the stochastic process underlying the labor income $\mathcal{Y}$.

$$\mathcal{U} = \mathbb{E}_{\mathcal{N},\mathcal{D},\mathcal{Y}}\left[\sum_{t=0}^{\infty}\left(\frac{1}{1+\rho}\right)^t u(c_t, W_{t+1})\right] \tag{6}$$

The stochastic household optimisation problem can be summarized as follows:

$$\max_{\substack{S_{t+1},W_{t+1},I_t,E_{t+1},P_{t+1},\\ t\in\{0,1,\dots\}}} \mathbb{E}_{\mathcal{N},\mathcal{D},\mathcal{Y}}\left[\sum_{t=0}^{\infty}\left(\frac{1}{1+\rho}\right)^t u(c_t, W_{t+1})\right] \tag{7a}$$

$$s.t.\ S_{t+1} = y_t\cdot(1-\Delta^y D_t) + (1+r_t(S_t))\,S_t - c_t - p^w(w_t) - p^P(E_{t+1}, W_{t+1}, P_{t+1}) - p^E(E_{t+1}) \tag{7b}$$

$$W_{t+1} = (1-\delta)(1-\Delta^W I_t)(1-(1-P_t)D_t)W_t + w_t \tag{7c}$$

$$(E_{t+1} - E_t)(1 - I_t) = 0 \tag{7d}$$

$$E_{t+1}\in[0,1]\ ,\ S_{t+1}\geq\underline{S}\ ,\ W_{t+1}\geq 0\ ,\ P_{t+1}\in[0,1]\ ,\ I_t\in\{0,1\}\ ,\ c_t\geq 0 \tag{7e}$$

$$(E_0, S_0, W_0, D_0, P_0)\ \text{exogeneous starting values} \tag{7f}$$

[9] This dependency on the exposure level is in accordance to actuarially fair insurance premiums, which are based on the expected costs for the insurer. See Equation (26) in Section 4 for further explanations.

[10] Cities are often built along bodies of water. Settling in location which are less prone for flooding coincides with settling further away from the city center, which in general offers the most economic opportunities. Consequently settling further away makes either time investments for traveling to the city center necessary or implies opportunity costs of missing out on economic possibilities.

[11] Households can still be characterized by the four characteristics presented in figure 1 as education is empirically shown to be transferred to the next generation with a high probability. Hence, due to the correlation of education with the other key characteristics, we can also assume, that they are likely to be passed on to the next generation.

$$\mathcal{N} \sim \begin{cases} \mathbb{P}[N_t = 1] = H_t \\ \mathbb{P}[N_t = 0] = 1 - H_t \end{cases} \quad , \quad \mathcal{D} \sim \begin{cases} \mathbb{P}[D_t = 1] = a_{t-1} E_t H_t \\ \mathbb{P}[D_t = 0] = 1 - a_{t-1} E_t H_t \end{cases} \quad , \quad \mathcal{Y} \sim (\mathbb{R}^+, \mathcal{F}, \mathcal{P}) \tag{7g}$$

The specific functional forms of e.g. living and prevention costs and other parametric specifications for the stochastic income process $\mathcal{Y} \sim (\mathbb{R}^+, \mathcal{F}, \mathcal{P})$ and the utility function are discussed in Section 4.

3.2. Household characteristics

As presented in Figure 1 the decision process at the household level depends on four key characteristics as well as the household income level. More specifically we propose that education is highly correlated to the other three characteristics and has a significant impact on the properties of the household's working income. In the following we discuss how each characteristic impacts the household's constraints and objective function.

Income

To model the stochastic nature of working income over time we assume that the mean-adjusted log-income $\widetilde{y}_t$ follows an AR(1)-process, with variance σ^2 and persistence ζ over time. As we denote the mean income by $\overline{y}$, we can define the income process as

$$y_t = \overline{y} \exp(\widetilde{y}_t) \tag{8}$$

$$\widetilde{y}_t = \zeta \widetilde{y}_{t-1} + \varepsilon_t \qquad \text{with} \qquad \varepsilon_t \sim WN(0, \sigma^2) \tag{9}$$

with ε_t being i.i.d. white noise.[12] For the numerical solution, we approximate the AR(1) process with a 5-dimensional Markov-Chain (see Section 4 for details.)

Based on the empirical literature and our own findings based on data from Thailand and Vietnam (see Section 4) education has a threefold impact on the income process as it affects not only the mean income level, but also the variance and persistence of the demeaned log-income. Hence, we introduce the subscript h to the parameters $\overline{y_h}$, σ_h^2 and ζ_h.

Access to prevention

Multiple empirical studies have shown, that households can vary significantly with respect to their access to disaster prevention measures. These variations result from differences in knowledge and social networks (which are both strongly affected by education) amongst others (Nawrotzki et al., 2015).

To reflect this heterogeneity in our framework, we argue that better access to prevention is equivalent to lower costs of prevention. We propose, that the efforts needed to ensure the same level of prevention P_t are lower for households with better access to prevention measures. The specific functional forms we apply for our numerical simulations are summarized in Section 4.

Awareness

Although households decide about their exposure level by adjusting their settlement location, assessing the true exposure level of a given settlement location is far from a trivial task at the individual level. Frequent previous disaster experiences can lead to better judgements of future potential exposure, but

[12]A similar setting for the modelling of education specific income process can be found in Krueger and Ludwig (2016).

longer periods of remaining unharmed might decrease the awareness of the true risk. As presented in Section 2 empirical studies have also shown that awareness is positively correlated to the education of households. Changes in the climatic conditions can increase the hazard of natural disasters (i.e. $\mathbb{P}[N_t = 1] =: H_t$) unexpectedly and pose another potential element of incomplete information for the households.

We include these various arguments on how awareness is built up and develops over time into the model by introducing an awareness parameter $a_t \in [0, 1]$ for each household. This parameter reflects all possible levels between full awareness of the exposure to natural disasters at different settlement locations ($a_t = 1$), and being completely ignorant towards any potential disaster ($a_t = 0$). Note, that we abstract from the overestimation of natural hazards (i.e. $a_t > 1$) since underestimation of disaster risk seems to constitute the more relevant situation concerning the identification of drivers of high vulnerability and exposure.

The awareness affects the households utility maximisation problem through the expectation operator $\mathbb{E}_{\mathcal{N},\mathcal{D},\mathcal{Y}}$ in the households aggregated utility presented in equation (6). While the true objective probability that a household is affected by a natural disaster corresponds to the exposure level E_{t+1} of the settlement location multiplied with the probability H_{t+1} of a natural disaster occurring, the household underestimates the risk by building its expectations based on the adjusted subjective probability $a_t E_{t+1} H_{t+1}$.[13]

Time preference

Another important factor that characterizes household risk behaviour is the time preference rate ρ. A higher time preference rate implies a stronger discounting of utility in future time periods. Empirical evidence such as e.g. Viscusi and Moore (1989) and Jung et al. (2021) indicates that higher educated individuals are more likely to be forward looking and consequently their time preference is higher.

3.3. Analytical results

The complete household optimisation problem consisting of maximizing the expected utility and several constraints as presented in the set of Equations (7) can be formulated in the equivalent Bellman-formulation.[14] The Bellman equation uses the value function $V(E, S, W, Y, D)$ to describe the optimal objective value depending on the initial value of the state variables exposure E, financial savings S, durable consumption goods W and the realisations of stochastic processes of income Y and disaster experience D. Due to the infinite time horizon and the time-invariance of the problem, the value function fulfils the system of equations (10).

$$V(E_t, S_t, W_t, y_t, D_t) = \max_{\substack{E_{t+1}\in[0,1],\ S_{t+1}\geq \underline{S},\ W_{t+1}\geq 0 \\ P_{t+1}\in[0,1],\ I_t\in\{0,1\},\ c_t\geq 0, w_t}} \Bigg\{ u(c_t, W_{t+1}) +$$

$$+ \frac{1}{1+\rho} \Bigg[a_t E_{t+1} H_{t+1} \cdot \mathbb{E}_{\mathcal{Y}} \left[V(E_{t+1}, S_{t+1}, W_{t+1} \cdot P_{t+1}, \mathcal{Y}, D_{t+1} = 1) \right] +$$

[13]The Bellman formulation of the dynamic household problem in Section 3.3 highlights the impact of awareness in the decision process.

[14]The Bellman-formulation facilitates the derivation of analytical results which allow for more intuitive interpretations compared to the stochastic problem formulation (7). Furthermore, the efficient numerical solution of the model is only possible through the Bellman-formulation.

$$+ (1 - a_t E_{t+1} H_{t+1}) \cdot \mathbb{E}_{\mathcal{Y}} \left[V(E_{t+1}, S_{t+1}, W_{t+1}, \mathcal{Y}, D_{t+1} = 0) \right] \Big] \Big\} \tag{10a}$$

$$S_{t+1} = y_t \cdot (1 - \Delta^y D_t) + (1 + r_t) S_t - c_t - p^w(w_t) - p^P(E_{t+1}, W_{t+1}, P_{t+1}) - p^E(E_{t+1}) \tag{10b}$$

$$W_{t+1} = (1 - \delta)(1 - \Delta^W I_t) W_t + w_t \tag{10c}$$

$$0 = (E_{t+1} - E_t) \cdot (1 - I_t) \tag{10d}$$

The Bellman-Equation (10a) illustrates that the optimal value function evaluated at time t in state $(E_t, S_t, W_t, y_t, D_t)$ is equal to the optimal trade-off between present utility $u(c_t, W_{t+1})$ from consumption and durable consumption goods in period t and the discounted expected value function in all future time periods. The expected value consists of two different terms. The first part contains the scenario with the household being affected by a disaster (i.e. $D_t = 1$), which consequently is weighted with the probability $a_t^h E_{t+1} H_{t+1}$. In this case the households enter the next time period with their durable consumption goods being equal to $W_{t+1} \cdot P_{t+1}$, hence this term enters the value function.[15] The second part covers the case of households not being hit by a natural disaster. The prevention measures have no effect here and the household enters the next time period with the same level of durable consumption goods they ended up with in the current period, i.e. W_{t+1}.

Solving the original stochastic problem over an infinite time horizon is equivalent to finding a value function $V(\cdot)$, which solves the problem in Bellman formulation (10a) - (10d). Furthermore through solving for the value function we directly obtain the optimal decision rules for household in all possible scenarios, i.e. all combination of (E, S, W, Y, D). These decision rules at the same time maximize the expected utility over the infinite time horizon presented in equation (6) and they are denoted as the corresponding policy functions. We are able to derive the analytical first-order optimality conditions for these policy functions as presented in Proposition 1.

Proposition 1 (First order conditions) *Assume that the value function $V(E, S, W, Y, D)$ for problem (10a) - (10d) is continuous differentiable in S and W. Furthermore, assume that the optimal solution $(E^*, S^*, W^*, P^*, I^*, c^*, w^*)$ is an interior solution in S^*, W^*, c^* and P^*. Than the optimal solution has to fulfil the first order optimality conditions (11), (12), and (13). (Note that we omitted the time indices here.)*

$$\begin{aligned} u_c(c^*, W^*) &= \frac{1}{1+\rho} \mathbb{E}_{\mathcal{D},\mathcal{Y}} \left\{ \frac{\partial V}{\partial S} \right\} \\ &= \frac{1}{1+\rho} \left[aE^*H \cdot \mathbb{E}_{\mathcal{Y}} \frac{\partial V}{\partial S}(E^*, S^*, W^* \cdot P^*, \mathcal{Y}, D = 1) + (1 - aE^*H) \cdot \mathbb{E}_{\mathcal{Y}} \frac{\partial V}{\partial S}(E^*, S^*, W^*, \mathcal{Y}, D = 0) \right] \end{aligned} \tag{11}$$

[15] Note that W_t used in the value-function-formulation (10) has a slightly different interpretation then W_t in the stochastic problem formulation (7). While the latter captures the durable consumption goods *before* a potential natural disaster (and needs to be adjusted accordingly), the former represents the durable consumption goods already *after* a potential disaster following the decision making in the previous period and hence no adjustment is necessary anymore (see Equation (10c)). We decided for this reformulation as it drastically simplifies the theoretical and numerical analysis. Without this adjustment the W_{t+1} would enter the value-function in both scenarios on the right hand side of the Bellman-equation (10a), but we would need to introduce the prevention decision of the previous time-period P_t as additional functional argument of the value-function $V(\cdot)$. Instead we can omit P_t as a separate argument, by replacing W_{t+1} with $W_{t+1}P_{t+1}$ in the value-function of the disaster scenario in the Bellman-equation (10a) and this slight change in interpretation. This adaptation leads to more intuitive interpretations of the FOCs and reducing the dimensionality of the value-function-problem dramatically reduces the calculation efforts for the numerical solution.

$$u_c(c^*, W^*) \cdot \left[\frac{\partial p^w}{\partial w}(w^*) + \frac{\partial p^P}{\partial W}(E^*, W^*, P^*)\right] = u_W(c^*, W^*) +$$

$$+ \frac{1}{1+\rho}\left[aE^*H \cdot P \cdot \mathbb{E}_{\mathcal{Y}} \frac{\partial V}{\partial W}(E^*, S^*, W^* \cdot P^*, \mathcal{Y}, 1) + (1 - aE^*H) \cdot \mathbb{E}_{\mathcal{Y}} \frac{\partial V}{\partial W}(E^*, S^*, W^*, \mathcal{Y}, 0)\right]$$

$$= u_W(c^*, W^*) + \frac{1}{1+\rho}\left[\mathbb{E}_{\mathcal{D},\mathcal{Y}}\left\{\frac{\partial V}{\partial W}\right\} - aE^*H(1 - P^*) \cdot \mathbb{E}_{\mathcal{Y}}\left\{\frac{\partial V}{\partial W}(E^*, S^*, W^* \cdot P^*, \mathcal{Y}, 1)\right\}\right] \tag{12}$$

$$u_c(c^*, W^*) \cdot \frac{\partial p^P}{\partial P}(E^*, W^*, P^*) = \frac{1}{1+\rho} aE^*H \cdot W^* \cdot \mathbb{E}_{\mathcal{Y}}\left\{\frac{\partial V}{\partial W}(E^*, S^*, W^* \cdot P^*, \mathcal{Y}, 1)\right\} \tag{13}$$

For the proof we set up the Lagrange function $\mathcal{L}$.

$$\mathcal{L} = u(c, W) + \frac{1}{1+\rho}\Big[aEH \cdot \mathbb{E}_{\mathcal{Y}} V(E, S, W \cdot P, \mathcal{Y}, 1) + (1 - aEH) \cdot \mathbb{E}_{\mathcal{Y}} V(E, S, W, \mathcal{Y}, 0)\Big] +$$

$$+ \lambda^S \left(-S + y_t \cdot (1 - \Delta^y D_{t-1}) + (1 + r_t)S_t - c - p^w(w) - p^P(E, W, P) - p^E(E)\right) +$$

$$+ \lambda^W \left(-W + (1 - \delta)(1 - \Delta^W I)W_t + w\right) + \lambda^I (E - E_t)(1 - I) \tag{14}$$

Taking the derivative of the Lagrange function with respect to the decision variables c, W, S and w leads to.

$$\frac{d\mathcal{L}}{dc} = u_c - \lambda_S \tag{15}$$

$$\frac{d\mathcal{L}}{dS} = \frac{1}{1+\rho}\Big[aEH \cdot \frac{\partial}{\partial S}\left[\mathbb{E}_{\mathcal{Y}} V(E, S, W \cdot P, \mathcal{Y}, 1)\right] + (1 - aEH) \cdot \frac{\partial}{\partial S}\left[\mathbb{E}_{\mathcal{Y}} V(E, S, W, \mathcal{Y}, 0)\right]\Big] - \lambda_S \tag{16}$$

$$\frac{d\mathcal{L}}{dW} = u_W + \frac{1}{1+\rho}\Big[aEH \cdot \frac{\partial}{\partial W}\left[\mathbb{E}_{\mathcal{Y}} V(E, S, W \cdot P, \mathcal{Y}, 1)\right] \cdot P + (1 - aEH) \cdot \frac{\partial}{\partial W}\left[\mathbb{E}_{\mathcal{Y}} V(E, S, W, \mathcal{Y}, 0)\right]\Big] +$$

$$+ \lambda_S \left(-p^P_W(E, W, P)\right) - \lambda_W \tag{17}$$

$$\frac{d\mathcal{L}}{dP} = \frac{1}{1+\rho}\Big[aEH \cdot \frac{\partial}{\partial W}\left[\mathbb{E}_{\mathcal{Y}} V(E, S, W \cdot P, \mathcal{Y}, 1)\right] \cdot W\Big] + \lambda_S \left(-p^P_P(E, W, P)\right) \tag{18}$$

$$\frac{d\mathcal{L}}{dw} = -\lambda_S \cdot \frac{d}{dw}\left[p^w(w)\right] + \lambda_W \tag{19}$$

The linearity of the expectation operator allows us to switch the order of the partial derivative and the expectation operators in equations (15) - (19). As we assume interior solutions, the derivatives of the Lagrange function have to be equal to zero in the optimal solution. Using equation (19) we obtain a relationship between the shadow prices for financial assets and durable consumption goods which allows for the elimination of λ_W from the system of equations. Finally, using the equality $\lambda_S = u_c$ following from equation (15) in equations (16), (17) and (18) implies the first-order optimality conditions presented in the proposition. ■

Equations (11), (12), and (13) summarise the trade-offs the households have to consider in their decision making.

- Equation (11) shows that in the optimum the marginal utility of consumption is equal to the expected marginal benefits of a marginal unit of additional financial assets. These benefits consist of the expected (with respect to stochastic income) marginal change in the value-function for the disaster and no-disaster scenarios, which are in turn weighted by the subjective probabilities of occurrence. Furthermore, these benefits are discounted at rate ρ as they only materialise in the next time period (compared to consumption).

- Equation (12) illustrates the trade-off between final good consumption and durable consumption goods. The left hand side contains the marginal utility gains if one marginal unit of durable consumption goods is used for final good consumption instead (the marginal utility of consumption multiplied with the marginal cost savings having fewer durable consumption goods). On the right hand side, we see that the benefits of durable consumption goods are twofold (in contrast to the benefits of consumption or financial assets). While consumption only generates utility gains in the current period and financial assets only affect future utility through the value function, durable consumption goods contribute through both channels. However, since they can get destroyed in case of a natural disaster (if not protected), the expected value of the derivative of the value function is smaller (in the disaster case the marginal gains are scaled with the prevention level P).

- Equation (13) relates the marginal utility gains through consumption (resulting from decreased preventive efforts) to the expected gains from higher prevention through the discounted value function in the next period. Since prevention efforts only become relevant in case of disaster occurrence, the benefits are limited to this case. Similar to the marginal prevention costs, also the benefits are more pronounced for higher levels of durable consumption goods due to the multiplicative nature within the value function.

These necessary optimality conditions for consumption, financial assets, durable consumption goods and prevention hold regardless of the relocation and exposure decisions of the household. Considering the remaining two parts of the overall optimal strategy gets slightly more complex. We cannot derive a first order optimality condition for the moving decision, because it is by definition a boundary solution on $[0, 1]$. However, distinguishing between the cases of relocation or remaining at the current location enables us to gain some insights into the decision process on the settlement location. Assuming an interior solution for the exposure level decision we obtain the first-order-optimality condition (20).

$$\begin{aligned} u_c(c^*, W^*) \cdot \left[\frac{\partial p^E}{\partial E}(E^*) + \frac{\partial p^P}{\partial E}(E^*, W^*, P^*)\right] - \lambda_I(1 - I^*) \;=\; \frac{1}{1+\rho}\Bigg[& aE^*H \cdot \mathbb{E}_{\mathcal{Y}} \frac{\partial V}{\partial E}(E^*, S^*, W^* \cdot P^*, \mathcal{Y}, 1) + \\ +(1 - aE^*H) \cdot \mathbb{E}_{\mathcal{Y}} \frac{\partial V}{\partial E}(E^*, S^*, W^*, \mathcal{Y}, 0) + aH \cdot \mathbb{E}_{\mathcal{Y}}\Big(V(E^*, S^*, W^* \cdot P^*, \mathcal{Y}, 1) &- V(E^*, S^*, W^*, \mathcal{Y}, 0)\Big)\Bigg] \end{aligned} \tag{20}$$

The right hand of (20) contains the marginal changes in the value function in the next period (similarly to the conditions in Proposition 1). The first two terms contain the marginal changes in the value function for marginal changes in E for the disaster and no-disaster scenario (respectively weighted). However, changes in the exposure level not only affect the value function, but also the probabilities at which a disaster affects the household. Hence, there is an additional term in (20), which represents the change in expected utility for a higher probability of disaster experience. This effect is weighted with the awareness a and the hazard H, so increasing higher awareness and increasing chance for natural disasters both lead to household acknowledging this aspect in the decision making to a higher degree. On the left hand side we find the marginal change in utility from consumption through changes in the costs with respect to the exposure level. However, there is the additional term $-\lambda_I(1-I)$ and for its analysis we need to distinguish two cases:

- In case it is optimal for the household to relocate (i.e. $I^* = 1$), the new exposure level for the settlement location is chosen optimally and the marginal benefits and marginal costs (in terms of consumption) have to be equal, since $\lambda_I(1-I^*) = 0$ holds.
- In case it is more beneficial for the household to remain in the same location (i.e. $I^* = 0$), λ_I contains the difference between marginal benefits and marginal costs related to the exposure level of the current settlement location.

We are able to derive similar FOCs from the stochastic formulation of the problem (7), which generate some additional insights regarding the long-run effect of the optimal decisions. We present these equations and a discussion in Appendix A.

Although we have analytically proven and gained some insights into the optimal trade-offs of the optimal household decisions, deriving further results for the solution of problem (10) (resp. problem (7)) is prohibited by the complexity of the problem. While the results of Proposition 1 require derivatives of the unknown value function $V(\cdot)$, the results of Proposition 2 (in Appendix A) depend on complex expected values of future behaviour. Both aspects are hard to overcome analytically, so we will focus on the numerical solution of the model for the remainder of the paper. As finding a numerical approximation of the unknown value function $V(\cdot)$ and the corresponding optimal policy functions is far from trivial itself and requires significant computational efforts, we provide a description of our approach in Appendix B.

4. Parametrisation and calibration

The Thailand-Vietnam-Socioeconomic-Panel (TVSEP) is a long term project collecting household panel data already over 8 waves starting in 2007. Each survey consists of almost 4400 households in 440 villages in rural areas of six provinces in Thailand and Vietnam. Since the questionnaire contains multiple questions on the risk behaviour and perception of households, the TVSEP is an appropriate database for the parametrisation and calibration of our model. In the following we discuss the choice of the parameters of our model and present the functional specifications. For our numerical analysis we use the wave from the year 2016 and add information from the previous wave in 2013 whenever we require longitudinal data. We also use the TVSEP to set up the distribution of households across key characteristics to initialize our simulations in Section 5. As only the questionnaire in Thailand contained a question on the time preference, we decided to focus on the data from Thailand and omit the data from Vietnam in our analysis.

In our model one period of time corresponds to two years and all parameters are adjusted accordingly to be representative for a two year period. In Table 2 we summarize all parameters and functional forms.

General parameters

For the depreciation of durable consumption goods we assume a rate of 2.5% per year, which implies $\delta = 0.0494$ over two years. The share of durable consumption goods lost during relocation is assumed to amount to 10% over two years, i.e. $\Delta^W = 0.1$. Similarly we assume that by converting durable consumption goods to financial savings, 10% are lost, i.e. $\kappa_Z = 0.9$. In the data we find the that average interest rate on savings is only 0.7% per year, while the average interest rate for borrowed assets is at

5.5% per year. To be able to replicate the empirical distribution of financial savings, we assumed the following step-wise constant function for the state-dependent interest rate:

$$r_t(S_t) = \begin{cases} r^+ & \text{if } S_t \geq 0 \\ r^- & \text{if } S_t < 0 \end{cases}. \tag{21}$$

The values for r^+ and r^- adjusted for the two-year-period are listed in Table 2. The share of income lost after suffering from a natural disaster can also be estimated from TVSEP data which contain specific information on the income households lost through natural disasters. Setting these losses in relation to the household income, we obtain a mean value of 8.34%.

Utility function

We assume an additive separable period utility function in consumption and durable consumption goods with each term being of the CRRA-type,

$$u(c, W) = \frac{c^{1-\gamma} - 1}{1-\gamma} + \theta \frac{W^{1-\beta} - 1}{1-\beta}. \tag{22}$$

A similar utility function has already been used by Strulik and Trimborn (2019). The authors also refer to the works of Bernanke (1984) and Iacoviello (2005) for empirical confirmation of the separability. The parameters $\gamma = 1.1$ and $\beta = 1.1$ are chosen according to the literature. $\theta = 0.75$ has been chosen based on the calibration of the model.

Living costs

Based on the value of land (normalised to the average landsize owned by households) we calculate an imputed rent as a measure for living costs $p_E(E)$. To obtain an estimate for the exposure at the household settlement location we use information on disaster experience provided by the TVSEP. We measure whether a household has experienced a natural disaster since the last wave of the TVSEP (from 2013 to 2016) and define a village average for this indicator. Each household consequently gets assigned the exposure level according to the village it is located in.

Having assigned an exposure level and living costs to each household, we assume the following functional form of the living costs as a function of the exposure/location level

$$p^E(E) = \underline{p_E} \exp(\phi(1-E)^2) \tag{23}$$

The parameter $\underline{p_E}$ provides the lower bound for the living costs in the most exposed locations, that is $E = 1$. The parameter ϕ captures the increase of living costs for decreasing exposure. We estimate both parameters from the data resulting in values of $\underline{p_E} = 0.2621$ and $\phi = 1.660$.

Income process

As already discussed in Section 3.2 we assume that the demeaned log-income follows an AR(1) process, i.e.

$$y_t = \overline{y} \exp(\widetilde{y_t}) \tag{24}$$

$$\widetilde{y_t} = \zeta \widetilde{y_{t-1}} + \varepsilon_t \qquad \text{with} \qquad \varepsilon_t \sim N(0, \sigma^2) \tag{25}$$

Based on TVSEP we estimate the mean income for the different educational groups $\overline{y} = \overline{y_h}$ for $h = \{1, 2, 3, 4, 5\}$. We have classified educational attainment into 5 groups starting from basic schooling up to high-school/university. Using the two waves from 2013 and 2016 allows us to derive estimates for the persistence of income ζ_h (calculated from the household income correlation between the two waves) and the variance of the idiosyncratic income shock σ_h^2 (calculated from the variance of the regression residual ε_t). Note that we normalised all income levels with respect to the mean income of the lowest education group. Hence we will measure all costs and expenditures in this calibration exercise in these Basic Income Units $[BIU]$. The numerical values of the education specific mean income, the persistence of income and the standard deviation can be found in Table 1.[16]

	Education category				
	1	2	3	4	5
$\overline{y_h}$	1.0000	1.3123	2.6701	3.5901	6.4096
ζ_h	0.2112	0.2142	0.1778	0.1548	0.5425
σ_h	1.0209	1.1253	0.8547	0.7523	0.9548

Table 1: Parameter estimates for the income process

Prevention costs

For the prevention costs we start with the actuarially fair insurance premium which is given by the expected pay-out by the insurance, i.e.,

$$p^P(E, W, P) = E \times [(1 - \delta) \cdot W \cdot P] + (1 - E) \times 0 \tag{26}$$

with the insurance paying out the depreciated value of protected assets in case of a disaster and paying out nothing if the household is not affected by the hazard.[17] To reflect the fact that access to prevention measures is different across households, we introduce a parameter φ, that may vary across households/education levels.

$$p^P(E, W, P) = (1 - \delta) \cdot E \cdot W \cdot P^{1+\varphi} \tag{27}$$

From this equation it directly follows that a higher value of φ implies lower costs for given values of the state variables E and W, and the prevention level P (recall that P is the share of prevention and less than one) . Hence, better access to prevention (captured by a higher value of φ) implies lower costs for prevention ceteris paribus. Note that full protection of all durable consumption goods of the household, i.e. $P = 1$, requires the actuarially fair insurance premia regardless of the specific level of access to prevention.

Since the stylized parameter φ is not directly measurable in the data, we assign households to one of three categories for the numerical solutions: low, medium or high access to prevention, which correspond

[16]For the numerical calculation and simulation we discretized the space of potential incomes into five different income realisations. Using the Tauchen algorithm (see Tauchen, 1986), we find the parameter estimates of a Markov-chain, that resamples the AR(1) process. We omitted the presentation of the different income levels and the transistion matrizes for each education group, as the AR(1) parameters are more instructive.

[17]Note that the households only pay for the depreciated value of the durable consumption goods $(1-\delta)W$. We assume that the disaster occurs between two time periods and the durable consumption goods from the last period get depreciated right at the beginning of the next time period. This means, that each durable consumption good, that the household has insured against damage from a natural disaster and gets replaced in case of occurrence also depreciates right afterwards. Hence the household actually only gets the present value of the assets from the insurance and hence should also only pay a premium according to the same value.

to a value of φ equal to 0.1, 0.35 and 0.6 respectively. We use the access to financial resources available in the TVSEP as a proxy for household access to prevention measures. We grouped households according to the average yearly interest rate they had to pay for money borrowed from different sources. Households with an average interest rate per year

- below 5% are classified in the high access category,
- between 5 an 10% are classified in the medium access category,
- above 10% are classified in the low access category.

Awareness

Similar to the prevention access, for the numerical solution we also assign households to one of three awareness level. Low awareness is associated with a value of $a = 0.5$, while high awareness is characterised by $a = 0.9$. Household showing medium awareness exhibit the average value between the two other groups with $a = 0.7$.

To assign households in the TVSEP dataset an appropriate awareness level, we compare their expectation of being affected by different natural disasters in the wave 2013 with the actual reported disaster experience reported in 2016. If they are able to exactly predict the number of natural disasters, they are assigned a high awareness. If they are one off in their expectations to get counted as medium awareness, while further deviation leads to them being assigned to the low awareness group.

Time preference

We also consider three different potential values for the time preference rate of households. The most forward-looking households are assigned the lowest value of 0.1581, which is around 1.4-times the interest rate r^-. The two less future-oriented groups on the other hand, are characterised by values of 0.2089 (1.85-times) and 0.2597 (2.3-times) respectively.

We identified households in the TVSEP dataset with different values of their time preference based on the question how willing they are to give up something now to gain more in the future. The answers were given on a scale of 0-10. Households with responses lower than 4 are assigned a high time-preference rate ($\rho = 0.2597$), while responses higher than 6 are classified as low time-preference ($\rho = 0.1581$). Reported values between 4 and 6 are categorised as medium time preference ($\rho = 0.2089$).

Education

For each household all members of the household are classified into one of five educational groups that differ by the years of education (ranging from discontinued primary education up to education at the university level). The household gets then assigned the median educational level of all its members.

Interest rate (savings)	r^+	$(1+0.0550)^2-1=0.1129$
Interest rate (credits)	r^-	$(1+0.0069)^2-1=0.0138$
Depreciation of phys. assets	δ	$1-(1-0.025)^2=0.0494$
Share of phys. assets lost during relocation	Δ^W	0.1
Value of phys. assets after liquidation	κ_Z	0.9
Share of income lost after disaster	Δ^y	0.0834
	γ	1.1
$u^1(c) = \frac{c^{1-\gamma}-1}{1-\gamma} + \theta\frac{W^{1-\beta}-1}{1-\beta}$	β	1.1
	θ	0.75
$p_E(E) = \underline{p_E}\exp(\phi(1-E)^2)$	$\underline{p_E}$	0.2621
	ϕ	1.6600
$y_t^h = \overline{y_h}\exp(\widetilde{y_t})$	$\overline{y_h}$	$(1.0, 1.3123, 2.6701, 3.5901, 6.4096)$
$\widetilde{y_t} = \zeta_h\widetilde{y_{t-1}} + \varepsilon_t$ with $\varepsilon_t \sim N(0,\sigma_h^2)$	ζ_h	$(0.2112, 0.2142, 0.1778, 0.1548, 0.5425)$
	σ_h	$(1.0209, 1.1253, 0.8547, 0.7523, 0.9548)$
Access to prevention	φ	$(0.1, 0.35, 0.6)$
Awareness	a	$(0.5, 0.7, 0.9)$
Time preference	ρ	$(0.1581, 0.2089, 0.2597)$

Table 2: Summary of functional specifications and parameters in the model.

Figure 2 provides an overview of the distribution of households across education, awareness, time preference, and prevention access as described above. The figure shows, that the majority of households has high awareness levels and only very few have low access to prevention measures. Furthermore, the distribution across education groups looks rather similar for combinations of the other household characteristics.

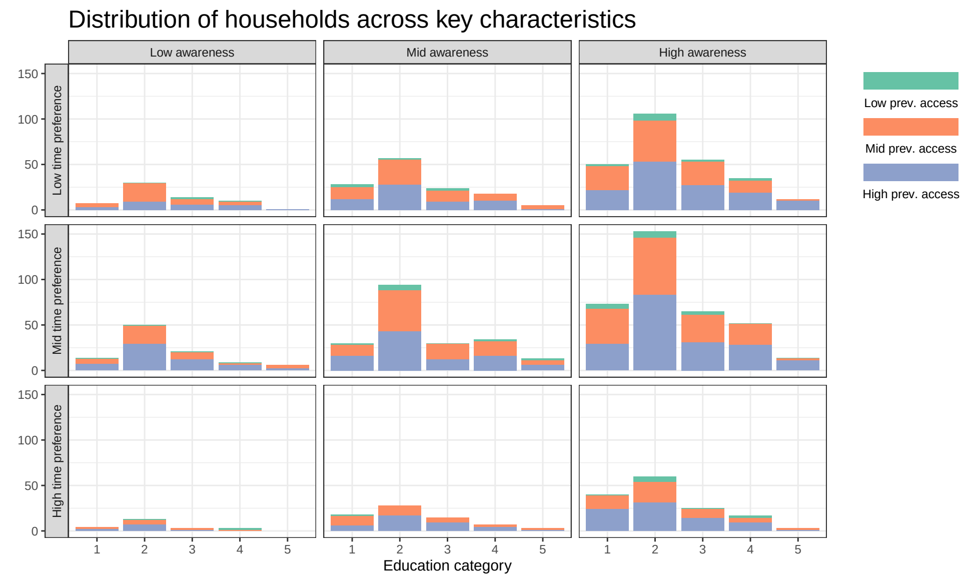

Figure 2: Distribution of households across the key characteristics education, awareness, time preference, and prevention access.

5. Numerical results

We structure the numerical results into four parts. Section 5.1 is devoted to the optimal household decision rules for the parametrisation as presented in Section 4. In Section 5.2 we present the long-run outcomes of households in form of equilibrium distributions across different variables and indicators. In Section 5.3 we investigate the role of household characteristics on the short-term decision rules and long-run outcomes for households. In Section 5.4 we assess the effectiveness of different types and intensities of policy interventions from a financial perspective and evaluate their potential for reduction of exposure, vulnerability and risk of all different types of households. For a more in-depth description of the numerical solution strategy and methods used we refer to Appendix B.

5.1. Household decision rules

The optimal household decision rules resulting from the solution of the optimisation problem (10) consist of five different decision variables (c, w, I, E, P) depending on a five dimensional set of state variables (E_0, A_0, W_0, Y_0, D_0). Hence, finding an appropriate illustration technique is far from a trivial task. In Figure 3 we present an extended phase diagram with the financial assets and the durable consumption goods on the x-axis and y-axis respectively. The arrows indicate the direction of the households net-change in financial assets (ΔS) and durable consumption goods (ΔW) and their colour represents the magnitude of these changes. The black and red line identify where the net-changes switch their sign, e.g. from a net-increase to a net-decrease. The color of the base of each arrow indicates whether a household decides to relocate (black) or remain at the same settlement location (white). The heatmap in grey-scale finally shows the exposure level after the relocation decision from exposure levels of 0 (white) to levels of 1 (black). The current income realisation Y_0 and disaster experience D_0 as well as the household characteristics are kept constant.

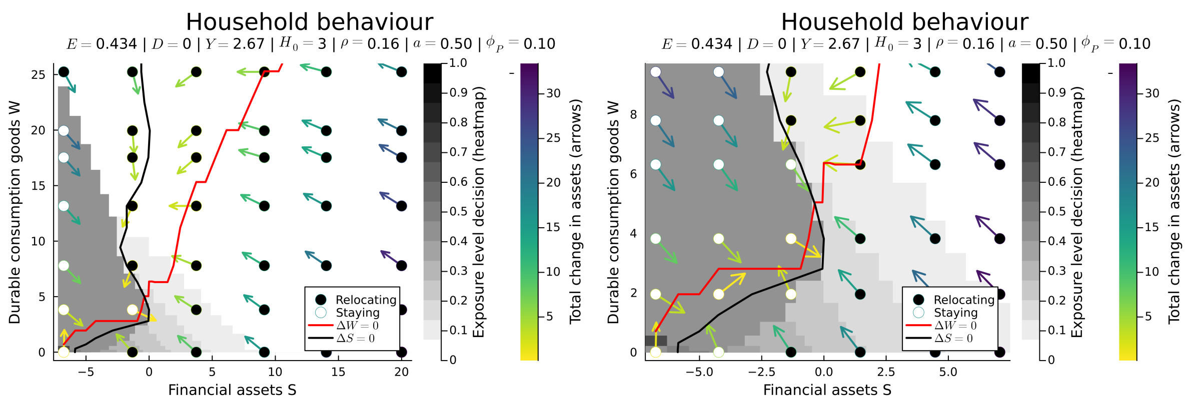

Figure 3: Household decision rules illustrated in a combined plot of a phase-diagram and heatmap. Left panel shows the diagram for a wider range of financial assets and durable consumption good combinations. The right panel zooms in on the area with switches in the relocation decision.

Figure 3 shows the optimal household decision rules for households with (i) a current settlement at exposure level $E = 0.434$, (ii) no disaster experience in the previous period ($D = 0$), (iii) income level of $Y = 2.67$ BIU, (iv) a medium education level $H_0 = 3$, (v) low time preference ($\rho = 0.16$), (vi) low awareness ($a = 0.5$), and low access to prevention ($\varphi_P = 0.1$). The right panel is an enhanced version of the left panel focusing on the area of a switch in the relocation decision.

First, we focus on the heatmap illustrating the exposure decision. We find the result that higher levels of financial assets allow households to relocate to less exposed areas more easily. For the durable consumption goods on the other hand, we find that for low levels they can have a prohibiting effect, by disincentivizing relocation (as durable consumption goods are lost in the process). Conditional on a positive relocation decision, however, an increase in either or both asset types (financial and durable consumption goods) allows households to decrease the exposure level of their new settlement location even further.

Secondly, the phase diagram in Figure 3 shows that households frequently substitute between financial assets and durable consumption goods. The shape of the black line provides an interesting pattern for the decision of financial savings. For relatively high levels of durable consumption goods, the line is close to 0 financial assets. This shows, that households do not want to go into significant debt and pay the high interest rate and debt r^- and instead transform some of their durable consumption goods into financial assets (phase-diagram arrows pointing downwards-right left of the line). At the same time the low interest rate r^+ on positive financial assets does not provide enough incentive to accumulate higher levels of financial assets. This pattern for the black line changes for low levels of durable consumption goods. Here the large marginal utility of durable consumption goods provides enough incentive for households to go into debt to finance additional durable consumption goods despite the high interest payments.

In Figure 4 we extend the analysis and consider the two additional state variables of the current income realisation and initial exposure level. Each plot in the grid of initial exposure levels (rows) and income realisations (columns) contains similar information as Figure 3.[18] Focusing on the effects of higher income realisations for the same level of initial exposure (i.e., focusing on one individual row of Figure 4) we find that the red line is shifted upwards while the black line is shifted towards the right. Hence, higher income levels directly imply a wider range financial assets and durable consumption goods endowments with positive net-investment in both types of wealth assets. This also means, that the intersection between the two lines is moved from the bottom-left towards the top-right. Figure 4 also shows that for a given exposure level higher income realisations allow households to move from more to less exposed areas in a wider range of scenarios, as the areas with the optimal decision to stay become smaller. Additionally there is also an effect of the income realisation on the exposure level of the new settlement, as higher income again allows for a relocation to lower exposed areas.

Considering effects of the initial exposure level for a given income level, we only find small effects on the red and black lines and even more interestingly that the initial exposure level only affects the decision on whether to relocate or not, but has no impact on the new exposure level (conditional on a positive relocation decision).[19] Still, the scenarios with households staying at the same settlement location change substantially. For low initial exposure levels households with durable consumption good stocks above 5 BIU or fairly high financial assets stay at this location for an additional time period. For slightly higher initial exposure levels, households with high asset levels decide to move to the safest locations while households with low levels of both asset types decide to relocate to even more exposed areas. When being exposed on a medium level, we find similar results as already discussed for Figure 3.

[18]For the clarity of the plots we replaced the arrow indicating the net change in the two assets at each point in the scatter plot, by green arrows representing the net-change in both asset types in each region separated by the black and red lines.

[19]This results from the fact, that if the household decides to relocate, only the new exposure level enters the objective and constraints of the optimisation problem. In case of a positive moving decision there is no element in the model depending on the difference between old and new settlement exposure level.

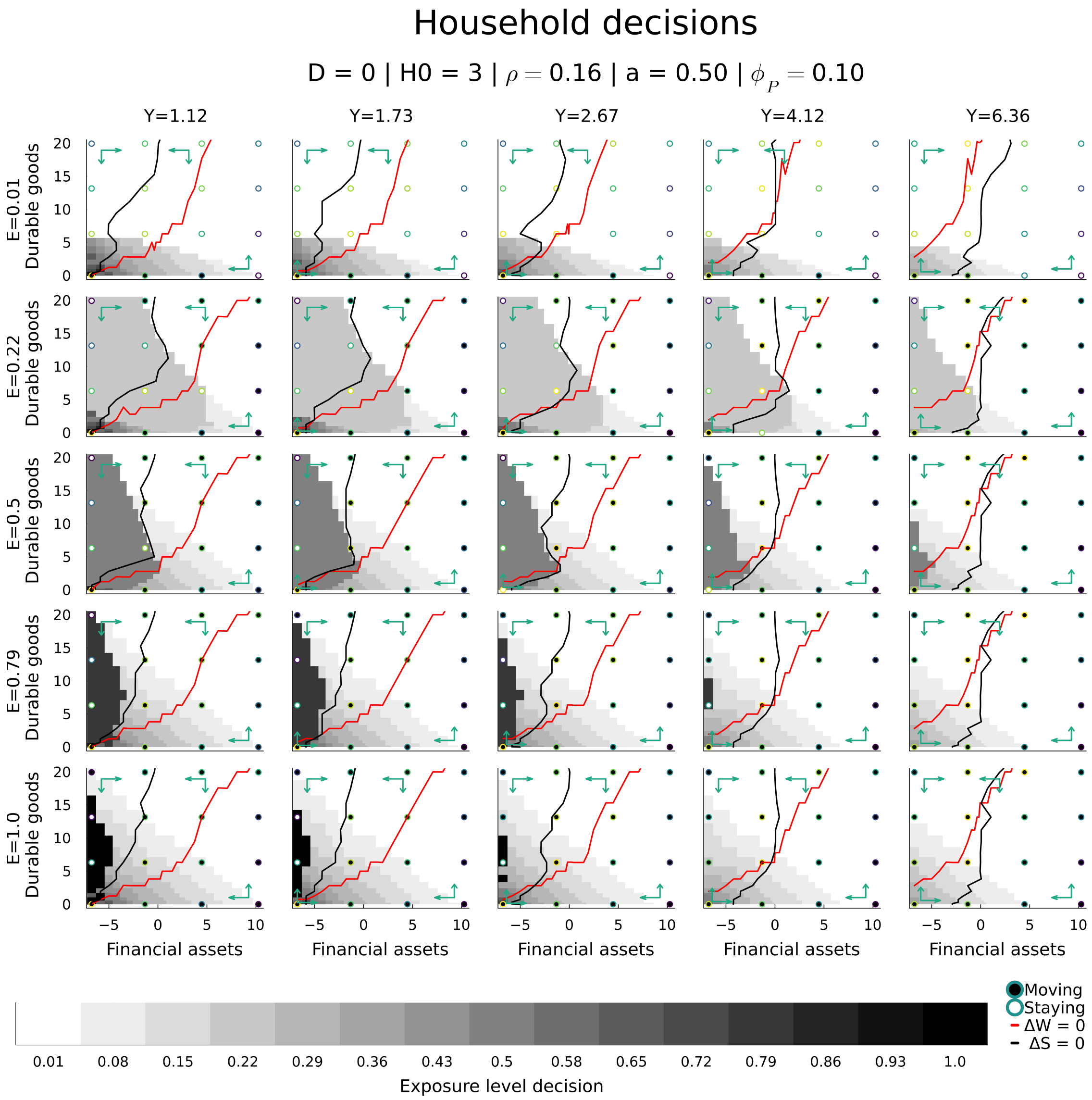

Figure 4: Household decision rules presented in a combined plot of a phase-diagram and heatmap for different initial exposure levels and income realisations.

For the two highest exposure levels presented in Figure 4, we find that for a combination of very low financial assets and medium levels stocks of durable consumption goods households rationally decide to remain at these highly exposed locations. This confirms the previously discussed prohibiting effect of durable consumption goods in certain scenarios.

5.2. Equilibrium distributions

To determine the long-run equilibrium distributions across the state variables, we apply a Monte-Carlo-Simulation with a synthetic population of 500,000 households reflecting the compositional distribution of characteristics presented in Figure 2 and following the optimal household decision rules as presented in Section 5.1. We also compare the model outcomes with the corresponding empirical data to stress the validity of our model set-up.

The empirical data of the TVSEP is not directly comparable to the variables in our models. On the one hand, some variables are empirically collected in more detail (e.g., consumption and durable consumption goods) and need to be aggregated. Other variables (e.g., exposure and disaster experience) on the other hand are not directly part of the questionnaire. We use the data of the wave 2016 from the TVSEP to construct the following variables.

- The exposure level of a household is constructed as presented in the functional specifications in Section 4.
- The financial assets are measured as the accumulated savings accounts adjusted for money borrowed or lent by the households.
- The durable consumption goods sum up all household wealth items including amongst others tractors, cars, bicycles, TVs, refrigerators and jewellery.
- Disaster experience is measured as a binary variable by whether or not a household suffered from a natural disaster between the waves 2008 and 2010.
- The income variable captures all types of working income of the household.
- Consumption contains all type of expenditures related to food, electricity, water, transport, communication, health, education and leisure expenditures.
- Expenditure for preventive measures are an explicit part of the questionnaire.

As the household sizes vary in the empirical data (what we do not consider in our framework), financial assets, durable consumption goods, income and consumption aggregated for the whole household are all consequently adjusted for the average household size.

In Figure 5 we present the equilibrium distributions for the key variables with appropriate data available in the empirical data. The left column presents the equilibrium data from our Monte-Carlo-Simulations, the right column shows the distribution in the TVSEP dataset. Note that all variables related to financial units (i.e. income, financial assets, durable consumption goods, consumption) are measured in terms of basic income units $[BIU]$, i.e. the mean period income of the lowest education group (see also the specification for the income process in Table 2).

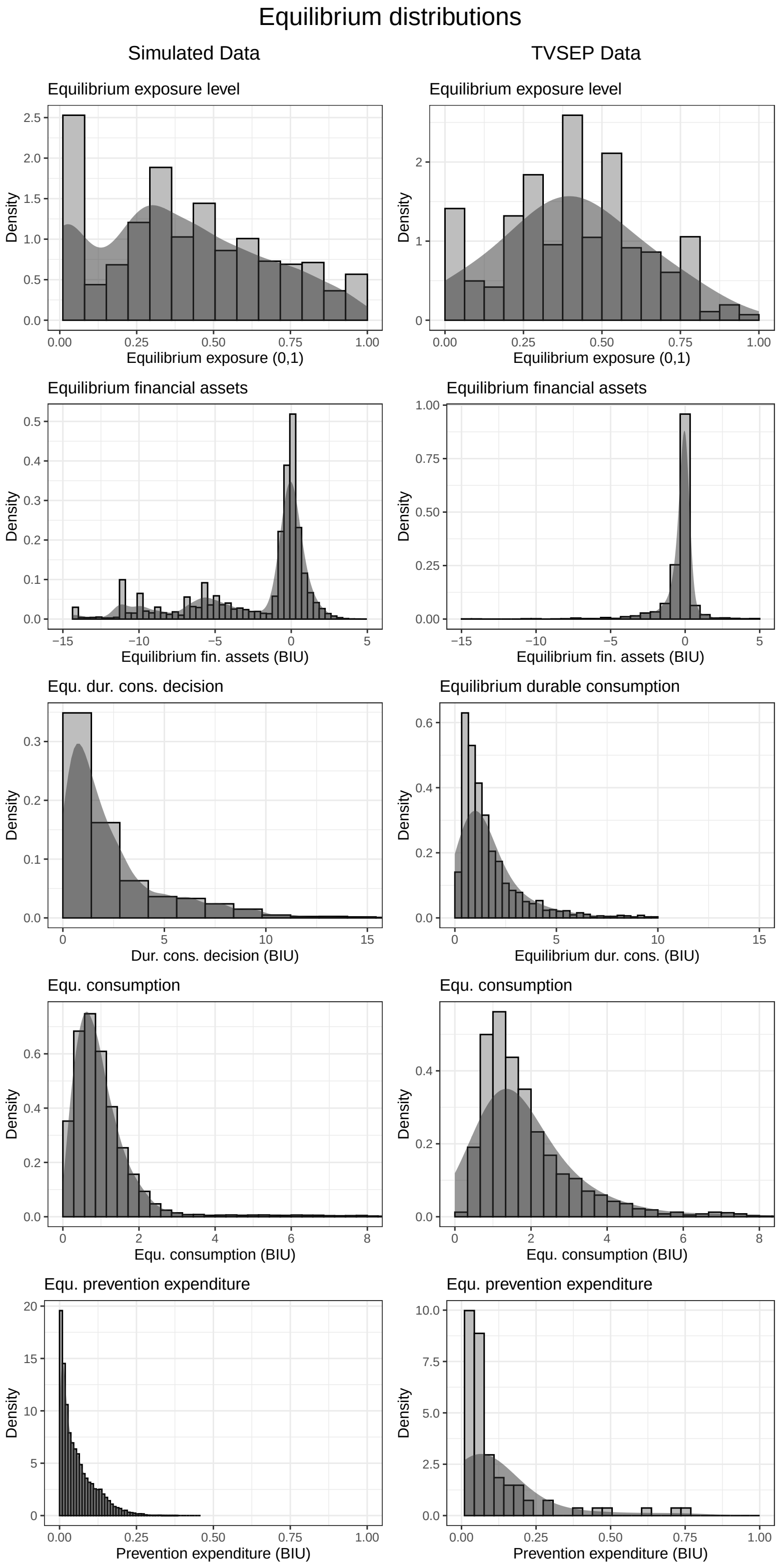

Figure 5: Equilibrium distribution of the main state an decision variables in the simulated and empirical data.

With respect to exposure, durable consumption goods, consumption, and prevention expenditure we find that the empirical data is replicated qualitatively and also quantitatively well. For financial assets, we also match the main part of the distribution centered around 0 very well, but we also find households in significant debt in the simulated data, which we do not observe in the empirical data.

Exposure: In the simulated data as well as in the empirical data we find households allocated along all different exposure levels. The most exposed locations are the least populated and a majority of the population is situated in locations with intermediate exposure between 0.25 and 0.75. The most significant difference between the empirical and the simulated data is in the share of households living at locations with zero (or close to zero) exposure, which the model would predict to be higher. Considering, that we used no proper exposure mapping for the household settlement location data, the model is able to replicate the empirical distribution fairly well.

Financial assets: While both distributions have their main peak around zero, the model would predict substantially more households with lower levels of financial assets/higher levels of financial debt. The small range of $\pm 2.5[BIU]$ in the data is rather surprising, as some households in the dataset have a period income of more than 5 $[BIU]$. For such high income levels we would intuitively expect them to be able to accumulate higher levels of financial assets than can be found in the data. This discrepancy between model and data can originate from either inconsistencies within the data or the simplifying assumptions of the model. We will discuss this aspect again in Section 5.3.

Durable consumption goods: The distributions for durable consumption goods overall coincide well for data and simulations with the levels ranging from 0 to 10 BIU, and the distribution being strongly right skewed.

Consumption: As for the durable consumption goods the empirical consumption distribution is replicated qualitatively well by the model. Still the empirical distribution exhibits a heavier right tail and therefore higher consumption levels are slightly underrepresented in the simulated data.

Prevention expenditure: For the prevention decision, we were not able to construct a corresponding variable in the empirical dataset, so we focus on the financial expenditures for preventive efforts. Here we also find a quite good match with the empirical data. Expenditures for the majority of households is below 0.25 BIU and a substantial share of the population has prevention expenditures close to 0.

5.3. The role of household characteristics

In this section we will assess the impact of the different social dimensions and household characteristics on the short-run decision making as well as the long-run outcomes. In Figures 6 and 7 we return to the phase-diagrams illustrating the decision rules for households and present them for different combinations of the four household characteristics education, awareness, time preference and prevention access.

Figure 6 shows that higher awareness decreases the variety of combinations of financial assets and durable consumption goods, where the household stays at a location with medium exposure. Furthermore, in case of a relocation decision, households with higher awareness move to less exposed area then less aware households. Meanwhile, the effects on the decisions of durable consumption good investment and net-savings are not significant. Higher education on the other hand has not only similar effects

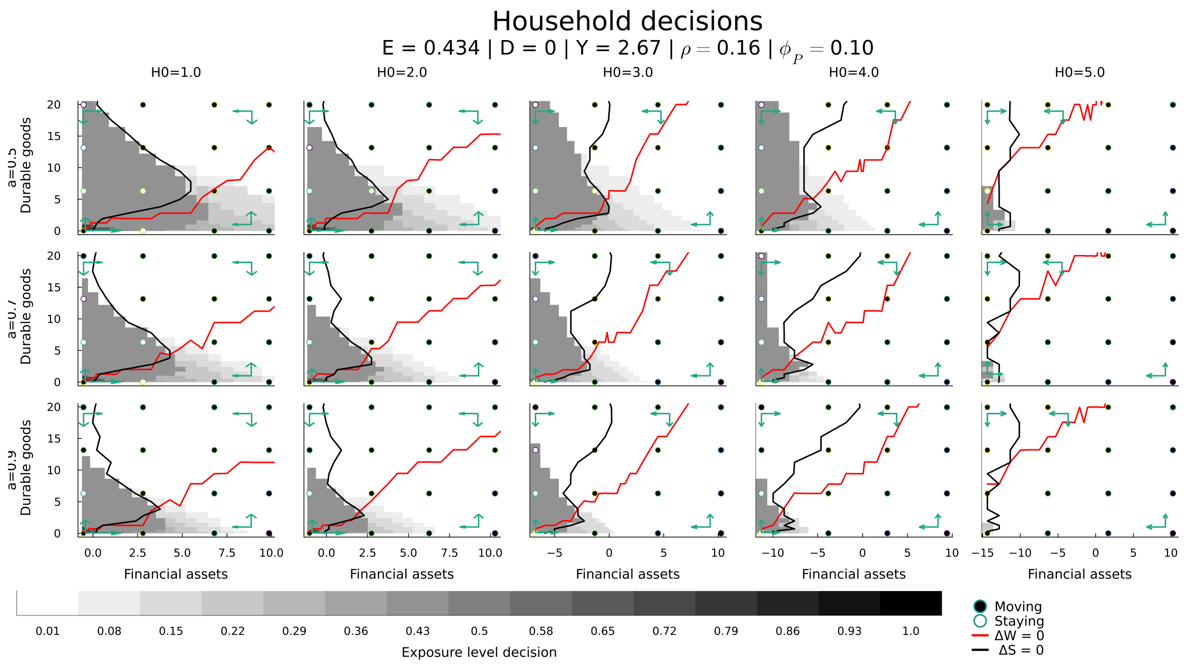

Figure 6: Household decision rules presented in a combined plot of a phase-diagram and heatmap for different awareness and education levels.

as higher awareness on the relocation and exposure level decisions, but also has a two-fold impact on net-savings and durable consumption good investment. The higher level of income realisations with increasing educational levels makes positive net-savings less often necessary (moving the black line indicating ($\Delta S = 0$) to the left[20]). At the same time this allows households to invest into their durable consumption goods more often (moving the red line indicating ($\Delta W = 0$) upward).

Turning to Figure 7 we find that the time preference rate also has an impact on the investment decisions for both asset types as well the exposure and relocation decision although the impact size is smaller compared to education and awareness. Counter-intuitively, households with a lower value for the time preference rate ρ are more reluctant to move to less exposed areas (larger dark grey area), although they put higher weight on their long-term outcomes. However, as can be seen in the left panel in Figure 8, in the long-run more patient households end up being located in less exposed areas on average. The figure shows the long-run equilibrium distribution of exposure level distinguished by the three different levels of time preference with the distributions being shifted to the right for an increasing time-discount rate. This discrepancy between the short-term decision making and long-run outcomes appears to be an effect of the small impacts of the time discount rate on the investment decisions for financial assets and durable consumption goods. These small differences can put households on completely different long-run trajectories.

Considering the impact of the access to prevention in Figure 7 we only find marginal differences for the behavioural rules presented. However, the substantial impact of the access to prevention can be found in the prevention decision. The right panel of Figure 8 shows the long-run equilibrium distribution for prevention efforts and we find that households with better access to prevention undertake significantly more prevention measures compared to those with lower access. However, as the distributions still cover

[20] Note the change of the x-axis for different education levels.

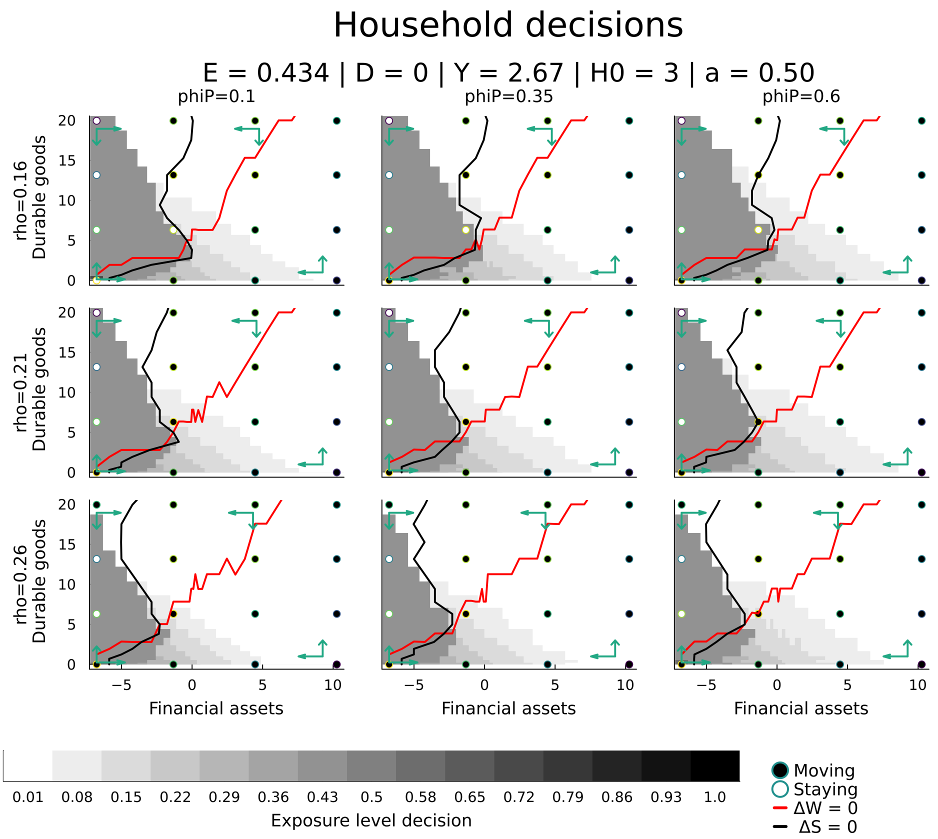

Figure 7: Household decision rules presented in a combined plot of a phase-diagram and heatmap for different time preference rates and levels of prevention access.

a wide range of values we also find households with low access and high prevention levels as well as high access and and low prevention efforts. This indicates that the other household characteristics and stochastic elements still play a crucial role.

In a last step we investigate the impact of education on the long-run outcomes for households. Figure 9 presents the equilibrium distributions across key variables for each educational level. Starting in the left column we see the distributions of exposure, vulnerability and risk. For exposure we find the intuitive result, that higher educated households on average reside in less exposed areas compared to lower educated households due to their higher income levels. Interestingly enough we still find a large variance in exposure levels for education groups 1-4 with group 2 actually covering all possible exposure levels. For vulnerability on the other hand, we find substantially less differences between the educational groups and only small advantages for the highest educated group. Since risk is the product of exposure and vulnerability, we find a similar pattern in the risk level distribution as for the exposure level.

For consumption and durable consumption goods we find similar patterns of distributions with the mean as well as the variance increasing for higher education levels. For the financial assets however, the results are quite different. While distributions for the lowest two education groups are centered around 0, the distributions shift to the left for the other three education groups. Interestingly higher education groups mostly remain in debt despite the high interest rates to finance higher consumption and durable

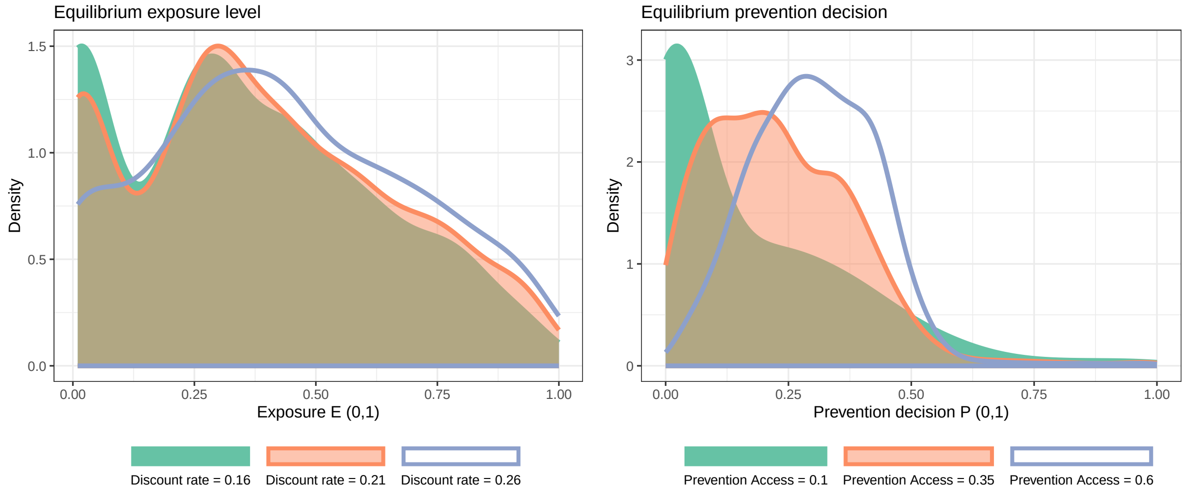

Figure 8: Long-run equilibrium distribution for exposure and prevention depending on different social dimensions.

consumption good levels as well as pay for the higher living cost in less exposed areas.[21]

Finally, the last column shows the distribution of prevention levels and prevention expenditures. While for the prevention level the distribution of the highest educated group is the only one to diverge from otherwise similar distributions, we find larger differences in the prevention expenditure distributions. As the prevention expenditures also depend on the levels of exposure and durable consumption goods as well as the access to prevention (which is positively correlated with education) we find that the second highest education group actually spends less on prevention than the three lower educated groups, while still having slightly higher prevention levels on average.

To summarise, we find that the household characteristics can have substantial effects on the short-term decision making as well as the long-run outcome of a household. The education level has the most pronounced impact on most decisions as the consistently higher income levels give the household a wider range of opportunities to accumulate durable consumption goods and afford housing in less exposed areas. Awareness has a similar effect as education on the settlement decision while not being able to provide the same advantages for wealth accumulation. While the short-run effects of the time-discount rate are rather small and counter-intuitive with respect to the exposure decisions, in the long-run more forward-looking household on average face less exposure in their settlements. Lastly, the access to prevention does not show relevant effects on the decision making accept for the prevention decision. As expected, better access to prevention also allows households to prevent more.

[21] Comment for Alexia: Makes sense in comparison to standard economic models, if we consider, that households can also use durable consumption goods to transfer wealth across time. Apparently the utility gains from higher durable consumption goods are so high that households are willing to pay the high interest instead of keeping more financial assets and less durable consumption goods.

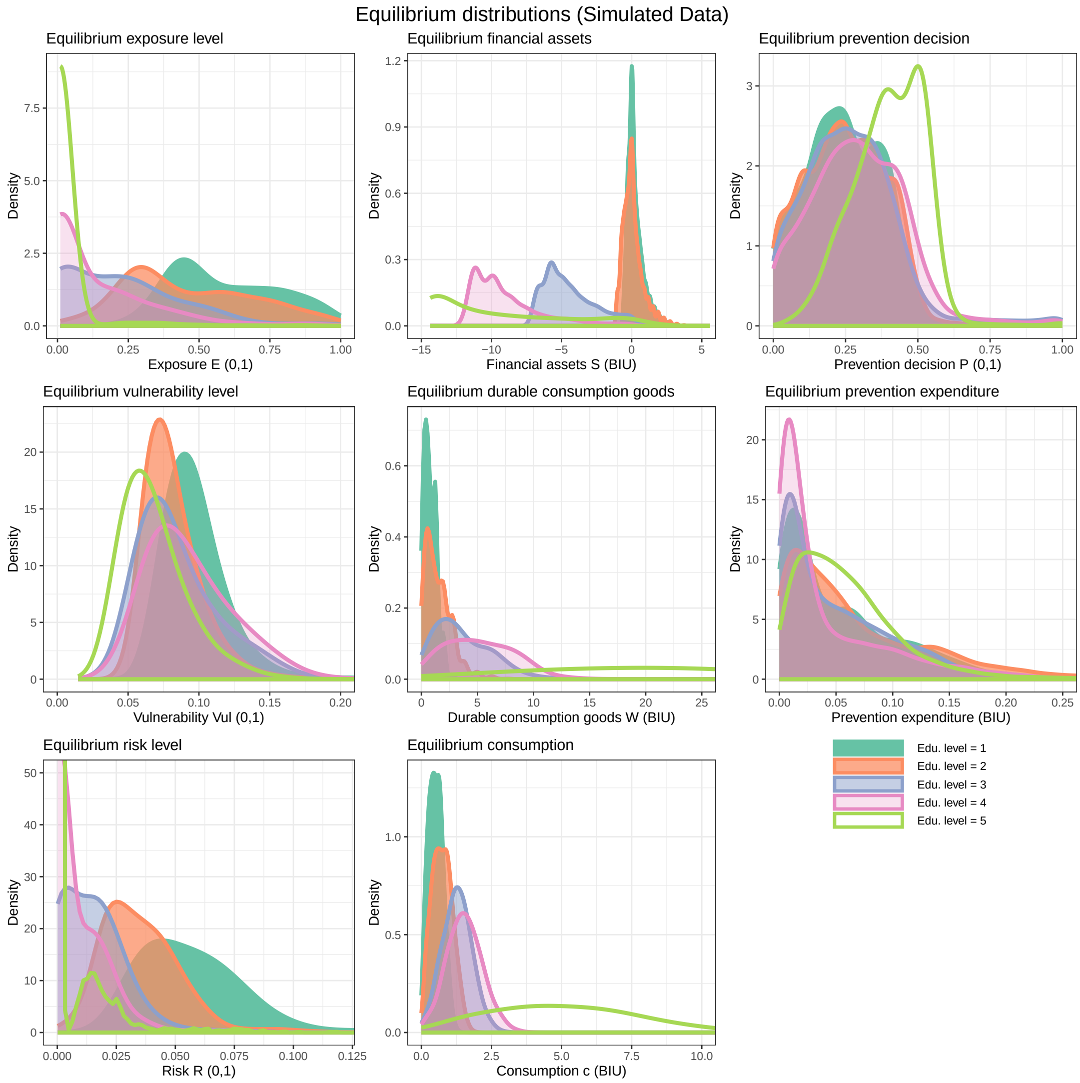

Figure 9: Long-run equilibrium distributions depending on the education level of households.

5.4. Policy Interventions

We consider five different types of permanent policy interventions[22] and vary the extent of each across three different levels. These different levels are denoted as low, medium, and high intensity intervention.

- **Housing cost subsidy (version 1):** Here we consider the policy maker to take over some of the living costs depending on the exposure level and make less exposed areas cheaper. We model this by a reduction of the parameter describing the increase of living costs depending on exposure level by 5%, 15% and 25%.
- **Housing cost subsidy (version 2):** In this scenario we propose a different subsidy structure with smaller subsidies for the least exposed areas. This is achieved by a change in the exponent in the $p^E()$-function from 2 to 2.4, 4.0 and 6.0 respectively.

[22]Note that temporary interventions would only have transitory effects, but after termination of the policy interventions, households would revert back to their old behavioural patterns and the benchmark long-run distributions would be reestablished.

- **Living cost transfer:** For this policy households in exposed areas receive a financial transfer to support them financially. We consider a linearly increasing transfer starting at an exposure level of 0.5, which reaches levels of at most 15% of the BIU or 30% oder 45% respectively.
- **Prevention cost subsidy:** We consider a reduction of the prevention expenditures of households. We model this by scaling down the prevention cost function $p^P()$ by factors of 25%, 45% and 55%.
- **Minimum income level:** In this scenario, we guarantee households a minimum income level of 60%, 120% or 160% of the BIU. Thereby households receive a direct financial transfer in case the income realisation falls short of this minimum threshold.

In Figure 10 we illustrate the impacts of the two housing-cost-subsidies on the function for living costs as well as the living-cost-transfer.

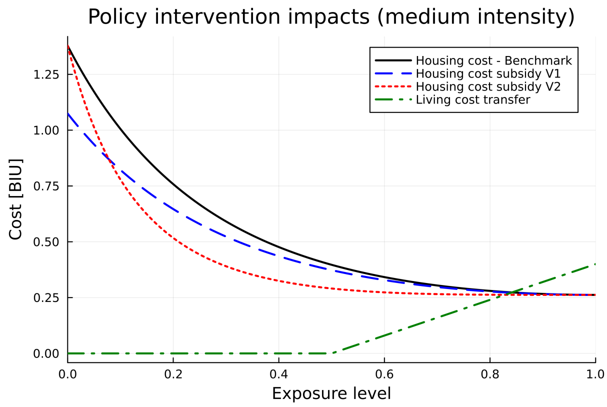

Figure 10: Effects of policy interventions on functional relationships (for medium intensity interventions)

For each of the five policy interventions and three intensities each, we again derive the optimal decision rules of households and simulate the long-run-equilibrium distributions. For these new equilibrium distributions we can calculate the average cost of the respective policy intervention.[23]

5.4.1. Benefit-Cost-Analysis

In Figure 11 we show the costs of each policy intervention in terms of the BIU. As the figure shows, the intensity parameters of the policies interventions have been calibrated to result in comparable long-run costs for the policy interventions.

How to measure the benefits of a policy intervention is less straightforward, especially if we want to compare their effectiveness in financial terms. Assessing differences in indicators like household utility or vulnerability would not let us directly compare benefits with the associated costs for each intervention as they would be measured in different units. Furthermore, we have to be careful in comparing flows like

[23] In this paper we do not consider the financing of these policy interventions. First, a wide range of financing options such as (i) different working income taxes (flat or progressive), (ii) capital gains tax, or (iii) a wealth tax on durable consumption goods could be considered. This would increase the number of combinations of policy interventions and financing strategies dramatically and thereby substantially exceed the extent of this paper. Second, numerically deriving the tax rate which generates enough tax income to finance the policy intervention completely would require an iterative approach. Thereby solving the bellman problem and simulating the long-run equilibrium distributions would be required several times. As the solution of the whole system for one set of parameters already takes around 6 hours (despite the usage of GPU-accelerated computation methods), this approach would require computation times in the range of weeks.

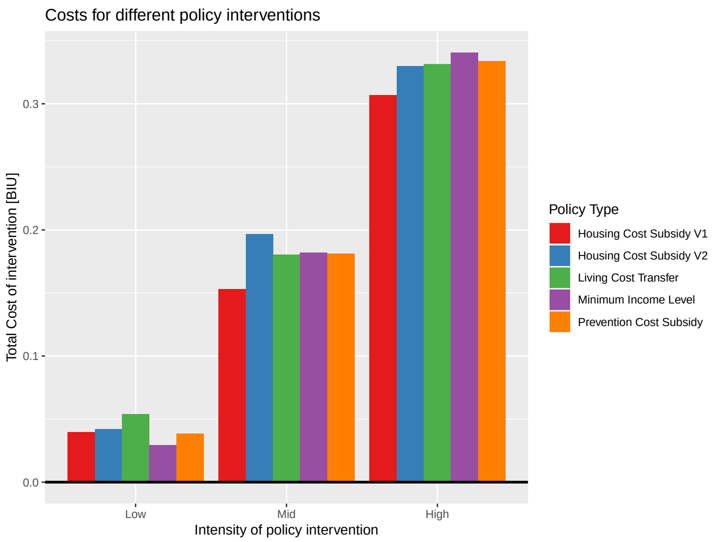

Figure 11: Average cost of policy interventions for benchmark population composition

the subsidies and transfers (which have to be paid every period) with stock variables, such as durable consumption goods. Hence, we decided to define the benefits as the sum of

- increased household consumption c (to reflect the micro-economic impact) and
- decreased value of durable consumption goods destroyed in natural disasters (to reflect the macroeconomic impact).

Figure 12 illustrates the benefits for the different types and intensities of policy interventions. We find, that the effects of the different types of policies vary drastically.

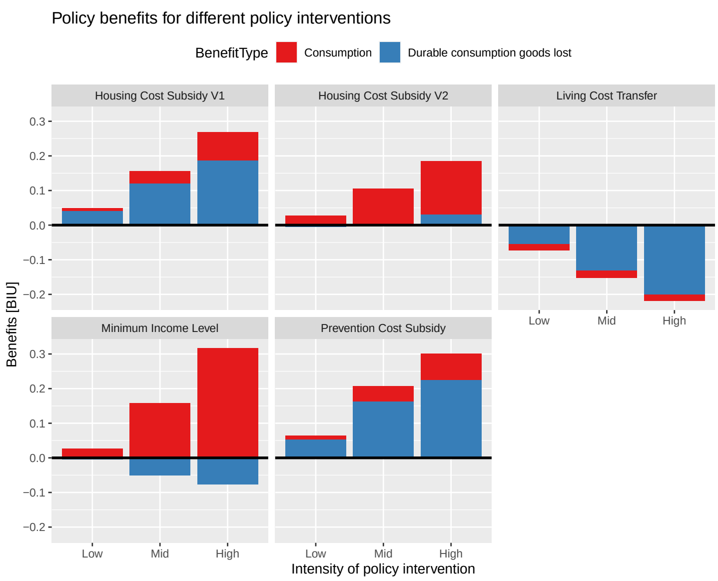

Figure 12: Average cost of policy interventions for benchmark population composition

Already the two housing cost subsidies show substantially different outcomes despite their similar structure. While version 1 leads to an increase in average consumption and an even more sizeable reduction in durable consumption goods lost, version 2 primarily leads to a substantial increase in average consumption and only slight reduction in durable consumption goods lost for the highest intervention intensity. The prevention cost subsidy leads to a similar outcome as the first version of the housing cost subsidy with even stronger total effect sizes. The living cost transfer for highly exposed households on the other hand not only leads to a decrease in average consumption, but also drastically increases the amount of durable consumption goods lost on average in every time period. Finally, the effects of a minimum income level are twofold. While the transfer allows households to increase their consumption drastically, in equilibrium more durable consumption goods are destroyed every period.

Assessing the financial viability we also find heterogeneous outcomes for the different policy types. Figure 13 shows the Benefit-Cost-Ratio (BCR)[24] analogously to Figure 12. Firstly, the negative benefits for the living cost subsidy directly translate to negative BCRs, which makes them a financially non-viable option. For the two housing cost subsidies we again find interesting differences. While the first version

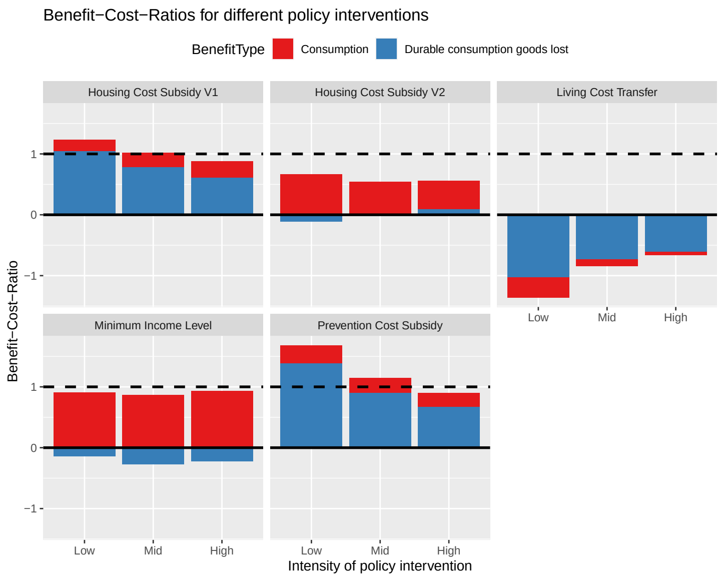

Figure 13: Benefit-Cost-Ratio for the average values of policy interventions for benchmark population composition

decreases in BCR for increasing intensity starting above one and dropping below, the BCR of the second version is more or less independent of the policy intensity, but stays below 1 throughout. The prevention cost subsidy again shows a similar pattern as the first housing cost subsidy version with an even higher BCR for the low intensity intervention. The minimum income level on the other hand also appears to be independent of the intensity and the BCR for consumption reaches levels close to 1, however the negative BCR for durable consumption goods lost reduces the total BCR.

All figures so far presented the average effects across the whole population, however in a heterogeneous population the costs and benefits can be distributed unequally between the population groups. Figure 14 presents a scatterplot of the total benefits and total cost for the different population sub-groups. The

[24] The BCR can be used to assess the financial viability of a policy intervention as it allows us to compare the effects with a counterfactual where the same policy expenditures are directly used to increase the average consumption and replace durable consumption goods lost. Policy intervention with a BCR above 1 can be considered more effective than the counterfactual, and those below 1 less effective. However, as these monetary benefits do not capture all impacts on household well-being the BCR should not be considered as the ultimate evaluation criteria, but as one amongst many different indicators.

color of each data point indicates the educational levels of the household and the shape identifies their awareness level. Furthermore, the size of the data points relates to the respective share of households with these characteristics in the empirical dataset.

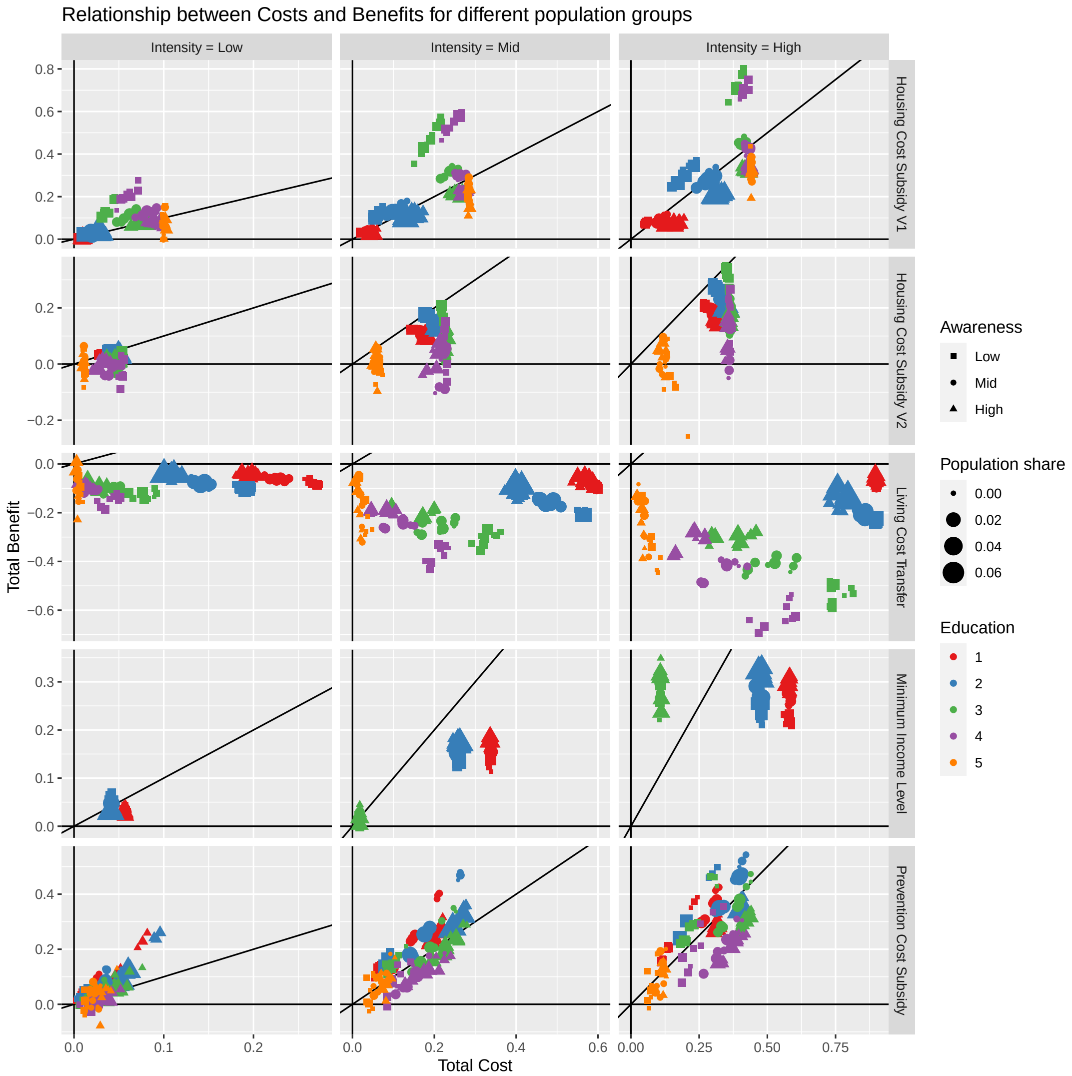

Figure 14: Scatterplot of the average cost vs average benefits of the policy interventions for the various population groups.

Figure 14 not only highlights the varying costs arising through the implementation of the policy interventions for different population groups and variation in benefits, but also that the different policy interventions vary substantially in their systemic impact. The housing cost subsidy in version 1 (shown in the first row) implies higher public expenditures and benefits for population groups with higher educational attainment, and we find that households with low awareness on average benefit more than households with high awareness. For the second version of the housing cost subsidy (shown in the second row) on the other hand the costs are more equally distributed between the education groups 1-4 and only low expenditures for the highest education group. The benefits are also in similar ranges for the three lower education groups, but we find negative benefits for some subgroups of the two highest education groups.

The minimum income level in the fourth row by design only benefits the lower education groups (all income realisations of the higher educated groups are above the minimum income level already) with the benefits being essentially in the same range for all education groups. Still we find, that the households with higher awareness benefit more than the ones with low awareness. Furthermore, we find that a prevention cost subsidy (present in the last row) leads to similar costs for educational groups 1-4, but with the lowest benefits generated in the population groups with the second highest overall educational attainment. Higher costs arise for households with higher awareness (which undertake more prevention on average) still resulting in only slightly higher total benefits.

Lastly, the third row in Figure 14 shows, that the negative benefits not only hold for the average of the whole population, but also for all sub-groups. This makes this policy highly ineffective and we will focus on the other four policies interventions in the next sections.

5.4.2. Risk-Reduction-Analysis

Since not all benefits of the policy interventions are covered by the benefits as defined in Section 5.4.1 we want to extend our analysis beyond the financial aspect and assess how effective the policy interventions are in reducing the risk level of households. As discussed in the introduction and in the conceptual framework, risk is a combination of three factors. While the model exhibits a variable directly representing the exposure of a household to hazards and with the hazard rate being an exogenous factor itself for the households, we need to define an indicator capturing the third argument of disaster risk, i.e. vulnerability. This value should represent the extent to which a household is affected in case a hazard occurs. We decided to define vulnerability as the loss in long-term expected utility in case of disaster experience relative to the utility in the no-disaster-scenario. For a formal definition of our vulnerability and risk indicators we refer to Appendix C.

In Figure 15 we compare the cost of the policy intervention with the reduction in the risk indicator. Again the different effects of the different policy types is apparent. The housing cost subsidy in version 1 in the first row exhibits a hump-shape with medium sized improvements for the lowest educated population groups while generating relatively low cost. The highest improvements can be found for the educational groups 2-4 (depending on the intensity of the policy intervention). Specifically interesting is the combination of sizable cost for the population groups with the highest educational attainment while resulting risk reduction levels close to zero.

The second version of the housing cost subsidy on the other hand shows drastic improvements in the risk indicator for the lowest educated households (especially higher than in the first version) and similar improvements for the groups 2 and 3 compared to the first version. Interestingly, we find the risk indicator becoming worse for some sub-groups with education level 4 and again no change in risk for the highest education group.

The minimum income level exhibits a convex risk reduction effect compared to its cost. Most costs are generated by the lowest educated population group, which also show the highest levels of risk reduction. We find no cost and no change in risk reduction for the higher education groups as all income level realisations lie above the minimum income level considered in the policy interventions. Furthermore, we want to stress that income transfer has a substantially higher variance of risk reduction within the same educational groups compared to the housing cost subsidies.

Finally, the plots for the prevention cost subsidies show the most widely scattered pattern of the three policy intervention types. While the variance of risk reduction levels within the same education group is

Figure 15: Reduction of household risk through policy interventions compared to the costs for different population groups.

similar to the minimum income level, the costs are now also more varied. As the education groups 1-4 generate similar ranges of average cost, the level of risk reduction is higher for the lower educated groups compared to the higher educated ones.

To get more insight into the heterogeneous effects of the policy interventions on different population groups, we will focus on policy interventions with medium intensity and allow for another distinction of the population groups. In Figure 16 the three columns present the data for the three different levels of access to prevention measures. As we have only analyzed the absolute changes in the risk indicator dependent on the cost, it might also be of interest to directly investigate the change in risk level from before to after the policy intervention.

The first thing to realize in Figure 16 is that benchmark risk level increases drastically with the educational attainment (as already shown in Section 5.3). Hence, the changes in risk level in Figure 15 have to be put into perspective for the benchmark risk level different population groups are starting from. Hence, the consistently small or close to negligibly reductions in risk for the highest educated households are no more surprising as they already start from very low levels. However, the low benchmark risk levels of the education group 4 make the substantial decrease in risk through the housing subsidy in the first version even more remarkable. The housing cost subsidy (version 2) meanwhile more effectively reduces

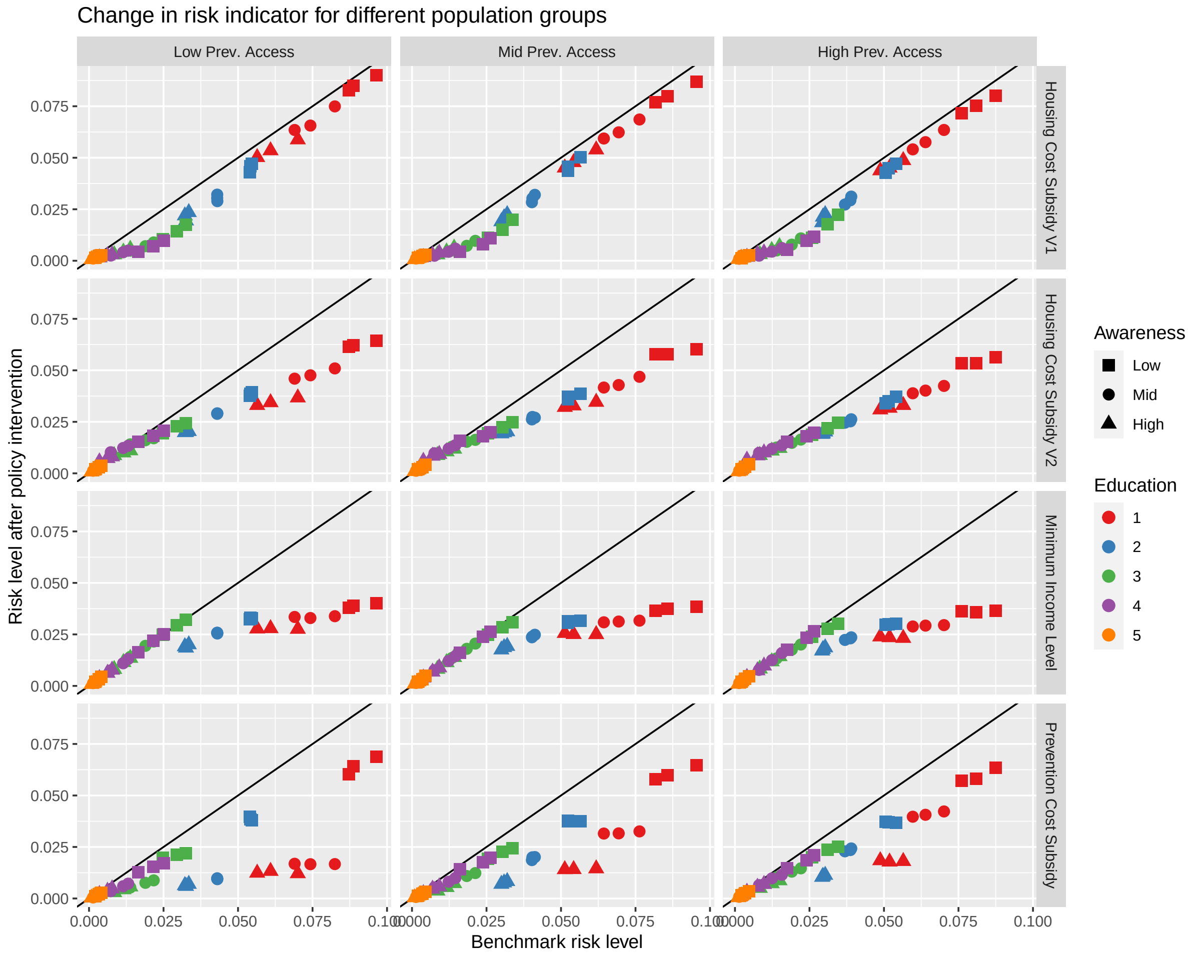

Figure 16: Change of household risk through policy interventions with medium intensity compared to the costs for different population groups.

the risk levels of households with high risk levels in the benchmark case. The effect of different levels of prevention access is negligible for these two intervention types.

The minimum income level also effectively reduces the risk levels of the two lowest educated population groups and lowers it to about that of households in education group 3. Furthermore, the figure also illustrates nicely that the effect of the minimum income level is stronger for the households with lower awareness. The policy is able to almost eradicate the differences in risk level for the lowest educated group.

For the prevention cost subsidy in the fourth row we find the most distinguishable effect of the different levels of access to prevention. Focusing on the population group with medium awareness we find, that the households with low access to prevention benefit substantially more than the other two groups, as we find the most sizeable reduction for this group.

5.4.3. Exposure and vulnerability effects

As changes in the household risk level can stem from changes in exposure, vulnerability or both of them, we use this section to highlight the distinct effects of the different types of policy interventions on exposure and vulnerability. Figure 17 shows the change in exposure and vulnerability after the policy intervention compared to the benchmark case on the x-axis and y-axis respectively. Again each of the

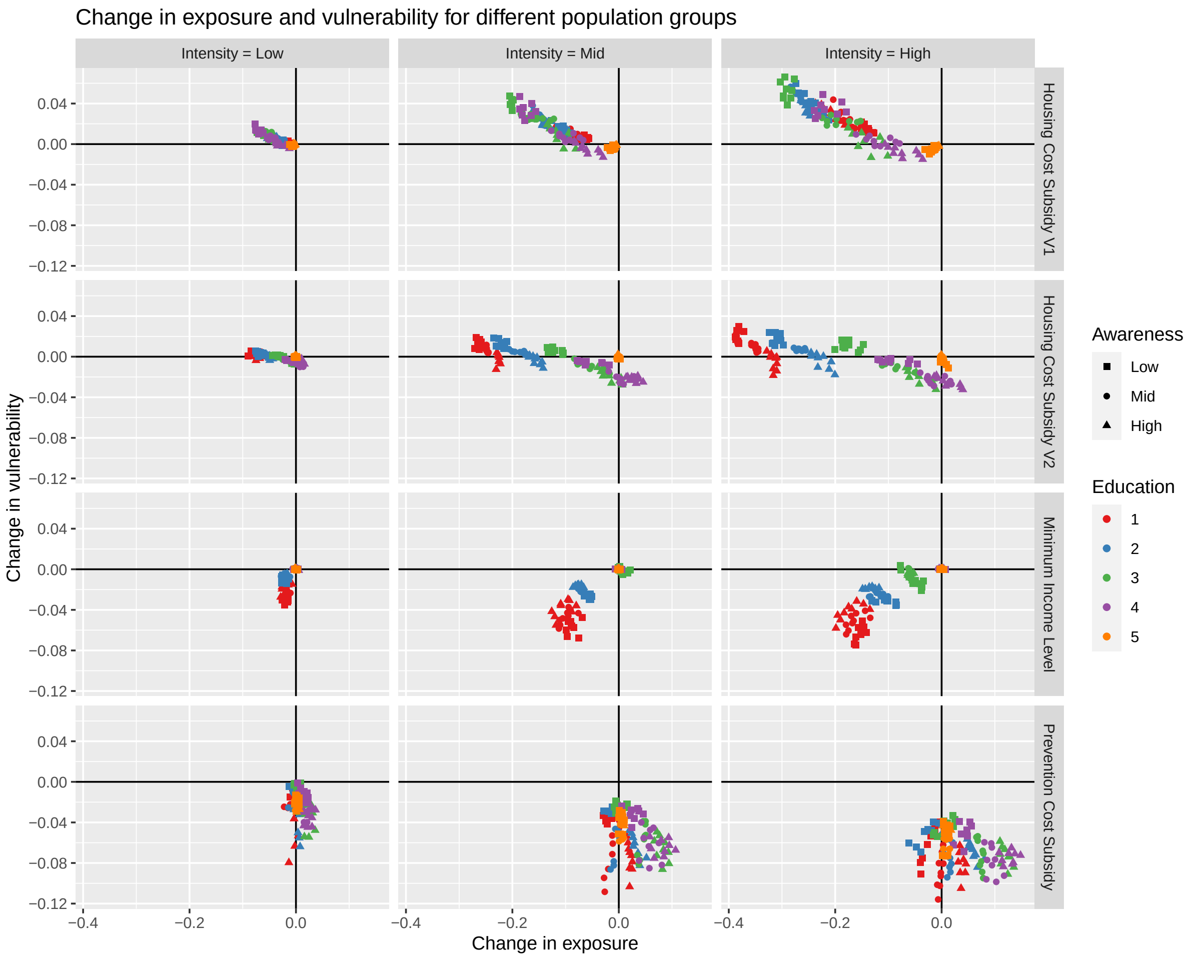

Figure 17: Change of household exposure and vulnerability through policy interventions compared to their benchmark values for different population groups.

four different policy interventions shows a specific pattern on how they change the households long-run outcomes. Intuitively, the housing cost subsidy in version 1 substantially decreases the exposure of households regardless of their characteristics. The effects on vulnerability on the other hand are two-fold. While the vulnerability for the lower educated groups 1 and 2 increases and for the highest educated group 5 decreases consistently, for the groups 3-4 the awareness plays a crucial role. Households with higher awareness do not decrease their exposure as much, but end up reducing their vulnerability as well, compared to households with lower awareness. This pattern can also be identified in Figure 18 where we focused on the impact of awareness by separating the different levels of awareness in the three columns and reducing the dataset to policy interventions with medium intensity. Overall the reduction effect on exposure is stronger in magnitude than the increase in vulnerability by around a factor of roughly 5.

For the housing cost subsidy in version 2 we find a similar pattern as for the first version, however there is a significant shift to the left for the lower educated households. Within in each of the educational groups 1-3 we find that all reduce their exposure level, households with higher awareness end up with slightly smaller improvements in exposure, but thereby also decrease their vulnerability. Households with lower awareness more substantially decrease their exposure, but wind up with higher vulnerability compared to their benchmark outcomes. For the two highest educational groups Figure 17 shows mixed results for the exposure change with some households residing now in more exposed areas then before, however all of the decrease their vulnerability to a higher degree. Figure 18 again shows, that awareness has substantial impact on the changes in exposure and vulnerability.

The third row of Figure 17 shows that the minimum income level implies a simultaneous reduction in exposure and vulnerability for households that actually benefit from this measure. Curiously we actually observe a slight increase in exposure of households within education group 3 after a medium intensity intervention. Figure 18 meanwhile shows, that for this policy intervention awareness only has small quantitative, but no important qualitative effects.

Finally, the results for prevention cost subsidy are presented in the fourth row and display the most heterogeneous outcomes. While we obtain the intuitively anticipated reduction in vulnerability for all population subgroups, the effects of the policy intervention on the exposure level is ambiguous. The effect size for the two lowest education groups as well as the highest are comparatively small with the sign depending on the awareness level of the household (see also Figure 18). For the education groups 3 and 4 on the other hand, we find an increase in exposure for (nearly) all types of households. These households use the cost savings of cheaper prevention to also save in living cost expenditures and move to more exposed areas while still overall reducing their risk level. In the fourth row of Figure 18 we furthermore find, that the prevention cost subsidy leads to a stronger decrease in vulnerability for households with lower access to prevention compared to households with higher access to prevention (which exhibit a lower vulnerability level already in the benchmark case).

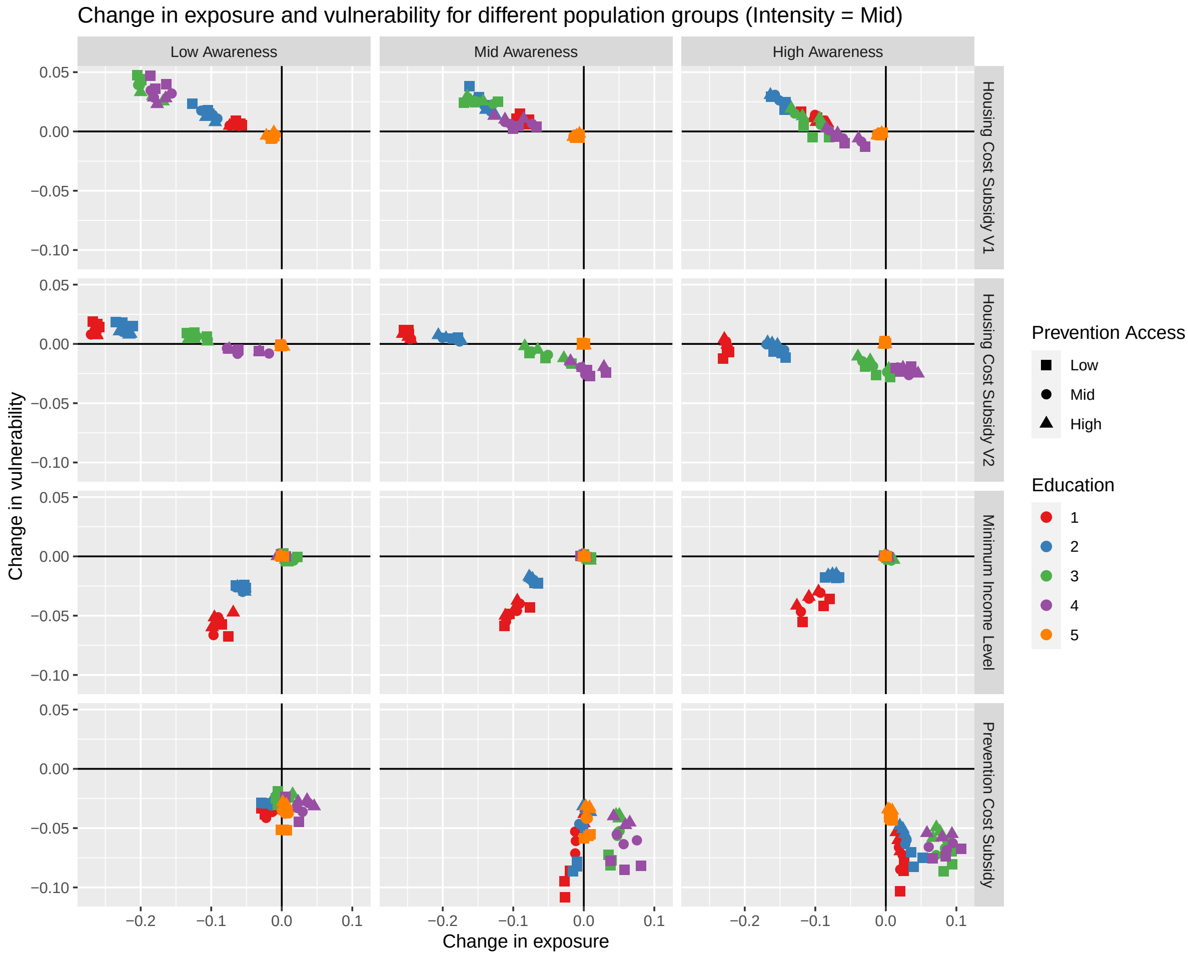

Figure 18: Change of household exposure and vulnerability through policy interventions with medium intensity compared to their benchmark values for different population groups.

6. Conclusion and discussion

In this paper we develop a framework for the modelling and analysis of household behaviour when households are subject to the hazard of a natural disaster. The modelling efforts are motivated through numerous empirical studies on the importance of education on different aspects of disaster risk. However, a holistic conceptual framework, which systemically incorporates and interconnects these aspects in a formal way, has been missing in the literature. The work presented in this paper aims to fill this gap.

We introduce a dynamic household model in discrete time, with households facing the hazard of natural disasters. Households can utilize several different ex-ante and ex-post strategies to mitigate the negative impact of natural disasters on their expected utility. Potential strategies include relocating, precautionary savings, and loss reduction efforts. We find that all households use a combination of those strategies in their optimal decisions and using the first order optimality conditions and the Bellman-equations we are able to derive equations describing the optimal trade-offs between different decisions variables.

In our extensive numerical analysis, we first discuss the optimal household decision rules and find that for relatively low levels of durable consumption goods additional amounts can have a prohibitive effect and discourage household from relocating from higher to less exposed areas. Conditional on a positive relocation decision higher levels of both durable consumption goods and financial assets allow the households to relocate to less exposed areas. We also find that households are not willing to go into large financial debts due to the high interest except for situations where they are facing low levels of durable consumption goods.

The second part of the numerical analysis consist of the long-run equilibrium distributions through Monte-Carlo-Simulations and the validation of the results against the empirical data from Thailand and Vietnam. Although we need to construct auxiliary variables from the data to be consistent with the model and some not directly measurable model aspects and parameters, we are able to replicate the empirical date qualitatively and quantitatively well.

In the next step we discuss the impact of different social dimensions on the short-run decision making as well as the long-run outcomes. While some part of the variations in outcomes and behaviour can be explained through the stochasticity of the labour income, certain household characteristics have a significant impact in the short and long-run. The consistently higher income levels for higher educated households allow them to relocate to safer areas in a wider range of state combinations and furthermore the new settlement are also generally less exposed then those of lower educated households in the same situation. Higher awareness has similar effects on the relocation decision, but in the long-run does not allow for the same durable consumption accumulation as higher education. The time preference rate and access to prevention also impact the short-term decision making and long-run outcomes for household, but with a smaller effect size.

The last part of our numerical analysis contains an extensive evaluation of several policy interventions targeting different aspects of the constraints households are facing. The benefit-cost-analysis for the population averages already reveals substantial differences in the effects of the policies with respect to changes in consumption and durable consumption goods. Adding a comparison between costs and benefits of different population groups highlights the highly heterogeneous effects of the interventions, unintended effects, and allows us to discard one of the interventions as not suitable. We even find substantial differences between two policies targeting the housing cost with slightly different implementations. We conclude the exercise with an analysis of the changes in household risk and decompose these effects into changes in exposure and vulnerability. Overall we are not able to identify one policy intervention being most effective, but the analysis provides guidance on which policy intervention to choose to improve specific disaster risk indicator and other outcomes for specific population sub-groups and what the effects on the rest of the population are.

Although our model contains a multitude of decision and state variables it is still limited in its ability to replicate some aspects of reality due to some short-comings in the framework. First of all, the model still only represents a partial equilibrium, as our framework features no production sector, which would allow us to endogenously define wages and interest rates. In the same regard, we have no direct interaction between households in the model and there is no market for housing determining the living costs. Furthermore we assume, that the infinitely livings households exhibit an exogenously given education level. A future adaptation of the model could contain the introduction of a life-cycle model for households making endogenous education decisions over their finite life-time. An extension for the cost of prevention efforts could also be considered as the cost function covers the access to prevention in a rather stylistic way and does not allow for a distinction between physical protection measures and insurance.

On the other hand the model results in this paper would also allow for more extensive investigations on many aspects just briefly covered here. With the households being heterogeneous along four dimensions and the 5 different policy interventions considered as well as distinction between short-term and long-run outcomes still leave a wide range of potential analyses unexplored. However, a different type of policy intervention, which targets the household characteristics, such as an awareness program or education investments are part of future planned work by the authors. Also additional case studies to evaluate the validity of our framework in different context is an aspect of future research.

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A. Analytical Results

In this section we present an additional Proposition 2. Applying the Lagrange-approach for stochastic constrained optimisation problems we can obtain insights into the inter- and intratemporal trade-offs in the households decision making process.

Proposition 2 (First order conditions (I)) *Assume an optimal solution*

$$(c_t^*, w_t^*, I_t^*, E_{t+1}^*, W_{t+1}^*, S_{t+1}^*, P_{t+1}^*)_{t=1,2,...}$$

for problem (7) exists. For points in time t, where the solutions $(c_t^*, W_{t+1}^*, S_{t+1}^*, P_{t+1}^*)$ are in the interior of the feasible region, the optimal solution fulfils the following first order optimality conditions. (To simplify the notation, we will not list all variables within each functional form, but indicate at which point in time the decisions are made, e.g. $u_c(t) := u_c(c_t, W_{t+1})$.)

$$u_c(c_t^*, W_{t+1}^*) = \frac{1 + r_t(S_t)}{1+\rho} \mathbb{E}_t \left\{ u_c(c_{t+1}^*, W_{t+2}^*) \right\} \tag{28}$$

$$u_c(t) p_P^P(t+1) = \frac{1-\delta}{1+\rho} \mathbb{E}_t \left\{ u_c(t+1)(p^w)'(t+1)(1 - \Delta^W I_{t+1}^*) W_{t+1}^* D_{t+1} \right\} \tag{29}$$

$$u_c(t) \left[p_W^P(t+1) + (p^w)'(t) \right] =$$
$$= u_W(t) + \frac{1-\delta}{1+\rho} \mathbb{E}_t \left\{ u_c(t+1)(p^w)'(t+1)(1 - \Delta^W I_{t+1}^*)(1 - (1 - P_{t+1}^*) D_{t+1}) \right\} \tag{30}$$

$$u_c(t) \left[p_W^P(t+1) + (p^w)'(t) \right] = u_W(t) +$$
$$+ \mathbb{E}_t \left\{ \sum_{i=1}^{\infty} \left(\frac{1-\delta}{1+\rho} \right)^i u_W(t+i) \cdot \prod_{j=1}^{i} \frac{(p^w)'(t+j)}{(p^w)'(t+j) + p_W^P(t+1+j)} (1 - \Delta^W I_{t+j}^*) \left(1 - (1 - P_{t+j}^*) D_{t+j}\right) \right\} \tag{31}$$

For the proof of Proposition 2 we first set up the Lagrange-function

$$\mathcal{L} = \mathbb{E}_{t=0} \Bigg\{ \sum_{t=1}^{\infty} \left(\frac{1}{1+\rho} \right)^t u(c_t, W_{t+1}) + \lambda_t^S \Big[- S_{t+1} + y_t(1 - \Delta^y D_t) + (1 + r_t(S_t)) S_t - c_t - p^w(w_t) -$$
$$- p^P(E_{t+1}, W_{t+1}, P_{t+1}) - p^E(E_{t+1}) \Big] + \lambda_t^W \left[-W_{t+1} + (1-\delta)(1 - \Delta^W I_t)(1 - (1 - P_t) D_t) W_t + w_t \right] +$$
$$\lambda_t^I (E_{t+1} - E_t)(1 - I_t) \Bigg\} \tag{32}$$

For the optimal decision made at the beginning of time period t, i.e. $(c_t, w_t, S_{t+1}, W_{t+1}, P_{t+1}, E_{t+1}, I_t)$, the household has access to the full information on the state of all current state variables and previous decisions made, i.e. $(E_t, S_t, W_t, P_t, D_t, y_t)$.

Hence taking the derivative of the Lagrange-function with respect to the decisions variables leads to the first-order optimality conditions.

$$\frac{\partial \mathcal{L}}{\partial c_t} = \mathbb{E}_t \left\{ \left(\frac{1}{1+\rho} \right)^t u_c(c_t, W_{t+1}) - \lambda_t^S \right\} = 0 \qquad \Longrightarrow \qquad u_c(c_t, W_{t+1}) \left(\frac{1}{1+\rho} \right)^t = \lambda_t^S \tag{33}$$

$$\frac{\partial \mathcal{L}}{\partial w_t} = \mathbb{E}_t \left\{ -\lambda_t^S \frac{dp^w}{dw}(w_t) + \lambda_t^W \right\} = 0 \qquad \Longrightarrow \qquad \lambda_t^S \frac{dp^w}{dw}(w_t) = \lambda_t^W \tag{34}$$

$$\frac{\partial \mathcal{L}}{\partial S_{t+1}} = \mathbb{E}_t \left\{ (1 + r_t(S_t))\lambda_{t+1}^S - \lambda_t^S \right\} = 0 \qquad \Longrightarrow \qquad \lambda_t^S = (1 + r_t(S_t))\mathbb{E}_t \left\{ \lambda_{t+1}^S \right\} \tag{35}$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial W_{t+1}} = \mathbb{E}_t \Big\{ & \left(\frac{1}{1+\rho} \right)^t u_W(c_t, W_{t+1}) - \lambda_t^S \cdot p_W^P(E_{t+1}, W_{t+1}, P_{t+1}) - \\ & - \lambda_t^W + \lambda_{t+1}^W (1-\delta)(1 - \Delta^W I_{t+1})(1 - (1 - P_{t+1})D_{t+1}) \Big\} = 0 \end{aligned} \tag{36}$$

$$\frac{\partial \mathcal{L}}{\partial P_{t+1}} = \mathbb{E}_t \Big\{ - \lambda_t^S \cdot p_P^P(E_{t+1}, W_{t+1}, P_{t+1}) + \lambda_{t+1}^W (1-\delta)(1 - \Delta^W I_{t+1}) D_{t+1} W_{t+1} \Big\} = 0 \tag{37}$$

Combining equations (15) and (16) leads to

$$u_c(c_t, W_{t+1}) \left(\frac{1}{1+\rho} \right)^t = (1 + r_t(S_t))\mathbb{E} \left\{ u_c(c_{t+1}, W_{t+2}) \left(\frac{1}{1+\rho} \right)^{t+1} \right\}$$

$$u_c(c_t, W_{t+1}) = \frac{1 + r_t(S_t)}{1+\rho} \mathbb{E} \left\{ u_c(c_{t+1}, W_{t+2}) \right\}$$

and consequently proof the consumption Euler equation (28). Equation (19) provides a direct relationship between the shadow-prices of physical and financial assets. Using this equality to substitute λ_{t+1}^W in equation (18) implies

$$\lambda_t^S \cdot p_P^P(E_{t+1}, W_{t+1}, P_{t+1}) = \mathbb{E}_t \Big\{ \lambda_{t+1}^S \frac{dp^w}{dw}(w_{t+1})(1-\delta)(1 - \Delta^W I_{t+1}) D_{t+1} W_{t+1} \Big\}.$$

Using again equation (15) we can reformulate the previous equation to

$$u_c(c_t, W_{t+1}) p_P^P(E_{t+1}, W_{t+1}, P_{t+1}) = \frac{1-\delta}{1+\rho} \mathbb{E}_t \left\{ u_c(c_{t+1}, W_{t+2}) \frac{dp^w}{dw}(w_{t+1})(1 - \Delta^W I_{t+1}) W_{t+1} D_{t+1} \right\}.$$

This equation directly corresponds to equation (29) in Proposition 2. The derivations for the FOC (30) follow analogously from combinations of equation (15), (19) and (17).

For the proof of FOC (31) we use (30) in the following simplified form.

$$u_c(c_t, W_{t+1}) = \frac{u_W(c_t, W_{t+1})}{g(t)} + \left(\frac{1-\delta}{1+\rho} \right) \frac{\mathbb{E}_t \left\{ u_c(c_{t+1}, W_{t+2}) f(t+1) \right\}}{g(t)} \tag{38}$$

$$g(t) := \left[p_W^P(E_{t+1}, W_{t+1}, P_{t+1}) + \frac{dp^w}{dw}(w_t) \right]$$

$$f(t) := \frac{dp^w}{dw}(w_t)(1 - \Delta^W I_t)(1 - (1 - P_t)D_t)$$

We can now substitute the term $u_c(c_{t+1}, W_{t+2})$ on the right hand side of (38) by using (38) for the time period $t+1$. This results in

$$u_c(c_t, W_{t+1}) = \frac{u_W(t)}{g(t)} + \frac{1-\delta}{1+\rho} \mathbb{E}_t \left\{ \frac{u_W(t+1) + \frac{1-\delta}{1+\rho} \mathbb{E}_{t+1} \left\{ u_c(t+2) f(t+2) \right\}}{g(t+1)} \frac{f(t+1)}{g(t)} \right\} \tag{39}$$

As the information set at time $t+1$ is a subset of the information set at t, this equation can be simplified to

$$u_c(c_t, W_{t+1}) = \frac{u_W(t)}{g(t)} + \frac{1-\delta}{1+\rho}\mathbb{E}_t\left\{\frac{u_W(t+1) + \frac{1-\delta}{1+\rho}\mathbb{E}_{t+1}\left\{u_c(t+2)f(t+2)\right\}}{g(t+1)}\frac{f(t+1)}{g(t)}\right\} \tag{40}$$

$$u_c(c_t, W_{t+1}) = \frac{u_W(t)}{g(t)} + \mathbb{E}_t\left\{\left(\frac{1-\delta}{1+\rho}\right)\frac{u_W(t+1)}{g(t)}\frac{f(t+1)}{g(t+1)} + \left(\frac{1-\delta}{1+\rho}\right)^2 u_c(t+2)\frac{f(t+1)}{g(t+1)}\frac{f(t+2)}{g(t)}\right\} \tag{41}$$

Taking a next step and replacing $u_c(t+2)$ in the last term makes the systematic structure finally even more apparent.

$$u_c(c_t, W_{t+1}) = \frac{u_W(t)}{g(t)} + \mathbb{E}_t\Bigg\{\left(\frac{1-\delta}{1+\rho}\right)\frac{u_W(t+1)}{g(t)}\frac{f(t+1)}{g(t+1)} + \tag{42}$$

$$+\left(\frac{1-\delta}{1+\rho}\right)^2\left(\frac{u_W(t+2)}{g(t+2)} + \left(\frac{1-\delta}{1+\rho}\right)\frac{\mathbb{E}_{t+2}\left\{u_c(t+3)f(t+3)\right\}}{g(t+2)}\right)\frac{f(t+1)}{g(t+1)}\frac{f(t+2)}{g(t)}\Bigg\} \tag{43}$$

$$u_c(c_t, W_{t+1}) = \frac{u_W(t)}{g(t)} + \mathbb{E}_t\Bigg\{\left(\frac{1-\delta}{1+\rho}\right)\frac{u_W(t+1)}{g(t)}\frac{f(t+1)}{g(t+1)} + \tag{44}$$

$$+\left(\frac{1-\delta}{1+\rho}\right)^2\frac{u_W(t+2)}{g(t)}\frac{f(t+1)}{g(t+1)}\frac{f(t+2)}{g(t+2)} + \left(\frac{1-\delta}{1+\rho}\right)^3\frac{u_c(t+3)f(t+3)}{g(t)}\frac{f(t+1)}{g(t+1)}\frac{f(t+2)}{g(t+2)}\Bigg\} \tag{45}$$

Using induction the validity of the FOC (31) in Proposition 2 can be easily shown. ■

After the formal proof we will now focus on the economic intuition behind these first order opttimality conditions.

Equation (28) provides the optimal time path of consumption as given by the intertemporal Euler equation. The marginal utility gain from consumption in the current period t has to be equal the expected marginal utility from consumption in the next period $t+1$ adjusted for gains through interest rate on financial assets and the utility discount rate.

Equation (29) illustrates the trade-off between prevention efforts and consumption. On the left hand side the marginal costs of additional prevention are measured in units of marginal utility from consumption. On the right hand side we have the expected benefits of prevention measured in discounted marginal utility from consumption in the next time-period ($\frac{u_c(t+1)}{1+\rho}$). The benefits of prevention materialize in form of additional units of durable consumption goods being protected and preserved in case of a natural disaster ($W_{t+1}D_{t+1}$). However, before the durable consumption goods can be liquidized ($(p^w)'(t)$) into financial assets and be used for consumption, we need to account for losses through depreciation $(1-\delta)$ and potential relocation of the household settlement in the next period $(1-\Delta^W I_{t+1})$. Note that the benefits of prevention are only present in case the household is affected by a natural disaster and there is no positive impact of prevention otherwise. This affect will become more apparent in equation (13) later on.

For the discussion of the trade-off between consumption and investments into durable consumption goods we present two different equations (30) and (31), which are equivalent, but allow for different interpretations. Equation (30) takes a similar approach to the prevention/consumption-trade-off as in (29). The additional costs of a marginal increase in durable consumption good investment measured in units of marginal utility from consumption constitutes the left hand side. These costs now consist of two parts: The first term covers the additional expenditures for prevention whereas the second term contains the direct investment costs. If the additional durable consumption good investment implies an increase in already positive durable consumption good investment, $(p^w)'(t) = 1$ holds. On the other hand, if reduced liquidation is implied, $(p^w)'(t) = \kappa$ holds. The right hand side of (30) also consists of two separate effects. $u_W(t)$ captures the direct impact of the additional durable consumption good investment in terms of utility gained in the present. The latter part in (30) allows for an analogue interpretation as Equation (29). The additional durable consumption goods are changed to $(1-(1-P_{t+1})D_{t+1})$, while the other parts of the terms are identical. In case of a natural disaster the additional durable consumption goods equate to P_{t+1} as only the protected share of the additional marginal durable consumption goods is transferred to the next period. Otherwise this term equals one and all assets are transferred.

Equation (31) illustrates the same trade-off, while avoiding the transformation back into units of consumption on the right hand side. The left hand side and the first part of the right hand side are identical to (30). The second part now contains the expected impact of the additional marginal durable consumption goods over the future infinite time-horizon. For each time-period the household has to adjust the gains in marginal utility $u_W(t+i)$ for depreciation of durable consumption goods and the discount factor of utility $\left(\frac{1-\delta}{1+\rho}\right)^i$. Furthermore the gains have to be adjusted for (i) potential losses through disaster experience $((1-(1-P_{t+j})D_{t+j}))$, (ii) potential losses resulting from settlement relocation $(1-\Delta^W I_{t+j})$, and (iii) additional costs resulting from additional prevention costs $\left(\frac{(p^w)'(t+j)}{(p^w)'(t+j)+p^P_W(t+1+j)}\right)$.

B. Numerical solution

B.1. Model transformation

While the introduction of the indicator decision variable I_t allowed us to formulate the problem in a very compact form for the numerical solution a different approach is more efficient. We formulate the decision whether to relocate or not similar to an option value approach splitting the optimisation problem (10) into two separate problems.

Solving the problem (10) at each point in time is equivalent to the household solving two optimisation problems (P1) and (P2) at each point in time.

(P1) The first problem is to maximize the expected utility (46) conditional on the household deciding to relocate. This only directly affects the durable consumption good accumulation equation as can be seen in (48).

$$V^1(S_t, W_t, y_t, D_t) = \max_{E_{t+1}, S_{t+1}, W_{t+1}, P_{t+1}} \Bigg\{ u(c_t, W_{t+1}) + \frac{1}{1+\rho}\Big[a_t E_{t+1} H_{t+1} \times$$
$$\times \mathbb{E}_{\mathcal{Y}} V(E_{t+1}, S_{t+1}, W_{t+1} \cdot P_{t+1}, \mathcal{Y}, D_{t+1} = 1) +$$
$$+ (1 - a_t E_{t+1} H_{t+1}) \cdot \mathbb{E}_{\mathcal{Y}} V(E_{t+1}, S_{t+1}, W_{t+1}, \mathcal{Y}, D_{t+1} = 0)\Big]\Bigg\} \tag{46}$$

$$S_{t+1} = y_t \cdot (1 - \Delta^y D_t) + (1 + r_t(S_t))S_t - c_t - p^w(w_t) - p^P(E_{t+1}, W_{t+1}, P_{t+1}) - p^E(E_{t+1}) \tag{47}$$

$$W_{t+1} = (1-\delta)(1-\Delta^W)W_t + w_t \tag{48}$$

It quickly becomes apparent, that the optimal decisions do not depend on the initial exposure level

E_{t-1} any more. However this optimisation still can be done for every combination of (S, W, y, D) and the optimal objective values are captured in the function V_1.

(P2) The second problem is to maximize the expected utility (49) conditional on the household staying at the same settlement location. Again, this mainly affects the durable consumption good accumulation equation (see (51)). There is no decision variable E_t anymore in this case and E_t gets replaced by E_{t-1} in all equations (49)-(51).

$$V_2(E_t, S_t, W_t, y_t, D_t) = \max_{S_{t+1}, W_{t+1}, P_{t+1}} \Bigg\{ u(c_t, W_{t+1}) + \frac{1}{1+\rho} \Big[a_t E_t H_{t+1} \times$$
$$\times \mathbb{E}_{\mathcal{Y}} V(E_t, S_{t+1}, W_{t+1} \cdot P_{t+1}, \mathcal{Y}, D_{t+1} = 1) +$$
$$+ (1 - a_t E_t H_{t+1}) \cdot \mathbb{E}_{\mathcal{Y}} V(E_t, S_{t+1}, W_{t+1}, \mathcal{Y}, D_{t+1} = 0) \Big] \Bigg\} \tag{49}$$

$$S_{t+1} = y_t \cdot (1 - \Delta^y D_t) + (1 + r_t(S_t))S_t - c_t - p^w(w_t) - p^P(E_t, W_{t+1}, P_{t+1}) - p^E(E_t) \tag{50}$$

$$W_{t+1} = (1 - \delta)W_t + w_t \tag{51}$$

Similar to the first case we store the maximized objective value for each possible combination of (E, S, W, y, D) in function V_2.

After calculating the optimal objective value for both scenarios the households bases its relocation decision on which scenario yields a higher expected utility. For the value function it consequently holds that

$$V(E, S, W, y, D) = \max \Big\{ V_1(S, W, y, D), V_2(E, S, W, y, D) \Big\}.$$

This problem transformation allows us to use a value function iteration (VFI) approach to find the unknown value function $V(\cdot)$ and the optimal policy function for all decision variables.

B.2. Numerical methods

To derive an approximation for the unknown value function and optimal policy function, in a fist step we discretize the state space. However, as our model consists of five state and seven decision variables, we face the curse of dimensionality when applying a value function iteration strategy over the discrete grid of state variables.[25] To increase computational efficiency and reduce the overall computation time, we use a combination of several strategies:

- When solving the maximization problem on the right hand side of (10a) we use a coordinate ascend method to reduce the number of functional evaluations compared to a full grid search over all possible combination of decision variables. Since the restriction in search directions for the coordinate ascend method, we check all neighboring points of an extended region of a fix point of the algorithm to ensure local optimality.

[25] Doubling the number of grid points for exposure, financial savings and durable consumption goods would imply

- that the number of state combinations, for which the optimisation problem has to be solved, increases 8-fold.
- that a complete grid search would need to cover 8-times the number of feasible decisions.

In total that would roughly increase the computational efforts 64-fold.

Furthermore we conduct a complete search over an even more extended neighborhood once the value function has converged. This allows us to escape local optima and we continue the value-function-iteration process until all policies cannot be improved within the extended neighborhood.

- Between iterations conducting an optimisation as described above, we apply Howards-Policy-Iteration-Strategy to increase the speed of convergence and reduce computation times.
- After convergence of the value function over a discrete approximation of the control/state space, we continue with iterations over the continuous control space until convergence[26] using general gradient-descent approach which uses a linear interpolation of the value function and its derivative. For the calculation of the gradient we use an efficient smoothing algorithm to avoid large changes in the gradient around the grid points.
- Finally we make use of GPU-accelerated computation methods to conduct the steps described above for thousands of combinations of state variables in parallel.

After having derived the optimal policy functions of the households, we use Monte-Carlo-Simulations to obtain the equilibrium distributions of households across all state variables. Thereby we again use GPU-accelerated methods to decrease computations times.

C. Definition of household vulnerability and risk

The value of vulnerability should represent the extent to which a household is affected in case a natural disaster occurs. We decided to define vulnerability as the loss in long-term expected utility in case of disaster experience relative to the utility in the no-disaster-scenario. As expected long-term utility is captured by the value function in our framework, this definition can be represented by equation (52). Thereby we adjust the value function by its minimum value over the feasible region of state variables $\underline{V}$ to ensure a positive denominator in equation (52). [27]

$$Vul := \frac{\mathbb{E}_{\mathcal{Y}}[V(E,S,W,\mathcal{Y},D=0)] - \mathbb{E}_{\mathcal{Y}}[V(E,S,W,\mathcal{Y},D=1)]}{\mathbb{E}_{\mathcal{Y}}[V(E,S,W,\mathcal{Y},D=0)] - \underline{V}} \tag{52}$$

We argue that this definition covers all aspects we would require for a reasonable vulnerability indicator: (i) it should capture long-term impacts of a natural disaster and not only short transitory effects, (ii) it should capture the impact of a natural disaster in a holistic way, (iii) it should take into account the not only absolute impacts, but also relative effects, and (iv) it should be a normalised indicator and independent of the units or scales used.

(i) Our indicator considers a long-term perspective compared to e.g. using the period utility function. A household temporary reducing consumption and/or adjusting in other ways, while being able to properly return to its previous living standard after 1-2 periods of time, intuitively should be

[26] Due to numerical issues we kept the exposure level decision over a discrete control space.

[27] We could ensure a positive denominator also by ensuring that the value function itself is always positive. This could be achieved by adjusting the utility function itself with a sufficiently large constant term to ensure positive utility for all combinations of consumption and durable consumption goods. Such a linear shift, however, does not affect the household behaviour and therefor has no impact on the outcomes of our model. As we only need a positive value-function for this small part of the analysis, we decided to make this adjustment only in the definition for the vulnerability indicator, as it also does not effect the qualitative results as explained above. Of course, we could also adjust the value function in nominator in Equation (52) by this constant term, but as this term would cancel out anyway, we decided to omit this part.

marked as less vulnerable compared to a household, which is put on a completely different trajectory by the shock for longer periods of time.

(ii) The value function is the result of all future decisions by the household and therefore includes multiple different impact channels compared to alternatively focusing on consumption or durable consumption goods in isolation.

(iii) The same absolute losses in consumption, physical assets, etc. should in general have less impact on wealthier households when discussing their vulnerability. Our definition accounts for this aspects in two ways. (a) We scale the difference in expected utility with the expected value function for the no disaster case. Hence, the same absolute difference in utility in the nominator results in lower vulnerability for households being well off in the first place compared to households in more precarious situations. (b) The decreasing marginal utility of consumption and durable consumption goods in the period utility function implies that losses in those two factors have less impact on utility if they are normally on a higher level already. Since the value function originates from the period utility, the difference in the nominator directly accounts for this wealth aspect to some degree.

(iv) We obtain an indicator which is normalised between 0 and 1 and is independent of the units or scales used in the framework.

Applying this definition of vulnerability we define the disaster risk level R of a household as the product of exposure and vulnerability. We omit hazard as it is an exogenous variable and would only scale risk by a certain factor for all households.

$$R = E \times Vul \tag{53}$$