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EL ROL DE LOS ESTUDIOS DE POBLACIÓN TRAS LA PANDEMIA DE COVID-19 Y EL DESAFÍO DE LA IGUALDAD EN AMÉRICA LATINA Y EL CARIBE

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The effect of education and past experience on disaster preparedness: a cross-country and cross-disaster analysis

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Abstract. The world has been witnessing an increasing number of climate-related events, such as wild fires, landsliding, droughts, and floods. Global databases suggest an exponential increase in the frequency and intensity of extreme weather episodes in the last decades, but climate change has made the timing and location of such events difficult to predict. Some studies suggest that the uncertainty brought about with climate change is the major explanation for the low levels of preparedness worldwide. As a consequence, societies have been experiencing non-negligible human and material damages after major disasters. Because of the economic and social importance of preparedness against natural and technological hazards, much effort has been made in the last years to understand the main drivers of preparedness behavior. In particular, risk experience and cognitive skills has been seen as key to understand why, when and how individuals prepare against hazards. Recent empirical studies have found that disaster experience and education are powerful resilience forces against potential loss among Asian countries. This study explores the ways in which education and previous experience with floods may work as complementary or substitutes for individual protective behavior against natural hazards in general, and against specific hazards in particular, such as floods, droughts and landsliding. We apply a set of four survey data sets, covering 3 types of disasters (droughts, landsliding and floods/storms) in 3 countries (Brazil, Thailand and the Philippines). Data for preparedness against droughts cover the surveys in Brazil (Seridó Survey, 1064 interviews) and Thailand (1310 interviews). Data for preparedness against floods/storms cover the surveys in Brazil (GV Survey, 1226 interviews), Thailand (1310 interviews) and Philippines (889 interviews). Finally, data for preparedness against landsliding cover the survey in Thailand only (1310 interviews). Preliminary findings show that for overall preparedness, education has a positive effect on preparedness for Thailand and the Philippines, but the opposite for Brazil. Despite the contrasting results, the

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mechanism behind it is quite similar: in Brazil individuals with high levels of education are already adapted, being less likely to adopt additional measures, while in the Asian countries there is still room for further adaptation as their level of education is lower on average and their disaster intensity is higher. Past experience seems to act as an incentive to induce preparedness, regardless of the country. In the Asian countries, in particular, the effect of education seems to operate among those with no experience, but has no effect among those who have already experienced a past event.
Keywords: Education, Natural disaster, Cross-country analysis.

1 Introduction

Every year many lives are lost due to floods worldwide. According to the Centre for Research on the Epidemiology of Disasters in Brussels, in cooperation with the United States Office for Foreign Disaster Assistance (CRED/OFDA), about 200,000 lives were lost and over 3 billion persons were injured, affected or became homeless by floods from 1990 to 2018. In the year 2018 alone, floods were responsible for 2,881 deaths and almost 35 million persons were somehow affected. In addition to human impacts, the material impacts of floods create additional burden for the households, increasing their vulnerability to new environmental and social stress [13]. The estimated material cost of floods from 1990 to 2018 has surpassed 730 billion dollars, 20 billions in 2018 alone (Centre for Research on the Epidemiology of Disasters, 2019; EM-DAT, 2019).

Floods are of special concern in areas where population vulnerability to flood hazard is high, such as in impoverished areas of developing countries. In these areas, unplanned urbanization coupled with deforestation of riparian forests and sewage discharges into rivers create an ideal scenario for flooding (UNISDR, 2015). Jonkman[13] estimates that the contribution of river floods to total number of killed and affected persons is dominated by episodes in Asia, compared to floods in the Americas and Europe. According to The International Disaster Database, however, Brazil is ranked highest, along with the United States, in terms of flood disasters among American countries, justifying attention to the study of behavioral patterns related to flood preparedness in the country (Centre for Research on the Epidemiology of Disasters, 2019; EM-DAT, 2019). Moreover, Brazil is a country very prone to both, coastal and river flooding, due to its highly complex river network and long seacoast, extending from South to North for over 8,000 km.

Although many studies on flood consequences focus on coastal areas [35, 11], river floods can be as or even more impacting when they reach intensively urbanized areas. Risks of waterborne diseases are commonly reported after main river floods, especially in areas where untreated sewage is discharged along with unprocessed garbage directly into the river [25, 27, 24, 10]. Recent improvements in risk reduction against natural disasters, such as landslides and flooding, have increased in many parts of the world [5, 35], and may lessen the negative consequences of floods on urban places. Recent data from Brazil show that the proportion of local goverments that implemented local strategies for disaster risk reduction increased from 23.1% in 2013 to 33.8% in 2017.

The measures taken by governments include all sort of preventive strategies, varying from mapping of areas under risk of flooding or landsliding, risk registering, contigency plans, governments' investments in structural infrastructure mitigation, implementation of early warning systems, planned evacuation routes and shelters to housing programs for settling low income individuals living in risk areas, monitoring of areas suceptible to disaster to avoid settlement, and finally the establishment of a fire department, a civil defense department and a municipal urban planning protocol defining flood and landslide prevention. All these government actions have been proved effective in reducing both human and material consequences of disasters in many places [3], but short term responses are still largely left for private measures [2]. These precautionary measures include low-cost actions in the form of emergency kits; seeking information about disaster consequences; finding evacuation routes, safe/high places in the neighborhood; creating a list telling what to do in case of an evacuation; agreeing with family, relatives, friends, and neighbors about how to help each other during an evacuation; use of construction materials to improve house resilience, and acquisition of insurance. In vulnerable and impoverished regions, private actions to protect against hazards may be key in the first 72 hours to keep individuals alive [30] and reduce risk of material damage to properties [11, 35].

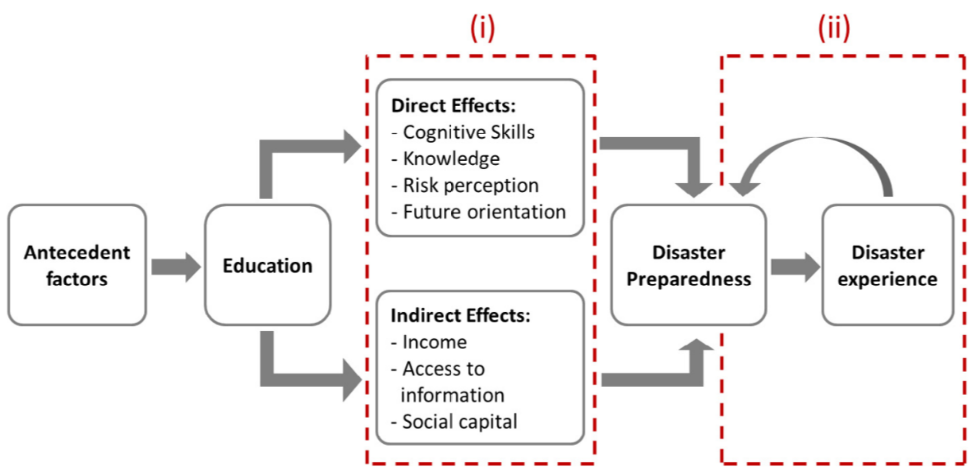
Despite the material and human impacts of floods, preparedness behavior to flood hazard is generally low worldwide [33], including flood prone areas [1]. To respond against the low levels of adoption, governments and NGOs have been promoting educational campaings and emergency trainings with varying levels of success in promoting awareness, preventive behavior and self-insurance [37, 26]. The biggest challenge in disaster management and risk reduction then is how to improve self-protection and awareness, along with household resilience, through educational campaings that are cost-effective and adherent to local behavioral patterns. The first step is to understand the complex determinants of the intention to adopt protective measures against natural hazards − a question that have occupied the mind of environmental psychologists and behavioral economists for decades [18, 17]. To date, an emerging empirical literature on private measures against natural and technological hazards start to point to major patterns among individuals under risk [35, 15, 19].

Evidence about adoption of flood preparations is mostly available for developed countries [36, 23, 34, 32, 16, 31, 35], although many urban areas in the tropical zone are under flood risk. Based on the Protective Action Decision Model (PADM) [20], this study explores the ways in which education and previous experience with floods may work as complementary or substitutes for individual protective behavior against flood hazards. Although not the first model to empirically test the PADM framework [35, 11], our model improves previous efforts in many ways: 1) it is based on a probabilistic sample, with 1,226 individuals interviewed in a city with a large share of the population under risk of river floods; 2) it introduces a hierarchical Bayesian ordered logistic model relating the probability of adopting protective measures against floods to covariates directly measured from individuals (education and previous experience with floods), as well as to latent covariates representing risk-aversion and perceptions about the effectiveness (PE) and the opportunity cost (PCO) of those measures; 3) it measures PE and PCO through Bayesian item response theory (IRT) models, appropriately quantifying the uncertainty inherent to such quantities; 4) it includes a random effect reflecting unmeasured individual features to correlate the individual responses to the different protective measures considered.

Our data were collected in urban households in the municipality of Governador Valadares, Brazil. The site was chosen because river floods are recurrent in the region, reaching thousands of households along the river [12]. The urban environment of Governador Valadares has undergone dramatic changes in the last decades, creating and ideal scenario for flooding: deforestation of the riparian forest, river silting, unplanned occupation of riverbanks, and garbage and sewage discharge into the river [7]. Our empirical data on PADM will provide the first population-based estimate of people's intention to prepare for floods in a Brazilian setting where risk is real and recurrent.

2 Education and Flood Experience: conceptual framework for preparedness against hazards

Fig. 1. Proposed framework on how education influences diaster preparedness and its interplay with disaster experience (Source: Hoffmann and Muttarak, 2017)



3 Data

The survey data used in this study come from a pioneering research project in Brazil addressing environmental attitude, awareness, and behavior at the local level, with detailed questions on climate change perception and adaptive measures under risk of flood hazards. Data are part of the research project entitled "Migration, Vulnerability, and Environmental Change in the Rio Doce Valley". The project was approved by the Research Ethics Committee at the *Universidade Federal de Minas Gerais* (CAAE Protocol 12650413.0.0000.5149).

Face-to-face interviews were conducted in the urban area of Governador Valadares between 2014 and 2015, based on a questionnaire successfully applied in other countries [15, 38] and for other hazards [35]. The survey was based on a multi-stage sampling design. The first stage used clusters of neighborhoods, with clustering based on spatial contiguity and socioeconomic status of the neighborhood. Within each cluster, sample was stratified by sex and age groups, and within each stratum households were randomly selected. A minimum sample size was estimated as 1,069 households, based on a significance level of 5% and a tolerance of 3% for sample proportions. Variance estimate was 0.25, yielding the most conservative minimum sample size [9]. Because of additional budget resources granted, sample size was increased to 1,226 households. Due to missing information on some characteristics selected for this analysis, our analytical sample reduced to 1,032 respondents.

Data used for modeling preparedness behavior were collected following the Protective Action Decision Model framework proposed in [20], with selected dimensions transformed into an structured questionnaire as used in [35]. The six response variables of interest measures the adoption intentions in relation to the following flood hazard actions: emergency kit (KIT), search for information about flood consequences, evacuation routs to safe places in neighbor (INFO), a list telling what to do in case of evacuation or flood (LIST), agreement with family or friends on how to help each other during evacuation (COOP), use of sandbags or flood skirts (SAB) and acquisition of contractual flood insurance (INSUR).

Covariates representing determinants of preparedness behavior were classified in two groups. Group 1 comprises individual-level characteristics: years of education, previous experience with floods, gender, married or cohabiting, time of residence (years), social capital, proportion of children (≤ 5) and older people (≥ 65) in the household, risk perception, and distance to the Doce River (meters). Social capital and risk perception were created as a combination of other variables in the questionnaire, as explained in Section 4.1. Although the questionnarie contained a direct question on education in interval categories, we simulated its continuous value applying the Integral Transform Theorem [4].

Group 2 includes the covariates that depend on both individuals characteristics and the protective actions. Such covariates are: effectiveness to protect people (EPa), effectiveness to protect properties (EPr), usefulness for other purposes (UP), cost to implement the action (COST), time to implement the action (TIME), effort needed in the action implementation (Effort), knowledge and skills required in the action implementation (KS) and the need for cooperation during action implementation (CoIA).

The response variables and covariates in Group 2, originally measured in the Likert scale with 5 categories, are transformed into binary variables assuming 0 if the response ranges from 1 to 3 (representing low to intermediate levels of effectiveness, opportunity cost or adoption intention) and 1 otherwise.

4 The Proposed Model

Assume that a random sample of n individuals is independently interviewed to obtain their opinion about J protective actions. Let Y_{ij}, $i = 1, \ldots, n$, and $j = 1, \ldots, J$, be

Given a latent continuous random variable X with its cumulative strictly increasing distribution function F_X, the Probability Integral Transform Theorem states that the variable $Y = F_X(X)$ follows a $U[0, 1]$ distribution. The observable variable $\tilde{X}$ is discrete and we aim to simulate a sample of X using an observable sample of $\tilde{X}$. Therefore, generating an i.i.d. sample $\{y_n\}_{nN}$ of Y and calculating $x_n = F^1 X(y_n)$, we obtain a sample $\{x_n\}_{nN}$ of a random variable with the same distribution of X.

a binary response variable assuming 1 if individual i has high intention of adopting the protective action j and 0, otherwise. Let $\boldsymbol{X}_i = (X_{1i}, \ldots, X_{pi})$ be the vector of observable covariates which responses represent individuals' features exogenous to the protective actions. In this study we use gender, household income, proportion % of hh with children, % of hh with elderly, social capital, Risk perception, Distance from river, Climate change, Age, Sex, Married, Household size, Years of residence as elements of $\mathbf{X_i}$ measured without any transformation. Let $\boldsymbol{W}_i = (W_{1i}, \ldots, W_{pi})$ be the vector of observable indicators used as proxies of latent covariates. We use risk perception and years of study as the two elements of $\boldsymbol{W}_i$. Such random variables are transformed to proxy their related latent analogs as discussed in Section 4.1.

Some covariates of interest are latent traits of the individuals. These latent covariates measure the perception θ_{ij} of subject i about the effectiveness of protective action j and the perception λ_{ij} of individual i about the opportunity cost of protective action j. Such latent covariates are indirectly measured through some observable covariates as discussed in Section 4.2.

Let $\beta_{0j} \in \mathcal{R}$ be the model intercept. Denote by $\beta_{\theta j}$, $\beta_{\lambda j}$, $\boldsymbol{\beta}^*_j = (\beta^*_{1j}, \ldots, \beta^*_{pj})$ and $\boldsymbol{\beta}_j = (\beta_{1j}, \ldots, \beta_{pj})$ is the real fixed effect related to covariates θ_{ij}, λ_{ij}, $\boldsymbol{X}_i$ and $\boldsymbol{W}_i$, respectively. Assume the linear predictor η_{ij} given by

$$\eta_{ij} = \beta_{0j} + \beta_{\theta j}\theta_{ij} + \beta_{\lambda j}\lambda_{ij} + \boldsymbol{\beta}^*_j \boldsymbol{X}_i^\top + \boldsymbol{\beta}_j \boldsymbol{W}_i^\top + \mu_i, \tag{1}$$

where μ_i is a random effect quantifying personal features of individual i not captured by the covariates. In the mixed logistic regression, the probability of the individual i has high intention of adopting the protective action j is given by $\pi_{ij} = P(y_{ij} = 1|\boldsymbol{\beta}^*, \boldsymbol{\beta}, \boldsymbol{\mu}, \boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{X}, \boldsymbol{W}) = \exp\{\eta_{ij}\}[1 + \exp\{\eta_{ij}\}]^{-1}$.

Assume that $y_{ij}|\boldsymbol{\beta}^*, \boldsymbol{\beta}, \boldsymbol{\mu}, \boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{X}, \boldsymbol{W} \overset{ind}{\sim} Ber(\pi_{ij})$, $i = 1, \ldots, n$ and $j = 1, \ldots, J$. As a consequence, the likelihood function is

$$f(\mathbf{y}|\boldsymbol{\beta}^*, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{X}, \boldsymbol{W}) = \prod_{i=1}^{n} \prod_{j=1}^{J} \left[\frac{\exp\{\eta_{ij}\}}{1 + \exp\{\eta_{ij}\}}\right]^{y_{ij}} \left[\frac{1}{1 + \exp\{\eta_{ij}\}}\right]^{1-y_{ij}}. \tag{2}$$

where $\boldsymbol{\gamma} = (\boldsymbol{\theta}, \boldsymbol{\lambda}, \boldsymbol{\mu})$, which represent the latent parameters of interest.

To complete the model specification, we assume that $\beta_{kj} \sim \text{Normal}(\mu_{kj}, \sigma^2_{kj})$ with mean $\mu_{kj} \in \mathcal{R}$ and variance $\sigma^2_{kj} \in \mathcal{R}^+$ for all k and all j, $\mu_i \sim \text{Normal}(m, v)$, where $m \in \mathcal{R}$ is a known parameter and $v \sim \text{Inv-Gamma}(a, b)$, where $a > 0$ and $b > 0$.

Before proceeding to the inference, we need to estimate $\boldsymbol{W}$, θ_{ij} and λ_{ij}.

4.1 Obtaining the proxies for social capital and risk perception ($\boldsymbol{W}$)

Social capital is considered key in situtions where official, instituional help is absent, distant or fragmented, or when disaster occurs unexpectedly [21, 20]. Social capital also reflects the strenght of embeddedness within the social networks in a community, representing the ability of individuals to quickly access resources and information [8]. A precise measure of social capital is usually quite challenging, but studies resort on approximations that are context and subject related [11]. In this study, we proxy social capital by two questions on environmental collective behavior: if the person would be willing to protest with others in the community against polluting companies and if he/she would be willing to take place in collective actions to help improve environmentally damaged areas in Governador Valadares. Although far for perfect, these reflect their indirect propensity to be involved in networks of mutual help related to environmental issues.

The question on perceived likelihood of a flood hit the household in the future, ranging from very unlikely (1) to very likely (5), was multiplied by the mean of four perceived consequences items (damage to the city public infrastructure, damage to the house structure and personal belongings, life treath, and long term disruption of daily life) to form a single measure of risk perception ranging from 1 to 25. The same strategy was used in Terpstra and Lindell [35], resulting in a perceived likelihood of flood risk weighted by its consequences. To mirror some results from Hoffmann and Muttarak [11], we transformed the scale into terciles and used the first tercile as the base category for regression modeling purpose.

4.2 Obtaining the individual perception the effectiveness and opportunity cost $(\boldsymbol{\theta}, \boldsymbol{\lambda})$

A key point in our model is the specification of the latent traits θ_{ij} and λ_{ij}. In this first modeling stage, we consider an item response theory (IRT) model to estimate such traits. One advantage of this approach, instead of fitting the model in (1) considering the covariates related to these traits in their original scale, is parsimony. A substantial reduction in the parameter dimension is obtained by using this method.

IRT is a well-known psychometric theory used in educational assessments and cognitive psychology [29, 6, 22]. IRT models relate the probability of a correct response in a test to latent traits, such as the individual abilities, intelligence or language dominance, as well as to the characteristic of the items, such as difficulty and discrimination. These traits are not directly measured but the responses given by a person to a test provide valuable information from which they can be inferred.

To estimate the perception θ_{ij} of subject i about the effectiveness of protective action j, we assume a "test" with the following three items (covariates): effectiveness to protect people (EPa_{ij}), effectiveness to protect properties (EPr_{ij}) and the usefulness for other purposes (UP_{ij}). These covariates are selected in agreement to the theory related to PADM discussed in Lindell and Perry [20].

For the sake of simplicity, was define the three different covariates as E_{ijk}, where k stands for the type of effectiveness. Assume that E_{ijk} is equal to 0 if the response of individual i in the Likert scale is up to 3, and is 1 otherwise, for $i = 1 \ldots, n$, $j = 1, \ldots, J$ and $k = 1, 2, 3$. We assume a probit IRT model as follows:

$$\begin{aligned} E_{ijk}|p_{ijk} &\overset{ind}{\sim} Bernoulli(p_{ijk}), \\ p_{ijk} &= \Phi(a_{kj}(\theta_{ij} - b_{kj})), \end{aligned} \tag{3}$$

in which a_k and b_k are, respectively, the discrimination and difficulty of item k and θ_{ij} denotes the perception (ability) of subject i about the effectiveness of protective action j. The link function $\Phi(m)$ is the cumulative distribution function (cdf) of the standard normal distribution evaluated at m. Under these assumptions, the likelihood function becomes

$$f(\mathbf{E}|\boldsymbol{\theta}, \boldsymbol{a}, \mathbf{b}) = \prod_{k=1}^{3}\prod_{i=1}^{n}\prod_{j=1}^{J} \left[\Phi(a_{kj}(\theta_{ij} - b_{kj})\right]^{E_{ijk}} \left[1 - \Phi(a_{kj}(\theta_{ij} - b_{kj})\right]^{1-E_{ijk}}.$$

The model specification is completed assuming *a priori* that $\boldsymbol{\theta}$, $\mathbf{a}$, and $\mathbf{b}$ are independent with $\theta_{ij} \overset{iid}{\sim} \text{Normal}(\mu_\theta, \sigma_\theta^2)$, $b_{kj} \overset{iid}{\sim} \text{Normal}(\mu_b, \sigma_b^2)$ and $a_{kj} \overset{iid}{\sim} \text{Gamma}(\alpha_a, \beta_a)$.

The perception λ_{ij} of individual i about the opportunity cost of protective action j is estimated using a similar probit IRT model. Following Lindell and Perry [20], to access λ_{ij} the "test" is composed by the items (covariates): cost to implement the action ($COST_{ij}$), time to implement the action ($TIME_{ij}$), effort needed in the action implementation ($Effort_{ij}$), knowledge and skills need in the action implementation (KS_{ij}) and the necessity of cooperation to implement the action ($CoIA_{ij}$). As for effectivness, we call all the costs above as C_{ijk}, where k represents each one of the five measures. We dichotomize the covariates C_{ijk} as previously described obtaining the following probit IRT model:

$$\begin{aligned} C_{ijk}|p^*_{ijk} &\overset{ind}{\sim} Bernoulli(p^*_{ijk}), \\ p^*_{ijk} &= \Phi(a_{kj}(\lambda_{ij} - b_{kj})), \end{aligned} \tag{4}$$

in which a_{kj} and b_{kj} are, respectively, the discrimination and difficulty of item k and λ_{ij} denotes the perception (ability) of subject i about the opportunity cost of protective action j.

We also assume that $\boldsymbol{\lambda}$, $\mathbf{a}$, and $\mathbf{b}$ are independent with $\lambda_{ij} \overset{iid}{\sim} \text{Normal}(\mu_\lambda, \sigma_\lambda^2)$, $a_{kj} \overset{iid}{\sim} \text{Gamma}(\alpha_a, \beta_a)$, and $b_{kj} \overset{iid}{\sim} \text{Normal}(\mu_b, \sigma_b^2)$.

4.3 Posterior inference

Given their complexity, we resort to MCMC algorithm to explore the posterior distribution. We use the Rstan package of the R software for the computational implementation of the models.

5 Fitting our proposed model to data on preparedness behavior against flood hazards in Governador Valadares, Brazil

To analyze the data presented in Section 3, we fitted the proposed model in (1) estimating the latent traits related to the individual perceptions about effectiveness and opportunity costs as proposed in Section 4.2. As the latent traits θ_{ij}, λ_{ij} and the difficulty parameter β_k are in the same scale, in the first stage of our modeling we follow the IRT literature and assume that $\theta_{ij} \overset{D}{=} \lambda_{ij} \overset{D}{=} b_k \overset{iid}{\sim} \text{Normal}(0, 1)$. We also assume a flat prior distribution for $a_k \overset{iid}{\sim} \text{Gamma}(0.01, 0.01)$. In the second stage, flat prior distributions are elicited for all fixed effects by letting $\beta_{kj} \overset{iid}{\sim} \text{Normal}(0, 100)$. For the random effects, we consider $\mu_i \overset{iid}{\sim} \text{Normal}(0, \tau^{-1})$ and $\tau \sim \text{Inv} - \text{Gamma}(10, 10)$.

To estimate the latent traits, in the MCMC we run 4000 iterations, discarded the first 3000 iterations as the burn-in. We did not observe autocorrelation in the chains. This resulted in a posterior sample of size 1000.

5.1 Modeling Strategy

We proposed three different *Bayesian models* and two different *Maximum Likelihood models*. The three Bayesian models differ in terms of the dependent variable, changing its structure: (1) Model 1 refers to a system of 6 binary logistic models (one for each protective measure from PADM) with random errors correlating equations for the same individual; (2) Model 2 refers to a system of 6 ordinal logistic models (one for each protective measure from PADM) with random errors correlating equations for the same individual, and (3) Model 3 is a single equation ordinal logistic model representing the number of protective measures undertaken by the person.

The two Maximum Likelihood models corresponds to the following dependent variables: (1) Model 1 is a binary logistic regression for adopting any (at least one) protective measure, and (2) an ordinal logistic model representing the number of protective measures undertaken by the person. While the Maximum Likelihood models were used to gain understanding on chanels through which education influences preparedness against floods (by direct and indirect effects), and allowing decomposing these effects through the KHB method [14], the Bayesian approach allowed us to gain more information on estimators (obtaining not only a moment of the estimator but its entire difference) and gaining in probability of rejecting H_0.

While in the Maximum Likelihood models, the effectiveness and opportunity cost measures were obtained through Exploratory Factor Analysis (results not shown here, but available upon authors' request), in the Bayesian models, these proxies were measured by Bayesian IRT binary models, appropriately quantifying their uncertainty. The factors performed very adequately with the PADM theory, the three first items loading heavily on one factor and the other five on the other. These scores also happened to be orthogonal, as suggested by Raad, Guedes and Raad [28].

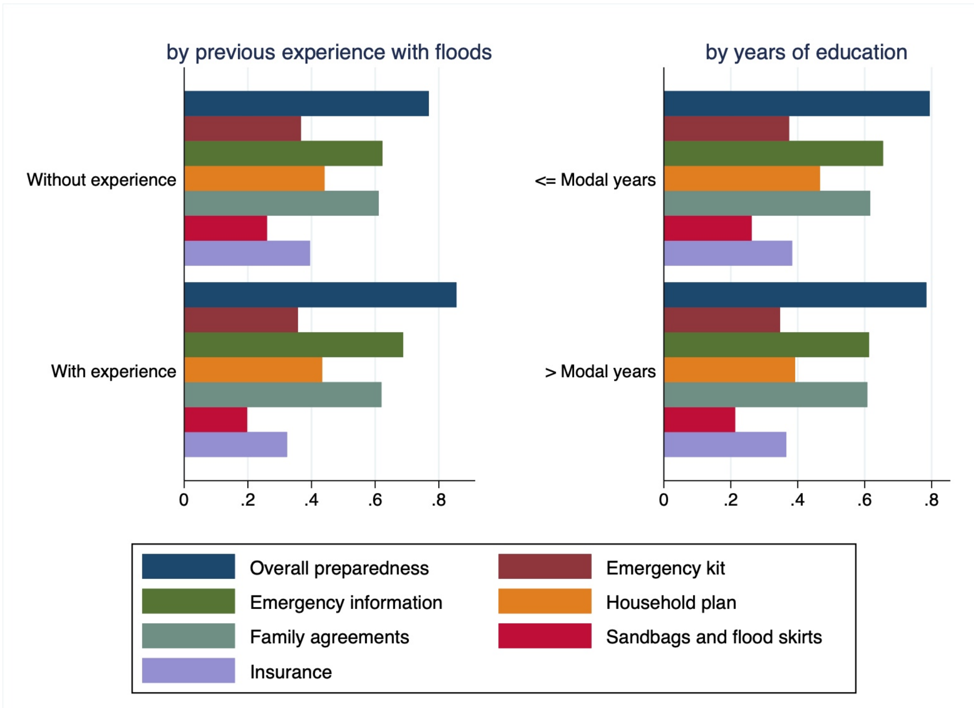
6 Results

6.1 Descriptive results

Figure 2 shows the proportion of sample individuals who intend to adopt each of the six protective measures against floods by previous experience with flood events and level of education. We see relevant differences in both stratification variables. As predicted, those with prior experience has an overall higher preparedness than those with no previous experience with floods. When we look at the particular measures, however, the same patter starts to change. For household plan, use of sandbags and flood skirts and insurace the average intention to adopt these measure is lower for thoese without experience. For the case of education, results are consistent - no matter if you look for both or for eacch measure - reflecting a higher likelihood of adopting among the lowest educational level.

Figure 3 gives an overall descriptive view of the sample. On average, 79% of respondents intend to adopt any (at least one) protective mesaure in the future to protect them and their family against any harm from floods. This is a quite high proportion, even higher than what as found in Hoffmann and Muttarak [11] for the Philippines (76%) and Thailand (32%). Number of preparedness in our study area (2.68) was on average also expected to be slighty higher than in those countries,

Fig. 2. Flood preparedness measures by previous disaster experience and educational level - Governador Valadares, Brazil, 2014/2015



2.28 and 0.88 respectively. If we look at each of the measures separately, seeking for emergency information is the most popular protective measure, followed by family agreements, againt the least popular use of sandbags and flood skirts and assembly of emergency kits. Average education sits close to high school completed and 25% of sample has had some past experience with floods. Mean age was 41.10, with a predominantly female sample (53%) and married/cohabiting (52%). As a city of constant in and out-migration, an average of 28.5 years of residence doesn't come as a surprise. Only 9% have some social capital (as proxied here) and the risk perception is relatively low. Knowlege on how climate change can affect local conditions is also how, reflecting a distance of resindents to the objective knowledge on the causes of floods. Only 5% of households had children (aged $\leq$ 5 years old), 14% had older people living there (14%) and household size is small (3.3 pessoas) - a reflection of the ongoing population aging process. Only 28% of individiuals interview have interest in acquaring a house.

6.2 Maximum Likelihood Estimates

Figure 4 reports the findings from the baseline models (both binary logit and ordered logit) with reported coefficients in exponentied form (odds-ratio) and standard-errors

Fig. 3. Measurement and summary statistics for dependent and independent variables of adoption intention models - Governador Valadares, Brazil, 2014/2015

	Range	Mean	SD
Outcome variables			
Emergency kit	0/1	0.36	0.48
Emergency information	0/1	0.64	0.48
Household plan	0/1	0.44	0.50
Family agreements	0/1	0.61	0.49
Sandbags and flood skirts	0/1	0.24	0.43
Insurance (house and flood)	0/1	0.38	0.48
Intention to adopt any protective measure	0/1	0.79	0.41
Number of protective measures intended	0-6	2.68	2.00
State explanatory variables			
Years of education	0-18	11.69	4.04
Flood experience	0/1	0.25	0.44
Control variables			
Age	18-79	41.10	16.35
Male	0/1	0.47	0.50
Married/Cohabiting	0/1	0.52	0.50
Years of residence	0-78	28.47	17.38
Social capital	0/1	0.09	0.28
Scale of risk perception	1-25	6.38	5.74
Climate change can aggravate floods	0/1	0.23	0.42
% children (aged $\leq$ 5) in household	0-60	0.05	0.11
% older people (aged $\geq$ 65) in household	0-100	0.14	0.27
Own household	0/1	0.28	0.45
Distance to river (meters)	13-5921	1398.25	1136.99
Household size	1-10	3.31	1.47

robust to heteroskedasticity. The baseline models include the two state variables (education and previous flood experience) and a set of control variables (gender, civil status, time of residence, household age composition, distance to river, effectiveness and opportunity costs of action). We found that education has a negative impact on flood preparadness (for the ordinal model only), while flood experience is also negative (for the binary model only). These results goes in direct contrast with the findings in the literature [11], but part of these effects may be contaminated by mediating and indirect effect that need to be disentangle. The impact of effectiveness for both models is much higher (and the only significative than opportunity cost0, as predicted by PADM [20].

Figure 5 extends models from Figure, now including - each at a time - mediating factors, that is, variables that influences education, which by its turn influences preparedness bahavior. For the ordered logistic especification, only risk perception seems to significantly mediate the role of education. The same table, in the lower panel, reprents the result of the KHB decomposition for each of the mediating factor here included (per capita household income, social capital, risk perception and perception that climate change can worsen floods. In the model however, it the last mediating factor didnt behave adequately and was excluded. As can be observed, in our sample, the effect of education seems to opperate predominantly in a straightfoward way, without mediating factors, since only the direct effects were relevant. The same result was found for the Philippines in Hoffmann and Muttarak [11].

6.3 Bayesian Estimates

Figures 6, 7 and 8 show the posterior densities of models coefficients as described in Section 5.1. Compared to Maximum Likelihood models from previous session, the Bayesian models improved significantly in finding more mass away from H_0, which gives more evidence that the effect of both, education (looking ahead) and preparedness (looking to the past) play an important role in explaining and predicting protective behavior against floods.

As Figures 6, 7 and 8, but mainly the latter reveal, the interplay between education and flood experience is predominantly working as substitutes than complementaries. And differently from previous studies who found positive, reinforcing or no effect of education on preparedness, we found that both variables are associated with *lower levels* of intention of future protection. As discussed by other authors [11, 35, 34, 18], adaptation and resilience may be key to interpret these results. While education may promote future preparedness to avoid additional loss, more educated individuals anticipate these costs and adapt early (the same with those who suffered from previous episodes of floods). Thus, the mechanisms behind the negative estimates found here are the same as those found in Hoffmann and Muttarak [11]: those more willingness to adapt because are more risk averse, knowleageble and have more resources available, are likely to be those who have already adapted against the risk. So, when asked if they will adapt in the future, they will likely say no because they are already resilient. Thefere, education and previous experience are very much substitutes here, with some variation depending on the type of protective measure you look at. If someone has to target a group to reduce their vulnerability to injury and loss with minimum suffer would be those with no previous experience and with low levels of education. At least

Fig. 4. Baseline Models: Maximum Likelihood Estimates with no Error Correlation between Equations - Governador Valadares, Brazil, 2014/2015

	Binary Logit (Model 1)		**Ordinal Logit (Model 2)**	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
State explanatory variables				
Years of education	0.97	[0.022]	0.954**	[0.014]
Flood experience	1.924**	[0.433]	1.224	[0.168]
Control variables				
Male	1.137	[0.193]	0.925	[0.107]
Married/Cohabiting	1.429*	[0.254]	1.279*	[0.157]
Years of residence	0.985**	[0.006]	0.994	[0.004]
% children (aged $\leq$ 5) in household	1.006	[0.009]	1.005	[0.006]
% older people (aged $\geq$ 65) in household	1.001	[0.003]	0.998	[0.002]
Distance to river (meters)	1.000	[0.000]	1.000***	[0.000]
PADM coefficients				
Effectiveness	7.407***	[1.348]	16.104***	[2.435]
Opportunity cost	1.237	[0.181]	1.602***	[0.178]
Mediating Factors				
Per capita household income	-	-	-	-
Social capital	-	-	-	-
Scale of risk perception				
2nd tercile	-	-	-	-
3rd tercile	-	-	-	-
Global warming increasing flood risk	-	-	-	-
Tau 1			0.108***	[0.029]
Tau 2			0.237***	[0.063]
Tau 3			0.565*	[0.147]
Tau 4			4.589***	[1.201]
Observations	1032		1032	
Pseudo R-squared	0.17		0.16	
AIC	900.5		2719.6	

Exponentiated coefficients; Heteroskedastic standard errors in brackets

Coefficient in first columns. SE displayed in brackets. P-value: + 0.1 * 0.05 ** 0.01 *** 0.001

Fig. 5. Extended Ordered Logistic Models: Maximum Likelihood Estimates Exploring the Impacts of Mediators on Flood Preparedness - Governador Valadares, Brazil, 2014/2015

Variable	1	2	3	4	5	6
State explanatory variables						
Years of education	0.954**	0.951**	0.953**	0.954**	0.953**	0.950**
	[0.014]	[0.015]	[0.014]	[0.014]	[0.014]	[0.015]
Flood experience	1.224	1.228	1.219	1.189	1.219	1.182
	[0.168]	[0.168]	[0.167]	[0.167]	[0.168]	[0.166]
Mediating Factors						
Per capita household income		1.019				1.015
		[0.036]				[0.036]
Social capital			1.202			1.181
			[0.244]			[0.239]
Scale of risk perception						
2nd tercile				0.754*		0.753*
				[0.104]		[0.104]
3rd tercile				1.029		1.029
				[0.161]		[0.161]
Global warming increasing flood risk					0.92	0.911
					[0.131]	[0.130]
Tau 1	0.108***	0.107***	0.109***	0.101***	0.106***	0.098***
	[0.029]	[0.029]	[0.030]	[0.027]	[0.029]	[0.027]
Tau 2	0.237***	0.235***	0.239***	0.221***	0.232***	0.215***
	[0.063]	[0.062]	[0.064]	[0.058]	[0.062]	[0.058]
Tau 3	0.565*	0.559*	0.570*	0.529*	0.552*	0.514*
	[0.147]	[0.145]	[0.149]	[0.137]	[0.145]	[0.136]
Tau 4	4.589***	4.546***	4.638***	4.324***	4.477***	4.214***
	[1.201]	[1.192]	[1.222]	[1.139]	[1.191]	[1.139]
KHB decomposition of education effects	Income		Social Capital		Risk Perception	
Total effect	0.954**		0.954**		0.954**	
	[0.014]		[0.014]		[0.014]	
Direct effect	0.951**		0.953**		0.954**	
	[0.015]		[0.014]		[0.014]	
Indirect effect	1.003		1.001		1.000	
	[0.006]		[0.001]		[0.001]	
Effect change in %	-0.0709		-0.0185		-0.0004	
Observations	1032	1032	1032	1032	1032	1032
Pseudo R-squared	0.158	0.158	0.158	0.159	0.158	0.160
AIC	2719.6	2721.2	2720.8	2718.3	2721.3	2722.9

Exponentiated coefficients; Heteroskedastic standard errors in brackets

Coefficient in first columns. SE displayed in brackets. P-value: + 0.1 * 0.05 ** 0.01 *** 0.001

Fig. 6. Posterior beta densities from binary logistic model of intention adoption of protective measures against flood hazard with random errors - Governador Valadares, Brazil, 2014/2015

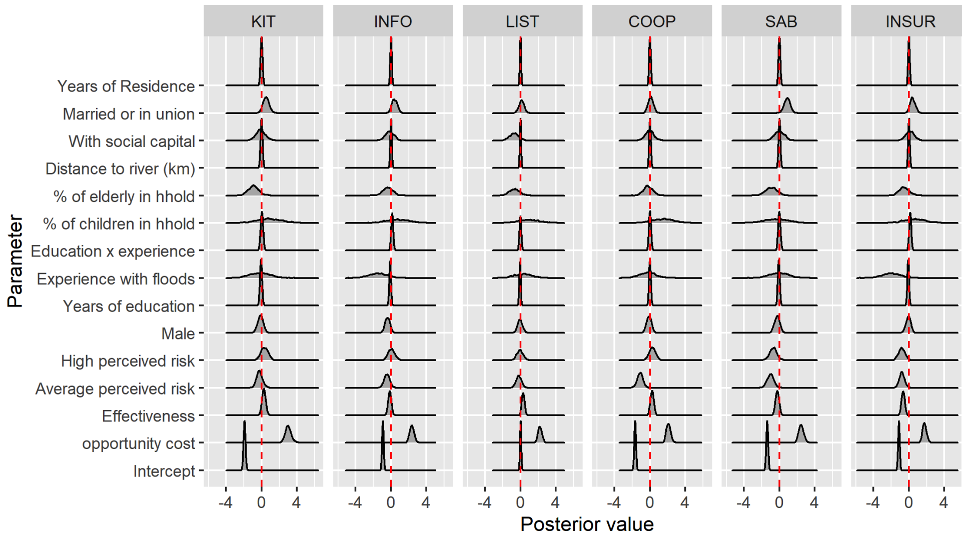


Fig. 7. Posterior beta densities from ordinal logistic model of intention adoption of protective measures against flood hazard with random errors - Governador Valadares, Brazil, 2014/2015

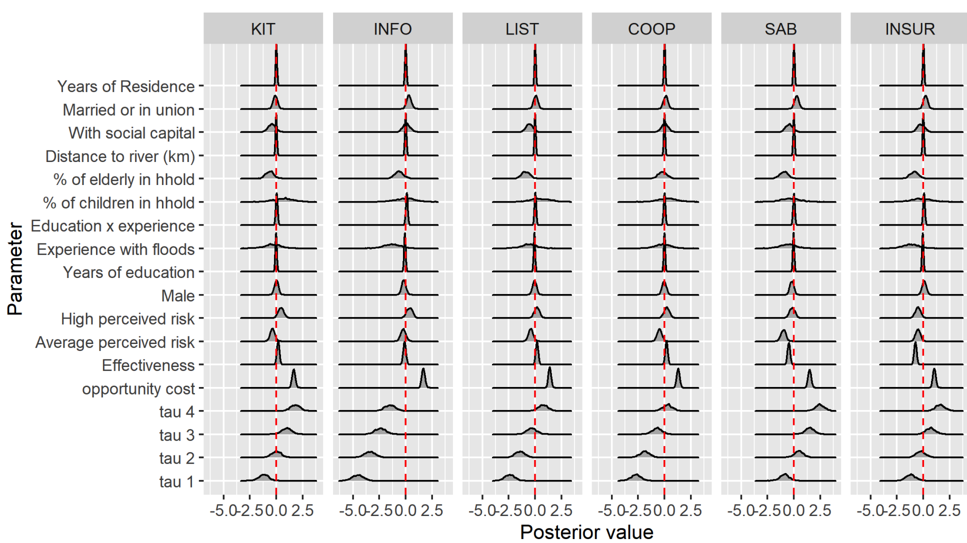
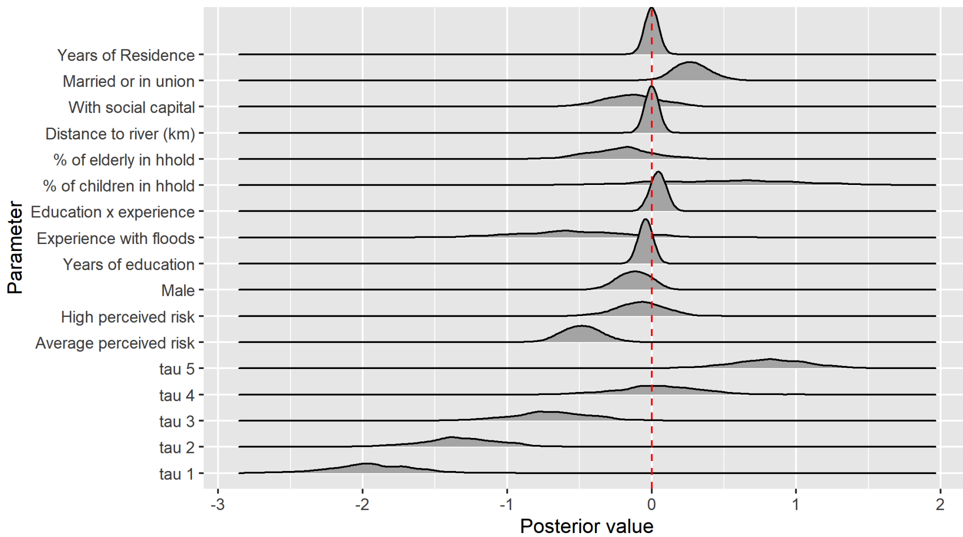


Fig. 8. Posterior beta densities from ordinal logistic model of number of intended protective measures against flood hazard with random errors - Governador Valadares, Brazil, 2014/2015



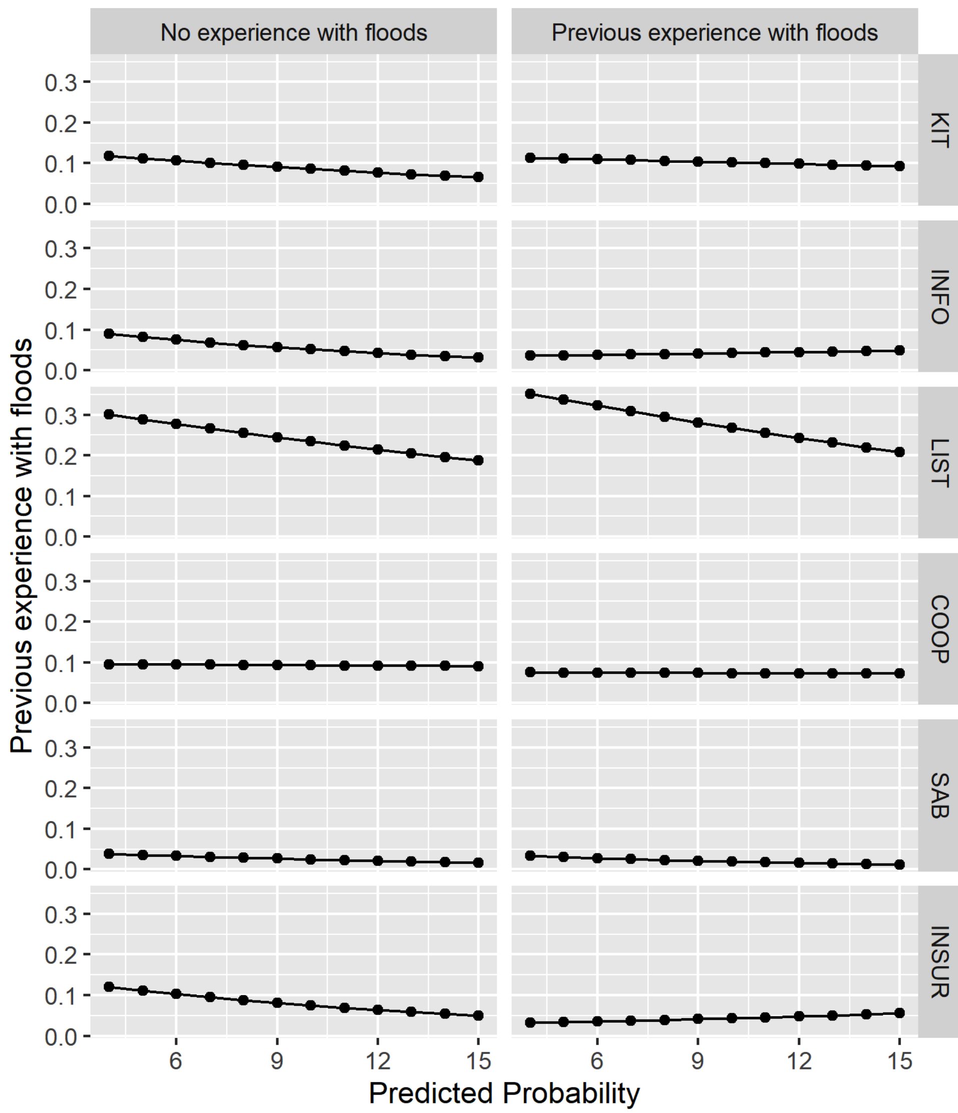
in our study area, those are the most willing to adapt, especially because they are the ones most pressed by the harsh environmental conditions.

7 Concluding Remarks

The world has been witnessing an increasing number of climate-related events, such as droughts, landsliding and floods. Global databases suggest an exponential increase in the frequency and intensity of extreme weather episodes in the last decades. The low levels of preparedness worldwide are one of the major causes of human and material damages after major disasters. Theoretical models of preparedness behavior suggest that perceived costs and effectiveness of protective actions are the most important forces behind these patterns. Risk experience and cognitive skills are also key to understand why, when and how individuals prepare against hazards. Recent empirical studies have found that disaster experience and education are powerful resilience forces against potential loss among Asian countries.

Based on the Protective Action Decision Model (PADM), this study explored the ways in which education and previous experience with floods may work as complementary or substitutes for individual protective behavior against flood hazards. Data analysis was based on a face-to-face probabilistic survey of adults under risk of river floods in Brazil. Our model improved previous efforts in many ways: it is based on a probabilistic sample, with 1226 individuals interviewed in a city with a large share of the population under risk of river floods; it introduces a hierarchical Bayesian ordered logistic model relating the probability of adopting protective measures against floods to covariates directly measured from individuals (education and previous experience

Fig. 9. Plots of marginal effects from binary logistic models displaying the probability of taking each of six protective measures by years of education and previous flood experience - Governador Valadares, Brazil, 2014/2015



with floods), as well as to latent covariates representing risk-aversion and perceptions about the effectiveness (PE) and the opportunity cost (PCO) of those measures; it measures PE and PCO through Bayesian item response theory (IRT) models, appropriately quantifying the uncertainty inherent to such quantities; it includes a random effect reflecting unmeasured individual features to correlate the individual responses to the different protective measures considered.

Different from previous studies, we found that education is negatively associated with the propensity to prepare against floods, especially among those with disaster experience. Previous adaptation strategies among the highly educated are the likely explanation for this behavior, suggesting that anticipation skills are positive externalities from education for risk reduction.

8 Acknowledgements

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A Appendix

Fig. 10. Posterior mean parameter estimates and 95% credibility interval from Model 1 and Model 2 Bayesian Models of Intention to Assemble an Emergency Kit against Flooding Hazard - Governador Valadares, Brazil, 2014/2015

	Model 1			Model 2		
Variable	Coefficient	95% Credibility Interval		Coefficient	95% Credibility Interval	
State explanatory variables						
Years of education	**-0.0592**	-0.1777	-0.0136	**-0.0167**	-0.1192	-0.0163
Flood experience	**-0.1985**	-3.3109	0.4252	**-0.3585**	-2.0192	0.8544
Interaction term	0.0388	-0.0145	0.2773	**0.0391**	-0.0961	0.1276
Control variables						
Male	**-0.1242**	-0.9308	0.1138	0.0099	-0.4278	0.3002
Married/Cohabiting	**0.5098**	-0.1645	0.9849	**-0.0975**	-0.3231	0.4342
Years of residence	-0.0018	-0.0170	0.0158	0.0106	-0.0070	0.0153
Social capital	-0.1107	-1.0755	0.7639	**-0.4355**	-1.1403	0.1283
Scale of risk perception						
2nd tercile	**-0.2310**	-1.1186	0.1331	**-0.3574**	-0.8793	-0.0165
3rd tercile	**0.3409**	-0.7025	0.8043	**0.4414**	-0.3288	0.6485
% children (aged $\leq$ 5) in household	**0.8430**	-1.8863	3.0938	**0.6611**	-1.1481	2.2810
% older people (aged $\geq$ 65) in household	**-0.9253**	-1.4030	0.6775	**-0.6343**	-1.6746	-0.1947
Distance to river (meters)	-0.0001	-0.0005	0.0000	0.0000	-0.0001	0.0003
PADM coefficients						
Effectiveness	**3.0126**	1.8567	2.8165	**1.6523**	1.1722	1.6366
Opportunity cost	**0.2627**	-0.4622	0.1609	**0.1799**	0.0032	0.3954
Constant	**-0.9249**	1.8537	4.4055			
Tau 1				**-1.2020**	-3.2983	-1.5578
Tau 2				-0.0047	-2.3048	-0.5706
Tau 3				**0.9730**	-1.1375	0.5739
Tau 4				**1.7876**	-0.1135	1.6501
Observations		1032			1032	

Fig. 11. Posterior mean parameter estimates and 95% credibility interval from Model 1 and Model 2 Bayesian Models of Intention to Get Information to Protect against Flooding Hazard - Governador Valadares, Brazil, 2014/2015

	Model 1			Model 2		
Variable	Coefficient	95% Credibility Interval		Coefficient	95% Credibility Interval	
State explanatory variables						
Years of education	**-0.1011**	-0.1777	-0.0136	**-0.0771**	-0.1368	-0.0176
Flood experience	**-1.4958**	-3.3109	0.4252	**-1.3136**	-2.9251	-0.0482
Interaction term	**0.1296**	-0.0145	0.2773	**0.1004**	-0.0189	0.2057
Control variables						
Male	**-0.4011**	-0.9308	0.1138	**-0.1850**	-0.5301	0.2279
Married/Cohabiting	**0.3956**	-0.1645	0.9849	**0.3109**	-0.1204	0.7190
Years of residence	-0.0018	-0.0170	0.0158	0.0013	-0.0105	0.0141
Social capital	-0.1663	-1.0755	0.7639	0.0835	-0.5933	0.7588
Scale of risk perception						
2nd tercile	-0.4653	-1.1186	0.1331	**-0.2380**	-0.6993	0.2240
3rd tercile	**0.0491**	-0.7025	0.8043	**0.3606**	-0.1801	0.8593
% children (aged $\leq$ 5) in household	**0.7327**	-1.8863	3.0938	-0.0600	-1.8884	1.6671
% older people (aged $\geq$ 65) in household	**-0.3718**	-1.4030	0.6775	**-0.6392**	-1.4241	0.1996
Distance to river (meters)	-0.0002	-0.0005	0.0000	**-0.0003**	-0.0005	-0.0001
PADM coefficients						
Effectiveness	**2.3592**	1.8567	2.8165	**1.6730**	1.4375	1.9539
Opportunity cost	**-0.1411**	-0.4622	0.1609	**-0.1049**	-0.3297	0.1327
Constant	**3.1495**	1.8537	4.4055			
Tau 1				**-4.5603**	-5.5371	-3.5372
Tau 2				**-3.4049**	-4.3307	-2.3425
Tau 3				**-2.4132**	-3.2997	-1.3448
Tau 4				**-1.4957**	-2.3979	-0.4422
Observations		1032			1032	

Fig. 12. Posterior mean parameter estimates and 95% credibility interval from Model 1 and Model 2 Bayesian Models of Intention to Make a List of What to Do to Protect against Flooding Hazard - Governador Valadares, Brazil, 2014/2015

	Model 1			Model 2		
Variable	Coefficient	95% Credibility Interval		Coefficient	95% Credibility Interval	
State explanatory variables						
Years of education	**-0.0564**	-0.1274	0.0355	**-0.0645**	-0.1192	-0.0163
Flood experience	**0.2702**	-1.4899	2.1285	**-0.5999**	-2.0192	0.8544
Interaction term	**-0.0091**	-0.1698	0.1342	0.0198	-0.0961	0.1276
Control variables						
Male	-0.0553	-0.5539	0.4906	-0.0522	-0.4278	0.3002
Married/Cohabiting	**0.1102**	-0.4718	0.6901	**0.0533**	-0.3231	0.4342
Years of residence	0.0003	-0.0175	0.0165	0.0056	-0.0070	0.0153
Social capital	**-0.7301**	-1.6950	0.2969	**-0.5373**	-1.1403	0.1283
Scale of risk perception						
2nd tercile	-0.1995	-0.7771	0.4032	**-0.4143**	-0.8793	-0.0165
3rd tercile	**-0.0736**	-0.7935	0.6566	**0.1627**	-0.3288	0.6485
% children (aged $\leq$ 5) in household	**0.9696**	-1.2319	3.6747	**0.4716**	-1.1481	2.2810
% older people (aged $\geq$ 65) in household	**-0.6784**	-1.7746	0.4616	**-0.8995**	-1.6746	-0.1947
Distance to river (meters)	0.0002	0.0000	0.0005	0.0001	-0.0001	0.0003
PADM coefficients						
Effectiveness	**2.2026**	1.8382	2.6487	**1.3861**	1.1722	1.6366
Opportunity cost	**0.2985**	0.0235	0.5865	**0.1811**	0.0032	0.3954
Constant	-0.1997	-1.4635	1.1399			
Tau 1				**-2.4185**	-3.2983	-1.5578
Tau 2				**-1.4436**	-2.3048	-0.5706
Tau 3				**-0.3286**	-1.1375	0.5739
Tau 4				**0.7565**	-0.1135	1.6501
Observations		1032			1032	

Fig. 13. Posterior mean parameter estimates and 95% credibility interval from Model 1 and Model 2 Bayesian Models of Intention to Plan what to do with Friend and Family to Protect against Flooding Hazard - Governador Valadares, Brazil, 2014/2015

	Model 1			Model 2		
Variable	Coefficient	95% Credibility Interval		Coefficient	95% Credibility Interval	
State explanatory variables						
Years of education	-0.0052	-0.0723	0.0799	-0.0040	-0.0615	0.0473
Flood experience	-0.2626	-2.0090	1.5308	-0.1918	-1.5539	1.1771
Interaction term	0.0009	-0.1417	0.1370	0.0018	-0.1101	0.1077
Control variables						
Male	-0.1163	-0.6106	0.4200	-0.0351	-0.4085	0.3205
Married/Cohabiting	0.0900	-0.4912	0.5999	0.1041	-0.3246	0.4471
Years of residence	0.0002	-0.0144	0.0178	0.0058	-0.0053	0.0166
Social capital	-0.0533	-1.0483	0.9462	0.0286	-0.6772	0.6356
Scale of risk perception						
2nd tercile	**-1.1268**	-1.7145	-0.4469	**-0.4812**	-0.8839	-0.0364
3rd tercile	**0.2729**	-0.4416	0.9843	**0.2096**	-0.3278	0.6628
% children (aged ≤ 5) in household	**1.4684**	-0.9347	3.9846	**0.2831**	-1.3168	2.0855
% older people (aged ≥ 65) in household	**-0.2161**	-1.1758	0.8082	**-0.1971**	-0.9603	0.5977
Distance to river (meters)	0.0002	0.0000	0.0005	0.0001	-0.0001	0.0003
PADM coefficients						
Effectiveness	**2.0910**	1.6540	2.4983	**1.2940**	1.0452	1.5423
Opportunity cost	**0.2394**	-0.0666	0.5684	**0.1867**	-0.0144	0.3838
Constant	**1.2120**	-0.0300	2.4913			
Tau 1				**-2.7266**	-3.5922	-1.7561
Tau 2				**-1.8791**	-2.7629	-0.9778
Tau 3				**-0.7271**	-1.6605	0.1395
Tau 4				**0.2740**	-0.6167	1.1512
Observations	1032			1032		

Fig. 14. Posterior mean parameter estimates and 95% credibility interval from Model 1 and Model 2 Bayesian Models of Intention to Use Sandbags and Flood Skirts to Protect against Flooding Hazard - Governador Valadares, Brazil, 2014/2015

	Model 1			Model 2		
Variable	Coefficient	95% Credibility Interval		Coefficient	95% Credibility Interval	
State explanatory variables						
Years of education	-0.0052	-0.0723	0.0799	-0.0040	-0.0615	0.0473
Flood experience	-0.2626	-2.0090	1.5308	-0.1918	-1.5539	1.1771
Interaction term	0.0009	-0.1417	0.1370	0.0018	-0.1101	0.1077
Control variables						
Male	-0.1163	-0.6106	0.4200	-0.0351	-0.4085	0.3205
Married/Cohabiting	0.0900	-0.4912	0.5999	0.1041	-0.3246	0.4471
Years of residence	0.0002	-0.0144	0.0178	0.0058	-0.0053	0.0166
Social capital	-0.0533	-1.0483	0.9462	0.0286	-0.6772	0.6356
Scale of risk perception						
2nd tercile	**-1.1268**	-1.7145	-0.4469	**-0.4812**	-0.8839	-0.0364
3rd tercile	**0.2729**	-0.4416	0.9843	**0.2096**	-0.3278	0.6628
% children (aged ≤ 5) in household	**1.4684**	-0.9347	3.9846	**0.2831**	-1.3168	2.0855
% older people (aged ≥ 65) in household	**-0.2161**	-1.1758	0.8082	**-0.1971**	-0.9603	0.5977
Distance to river (meters)	0.0002	0.0000	0.0005	0.0001	-0.0001	0.0003
PADM coefficients						
Effectiveness	**2.0910**	1.6540	2.4983	**1.2940**	1.0452	1.5423
Opportunity cost	**0.2394**	-0.0666	0.5684	**0.1867**	-0.0144	0.3838
Constant	**1.2120**	-0.0300	2.4913			
Tau 1				**-2.7266**	-3.5922	-1.7561
Tau 2				**-1.8791**	-2.7629	-0.9778
Tau 3				**-0.7271**	-1.6605	0.1395
Tau 4				**0.2740**	-0.6167	1.1512
Observations	1032			1032		

Fig. 15. Posterior mean parameter estimates and 95% credibility interval from Model 1 and Model 2 Bayesian Models of Intention to Buy House and Life Insurance - Governador Valadares, Brazil, 2014/2015

	Model 1			Model 2		
Variable	Coefficient	95% Credibility Interval		Coefficient	95% Credibility Interval	
State explanatory variables						
Years of education	-0.0052	-0.0723	0.0799	-0.0040	-0.0615	0.0473
Flood experience	-0.2626	-2.0090	1.5308	-0.1918	-1.5539	1.1771
Interaction term	0.0009	-0.1417	0.1370	0.0018	-0.1101	0.1077
Control variables						
Male	-0.1163	-0.6106	0.4200	-0.0351	-0.4085	0.3205
Married/Cohabiting	0.0900	-0.4912	0.5999	0.1041	-0.3246	0.4471
Years of residence	0.0002	-0.0144	0.0178	0.0058	-0.0053	0.0166
Social capital	-0.0533	-1.0483	0.9462	0.0286	-0.6772	0.6356
Scale of risk perception						
2nd tercile	**-1.1268**	-1.7145	-0.4469	**-0.4812**	-0.8839	-0.0364
3rd tercile	**0.2729**	-0.4416	0.9843	**0.2096**	-0.3278	0.6628
% children (aged ≤ 5) in household	**1.4684**	-0.9347	3.9846	**0.2831**	-1.3168	2.0855
% older people (aged ≥ 65) in household	**-0.2161**	-1.1758	0.8082	**-0.1971**	-0.9603	0.5977
Distance to river (meters)	0.0002	0.0000	0.0005	0.0001	-0.0001	0.0003
PADM coefficients						
Effectiveness	**2.0910**	1.6540	2.4983	**1.2940**	1.0452	1.5423
Opportunity cost	**0.2394**	-0.0666	0.5684	**0.1867**	-0.0144	0.3838
Constant	**1.2120**	-0.0300	2.4913			
Tau 1				**-2.7266**	-3.5922	-1.7561
Tau 2				**-1.8791**	-2.7629	-0.9778
Tau 3				**-0.7271**	-1.6605	0.1395
Tau 4				**0.2740**	-0.6167	1.1512
Observations		1032			1032	

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