Is There a Demand for Flood Insurance in Vietnam? Results From a Choice Experiment

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Abstract Vietnam is one of the countries which is the most affected by floods. Despite a high level of exposure to this risk and repeated calls from international organizations, it is surprising to observe the very low penetration of flood insurance in Vietnam. In this paper we then investigate if there is a demand for flood insurance by Vietnamese households. A choice experiment has been employed to estimate how Vietnamese households value flood insurance. We compute their willingness to pay (WTP) for various flood insurance programs and we identify the relationships between WTP and the different attributes of insurance schemes (type of risk covered, level of cover, insurance provider, billing frequency, insurance premium). We first show that Vietnamese households exhibit strong preference for the status quo option (no insurance). We do, however, document significant and positive WTP for some flood insurance policies, especially those covering the health consequences of flooding. We show that two nonprice demand frictions may help understanding the low adoption rate of flood insurance in Vietnam: the level of household trust in institutions providing flood insurance policies and the liquidity constraint of households. Finally, we stress the high level of heterogeneity in household preferences for flood insurance policies. These results call for a very careful design of flood insurance mechanisms in Vietnam, and more generally in developing countries subject to high risk of natural disaster.

Keywords Flood · Insurance · Vietnam · Valuation · Choice Experiment

JEL Codes: Q51, Q53, Q25

1 Introduction

With 89.4% of its GDP generated in areas at risk, Vietnam is the seventh most exposed country in the world to natural disasters (WorldBank 2005). The average annual cost of natural disasters (including damage to residential housing and public-sector properties, agriculture and infrastructure) is estimated to represent 1 percent of Vietnamese GDP, with a peak at three percent in 2006. However, these figures should be viewed as a low lower bound of real flood costs (WorldBank 2010). Of all the categories of natural disaster, flooding is the single most important cause of loss, accounting for 49 percent of total economic losses in Vietnam (WorldBank 2010).

Among the portfolio of policies which can be implemented by public authorities, the development of insurance schemes against natural catastrophes has been promoted for Vietnam by international organizations such as the World Bank (WorldBank 2010) or the Asian Development Bank (AsianDevelopmentBank 2007). However, despite the high level of exposure to flood risk, it is surprising to observe the very low penetration of catastrophe insurance in Vietnam. Whereas damage to properties may be typically covered by property insurance, this market is poorly developed in urban areas and almost non-existent in rural ones, (WorldBank 2010). Agricultural crop and livestock insurance is also extremely restricted in Vietnam despite several past attempts to introduce them.

The limited role played by flood insurance in developing countries has already been documented. In Bangladesh, (Brouwer and Akter 2010) test the conditions under which rural households favor micro flood insurance to protect themselves against the negative impacts of catastrophic floods. As expected, affordability of

insurance premiums plays an important role. In Vietnam, (Navrud, Tuan, and Tinh 2012) measure household willingness to contribute to flood prevention programs. They find that households are willing to contribute on average 6.7 person-days per year and per household. Still in Vietnam, Brouwer et al. (2014) investigate household willingness and ability to pay for flood micro insurance. They show that there exists a demand for flood insurance, even though a considerable share of population indicate that they are unable to afford to pay for such insurance. Abbas et al. (2015) explore the household WTP for flood insurance in a flood-prone areas of Pakistan. Although a large proportion of household would be ready to buy a flood insurance, their willingness to pay remains limited to around 0.27% of the mean monthly household income. More recently, (Ren and Wang 2016) have estimated the willingness to buy flood insurance in rural China. They report that about two-third of the population would be ready to participate fo a flood insurance program. They also find that the influencing factors in the insurance demand include the recent frequency of floods, income, and past experience with lack of flood insurance.

Several explanations of the low penetration of catastrophe insurance in developing countries have been proposed including problems of adverse selection, lack of awareness and understanding by rural households of the role and operation of flood risk insurance, high administrative costs and high financial exposure due to highly correlated risks. Here, we explore the demand-side of the flood insurance market by estimating the willingness to pay (WTP) of Vietnamese households for various flood insurance programs using a choice experiment (CE) approach. Flooding is a low-probability, high-consequence event. Household WTP for flood insurance can then be derived from a standard model of insurance demand in which a risk-averse

household makes some tradeoffs between the probability of flood occurrence, the magnitude of associated loss and the insurance premium (Kunreuther 1996).

We contribute to the literature on household flood insurance demand in developing countries in several ways. First, we consider flood insurance policies covering either health expenditures, agricultural losses or home damage. This allow us to check if the WTP for flood insurance differs according to the domain covered. To our best knowledge, only (Brouwer and Akter 2010) considers also several type of insurances within a choice experiment approach. Second, we examine if some non-price demand frictions may help understanding the low adoption rate of flood insurance in Vietnam. We focus in particular on two non-price frictions which have been shown to limit insurance demand: the lack of household trust in institutions providing flood insurance policies and the liquidity constraint of households (Petrolia, Landry, and Coble 2013, Cole et al., 2013). Third, using a random parameter logit model, we investigate preference heterogeneity across household for flood insurance policies and we conduct some welfare analyses. Fourth, we analyze how past experiences of flooding event impact on the household WTP for flood insurance. There is indeed empirical evidence showing that recent disasters affect the future demand for insurance (Browne and Hoyt 2000, Ganderton et al. 2000).

This paper is organized as follows. Section 2 describes flood risk and the status of flood insurance in Vietnam. Section 3 presents the design of the choice experiment and its administration. The results of the econometric model are reported in Section 4, and Section 5 concludes the paper.

2 Flood risk and flood insurance in Vietnam

2.1 Flood risk in Vietnam

Being located in the South China Sea, the Vietnam lies within the tropical monsoon sea belt. As a result Vietnam receives heavy rain ranging from 1200 to 3000 mm a year with nearly 90% of these precipitations occuring during summer. In addition to these monsoon rains, 6 to 8 typhoons hit the Vietnamese coasts every year an average. The combination of typhoon and monsoon seasons defines the flooding season which usually starts in July and ends in November.

As a result, Vietnam is ranked as the seventh country in the world the most exposed to natural disasters, flooding being the single most important cause of damage accounting for 49 percent of total economic losses due to natural disasters (WorldBank 2010).

The social cost of flooding is especially high due to the uneven distribution of the population within the territory. In Vietnam, most of the population (70%) lives in coastal areas, the majority being located in the Red River Delta in the north and in the Mekong Delta in the south (WorldBank 2010). This coastal population is particularly vulnerable to typhoons and floods since people usually live only a few meters above sea level (Mai, Stive, and VanGelder 2009). Vietnamese people living in mountain areas (30%) are also vulnerable to flood disasters. Due to the steepness of the terrain, river beds are easily filled by the monsoon rains, frequently leading to flash flooding. This explains why floods have also resulted in a substantial number of deaths and injuries in mountainous areas.

2.2 Flood insurance in Vietnam

Even if there has recently been a noticeable change in public flood management policies from mainly large-scale engineering measures toward non-structural approaches, use of risk transfer tools such as flood insurance is still very limited in Vietnam. (SwissRe 2015) reports for example that although the reported economic losses for the Typhoon Mirinae in 2009 have been estimated to be around USD 280 million, the insured losses have only accounted for USD 10 million.

Cover for natural catastrophe perils such as flooding is typically included in some homeowner property insurance policies. However, property catastrophe insurance penetration is still limited. According to (WorldBank 2010), subscriptions to property insurance are limited in urban areas and almost non-existent in rural areas. Developing property insurance against flooding in rural areas is especially challenging, first since many homeowners do not have any formal property title, second because many houses which have been built in bamboo or other light wood may not be eligible for an insurance scheme and lastly since marketing and monitoring costs are expected to be very high. Although it is developing very quickly, the Vietnamese market for life and non-life insurance remains small. In 2011 it only represented 1.5% of GDP (22 USD per capita) compared to 5.8% on average for all Asian countries (SwissRe 2012).

The availability of agricultural crop and livestock insurance is also extremely restricted in Vietnam and government disaster relief payments are often the only source of compensation received by farmers following a major flood or storm (WorldBank 2010). Past attempts to introduce multiple-peril crop insurance have been unsuccessful. In 1999, the Vietnamese insurance group *Bao Viet* stopped of-

fering multiple-peril crop insurance after having experienced high losses. In 2001 the French mutual agricultural insurer *Groupama* started to sell crop and livestock mortality insurance products. The company has since withdrawn from crop insurance. In July 2012, Vietnam launched a three-year pilot agricultural insurance program. Preliminary results suggest very low adoption rates despite the fact the the proposed insurance schemes have been highly subsidized. According to the Vietnamese Finance Ministry, approximately 1 percent of farmers are now insured against damage to crops, 0.24 percent for cattle, 0.1 percent for pigs and 0.04 percent for poultry. In fact, most farmers who are at risk do not purchase flood insurance because they rely on informal risk-sharing mechanisms (off-farm labor, rotating savings and credit association) or simply because they are unfamiliar with the concept of insurance as a risk management tool.

The third dimension of a flood insurance is the coverage of health expenditures. The responsibility for disaster-related health issue has been assigned to the Vietnamese primary healthcare system. However, the primary care system capacity in Vietnam remains inadequate for responding to preventive and treatment healthcare for storm and flood-related health problems (Van Minh et al. 2014).

3 Design of choice experiment

3.1 Sampling strategy

Our case study is the Nghe An Province located in the central part of Vietnam. The topography of the Nghe An province is quite complicated with mountains and hills in the East and rivers and streams flowing from the North-West to the South-East. The risk of flooding differs significantly depending on the location.

In the mountains, households face the risk of flash-flooding with the associated risk of landslides. In coastal areas, people are directly affected by typhoons and tropical storms. Finally, people located along rivers or living in river delta areas are affected by floods resulting from rivers bursting their banks.

Our sampling strategy is as follows. First, 14 districts (out of 17 in the Nghe An Province) were selected based on a geographical location criterion (costal area, plain area, mountain area). Then, based on discussions with local representatives of the Vietnamese Ministry of Agriculture and Rural Development (MARD), two "representative" villages/communes were targeted within each district (there are 417 villages/communes in the Nghe An Province). Finally, within each village/commune 16 households were randomly selected from the village/commune listing of registered citizens. Our sampling stratification based on geographical location ensures that our data include all types of floods which may affect the population in the Nghe An Province. Random selection of households guarantees that our sample is representative of the Nghe An population. Our sample thus consists of 448 households from 28 villages/communes from 14 districts in the Nghe An province.

The survey was carried out in Spring 2012 using face-to-face interviews. To minimize cultural bias, all interviewers came from the Vanxuan University of Technology at Cua Lo (Nghe An Province). Some households refused to participate in the survey but they represent only a small proportion of all the households contacted (less than 10%). In fact, before contacting any households in a village, we met the head of the village People's Committee in order to obtain formal approval for the survey. During this meeting, the head of village's People Committee was shown documents stating that the survey was officially conducted by members of

the VanXuan University of Technology and approved by the Department of Science and Technology of Nghe An Province. At the beginning of each household interview, the official approval of our survey was mentioned. The average duration of the whole interview was 1 hour and 33 minutes. The respondent to the survey was the household's head or his spouse in 94.7% of the cases. When the respondent was not alone for passing the survey, the interviewer reports that the presence of other persons have had little or no effect on respondent in 98.8% of the cases.

3.2 Questionnaire Development

The design of the questionnaire followed a highly iterative process.[1] During the design of the survey (June 2011 - December 2011), experienced stated choice researchers, natural resource economists and water management experts (both Vietnamese and French) reviewed different versions of the questionnaire. Various meetings involving research team members, water experts and local representatives were organized in Vietnam (Nghe An Province). An initial meeting was held in October 2011 with the representative of the Vietnamese Ministry of Agriculture and Rural Development (MARD) in charge of flood protection in the Nghe An Province. The questionnaire was significantly modified after this meeting. A second version was presented in November 2011 to a household representative in the city of Vinh (Cua Lo district), to a farmer's representative in the Cua Lo district and to a politician in the Quy Hop district. These meetings turned out to be useful in checking the respondents' understanding of the survey and resulted in several adjustments to the formulation of explanations and questions. The questionnaire was also signifi-

[1] The questionnaire includes in fact two CE. The first CE which aims at assessing the willingness of Vietnamese households to pay for flood risk reduction has been analyzed in (Reynaud and Nguyen 2016). We focus here on the second CE dedicated to flood insurance.

cantly reshaped after those meetings. After incorporating these comments the pilot version of the questionnaire was tested in December 2011 using face-to-face interviews. Six trained and carefully supervised interviewers interviewed 30 randomly selected households. A preliminary econometric model was then estimated using the pilot data and some modifications were made to the questionnaire. In particular the number of choice sets was increased from six to eight since it appeared that such a number was not incompatible with cognitive capacities of respondents. The final survey took place from April 4th to June 10th 2012, a period of time during which no floods and no natural disasters were recorded in the Nghe An Province.

3.3 Attributes of flood insurance programs

The first step of any CE is to define the good to be valued (Hoyos 2010). The good to be valued in our CE study is a flood insurance policy. The next step is to select a set of attributes characterizing flood insurance policies in a coherent way. The attribute choice is based on the one hand on the existing literature on flood insurance, and on the other hand on several meetings held in the Nghe An Province with experts, local representatives in charge of flood management policy and household and farmer's representatives. During the design phase of the study, the main objective assigned to the meeting with local representatives was to explore the relevant attributes of flood insurance schemes.

The exploratory research resulted in the selection of five attributes to describe flood insurance programs: (1) Insurance type; (2) Insurance provider; (3) Maximal annual insurance cover; (4) Annual insurance premium and (5) Monthly payment. In Table 1, we report the list of attributes with their associated levels.

[Table 1, about here]

Attribute (1) describes the type of flood insurance. Health insurance covers all medical expenditures due to the occurrence of a catastrophic flood.[2] Agricultural insurance covers crop, livestock and fish losses. House insurance protects respondents' homes and home contents. Damage to homes and home contents was also used by (Botzen and van den Bergh 2012) in the context of flood insurance valuation in the Netherlands. (Brouwer and Akter 2010), in the context of flooding in Bangladesh, considered four insurance schemes covering property damage, crop damage, cost of illness and loss of income due to temporary unemployment.

Attribute (2) describes the provider of the flood insurance which can be either a state-owned firm, a privately-owned firm or an NGO. (Brouwer and Akter 2010) proposed a similar distinction between insurance providers, citing private insurance companies, central government, local micro credit providers and local user-group cooperatives. This attribute has also been included by reference to the existing literature showing that the perceived credibility of the insurer has a positive influence on the probability of taking out flood insurance (Petrolia, Landry, and Coble 2013).

Attribute (3) is the maximal annual insurance cover. It corresponds to the maximum amount of money a respondent can be reimbursed in the case of a catastrophic flooding event. Maximum cover has been previously used as a program

[2] In a household survey carried out in the Dong Thap Province of Vietnam, 75% of respondents identified the impact of flooding on the prevalence of disease and ill-health (USSH 2002). The most direct health impacts of flooding are perhaps the deaths and injuries caused by the existence of floodwater in or around people's homes as stressed in (Few, Tran, and Hong 2004). Indirect impacts of flooding on health include diseases related to disruption of normal water/sanitation services and the spreading of contamination by floodwaters (diarrhea and sometimes typhoid, dysentery and cholera) and mosquito-borne diseases related to changes in the breeding conditions for mosquito larvae (malaria or dengue fever).

attribute in the context of flood insurance by (Botzen and van den Bergh 2012) and (Brouwer and Akter 2010).

Attribute (4) describes the annual insurance premium which must be paid by the respondent to have access to the proposed flood insurance scheme. Risk premiums vary from one type of insurance to another. They are computed as a percentage of the maximal annual insurance cover.

Attribute (5) identifies whether or not the respondent has the opportunity to pay the insurance premium on a monthly basis instead of annually. This attribute is introduced in order to capture the impact of household liquidity constraints and imperfect access to the credit market in Vietnam.

To construct the choice sets we implemented a fractional factorial design using the Ngene Software. We then selected a particular subset of complete factorials, so that particular effects of interest could be estimated as efficiently as possible according to the D-optimal criterion.[3] We constructed 32 choice sets, each consisting of three alternative scenarios (two flood insurance programs and the status quo scenario). Because of the respondents' cognitive capacity, the 32 choice sets have been grouped into 4 versions of the CE, each containing 8 choice sets. An example of the choice sets used for the CE is provided in the Supplementary Material: Instruction sheet for the DCE on flood insurance.

[3] The D-optimal criterion has become the most widely used measure of efficiency because of its insensitivity to the magnitude of the scale of the parameters (Street, Burgess, and Louviere 2005). Other designs may have been considered, in particular to take into account alternative-specific attributes. The literature on CE has provided some evidence of a limited impact of different experimental designs on underlying parameter estimates (Viney, Savage, and Louviere 2005).

3.4 Modeling of individual choices

We assume that the unobserved utility of a flood insurance program j can broken down into two components. The first component, which is deterministic, is expressed by the indirect utility function V defined as a function of the attributes of alternatives, characteristics of the individuals, and a set of unknown parameters. The second component, which is stochastic, is represented by a random component ϵ which is an error term that captures factors that influence utility, but are not observable by researchers. Then, the random utility gained by individual i from choosing program j in a particular choice task k may be written:

$$U_{ijk} = V(X_{ijk}|\beta) + \epsilon_{ijk} = V_{ijk} + \epsilon_{ijk} \tag{1}$$

where X_{ijk} denotes a vector of explanatory variables describing program j and respondent i, and β denotes the corresponding vector of coefficients. Respondents are assumed to choose the program j if the utility obtained with this program is greater than that of any alternative program j'. Because the observed outcome of each choice task k is the selection of one out of J programs, the appropriate econometric model is a discrete choice model expressing the probability that program j is chosen over any other program j' in choice task k.

3.5 Hypotheses to be tested

Our methodological framework allows to test several hypotheses regarding household demand for flood insurance in Vietnam.

H1. *The demand for flood insurance decreases when the price goes up.*

This hypothesis is simply based on utility-maximizing households who make tradeoffs between the cost of buying an insurance scheme and the benefits they get from it. We test the hypothesis in the experiment by varying the annual insurance premium. We expect a negative coefficient for the annual insurance premium.

H2. *The demand for flood insurance is domain-specific.*

Working in Bangladesh, (Brouwer and Akter 2010) have shown that there is a high level of preference heterogeneity across households for flood insurance covering property losses, crop damage and health expenses. A similar result is expected for Vietnam since (Reynaud and Nguyen 2016) have shown that the WTP of Vietnamese households for reducing flood risk exposure also varies when considering property losses, crop damage and fatality rate. We test this hypothesis in the experiment by varying the domain of the flood insurance (house and house content, agricultural production, health expenditures). Since (Reynaud and Nguyen 2016) report a high WTP for reducing flood fatality rate, we expect to find a high WTP for flood insurance covering health expenses.

H3. *The demand for flood insurance is impacted by past experience of flooding.*

Empirical evidence suggest that past experiences of disasters affect the demand for insurance (Browne and Hoyt 2000, Ganderton, Brookshire, McKee, Stewart, and Thurston 2000). Similar findings are reported for flood insurance (Navrud, Tuan, and Tinh 2012) although the effect of flood events on insurance purchase fades after a few years (Atreya, Ferreira, and Michel-Kerjan 2015). There are several reasons why past flood experience matters to understand households adoption

of flood insurance (Reynaud and Nguyen 2016). First, flood occurrence can be viewed as a shock that may contain new information about flood probabilities. Households may rationally update their beliefs on background risk, with a subsequent impact on the decision to buy a flood insurance (Cameron and Shah 2015).[4] Second, disaster exposure brings more experience, and this, together with the fact that a person has survived and coped with a disaster before, may make her more likely to better cope in the future which may reduce demand for flood insurance .[5] Third, having experienced a disaster before may on the contrary result in more fear and anxiety (see (Hussain, Weisaeth, and Heir 2011) on psychiatric disorders following a natural disaster) with a positive effect on flood insurance purchase. Although not fully conclusive, the psychological literature convincingly suggests the existence of a relationship between past flood experience and flood protective motivations.

H4. *Non-price demand frictions (trust and liquidity constraints) can explain willingness to pay for flood insurance.*

A growing empirical literature has shown the importance of various types of frictions driving the demand for insurance.[6] Demand frictions have been shown to limit flood demand (Petrolia, Landry, and Coble 2013). In the CE, we consider two types of non-price frictions: the level of household trust in institutions providing

[4] The process of updating probabilities after experiencing a flood may not be rational, for example if households are subject to the representative heuristic. In such a case, households overreact after a disaster occurs and overestimate the probability of a disaster. This distortion leads them to demand more insurance than a Bayesian individual (Volkman-Wise 2015).

[5] This is in line with the 'inoculation hypothesis', which states that individuals who have experienced a similar type of natural disaster in their past are less likely to suffer from long-term psychological distress after subsequent disasters (Norris and Murrell 1988).

[6] (Handel and Kolstad 2015) have for instance documented the role played by information frictions in explaining the choice of health insurance plans.

flood insurance policies and a measure of household liquidity constraint (imperfect access to credit market).[7] We hypothesize that the lack of trust in the institution providing flood insurance may have a detrimental impact of flood insurance demand. The impact of liquidity constraints on insurance demand has been studied for a long time (Gollier 2003). We expect to find that liquidity constraints reduce insurance demand as reported in previous empirical studies (Cole et al. 2013).

4 Empirical Analysis

4.1 Preliminary statistical analysis

As a starting point for the empirical analysis, we give some basic statistics for our sample, focusing especially on the perception of flood risk by Vietnamese households, on the cost of flooding and on the use of flood insurance. In Table 2, we give some basic socio-demographic characteristics of our household sample.

[Table 2, about here]

In our sample, the head of the household is 49.8 years old on average. The average household size is just over 4. 16.7% of households have at least one child of under 3 years old. The average household income in 2011 was 32.5 million VND per year, a figure lower than the average for the Nghe An province in 2010 (48 million VND).[8] In 79.2% of cases, the main occupation of the head of the household is farming (or fishing). Employees represent 5.6% of our sample and

[7] In Vietnam, the rural credit market has a dual structure in which formal and informal finance exist side by side. (Duong and Izumida 2002), who have studied rural development finance in Vietnam, report that as many as 30% of the households in their sample are credit-constrained due to a limited access to the formal lending sector.

[8] The 2011 exchange rate between 1 USD and VND was around 21,000.

retired households 5.1%. 30.6% of household heads have attended at least high school.

[Table 3, about here]

As mentioned previously, the Nghe An province is highly susceptible to flooding. In Table 3 we give data about households' past experience with floods since this has been shown to be an important determinant of the adoption of flood insurance (Petrolia, Landry, and Coble 2013). In our sample, 40.4% of households report that their house had been flooded at least once in the previous 5 years.[9] 20.3% of households had been evacuated from their home at least once over the previous 5 years because of a flooding event. Only 4.9% of the respondents reported that one member of the household had been injured in the previous 5 years, due to flooding.

Concerning the economic impact of floods, 76.1% of our sample households consider that flooding had represented a significant expenditure over the previous 5 years. To have an idea of the actual cost of flooding for respondents, they were asked to provide an estimate of the average annual cost of flooding for their household in the previous 5 years, distinguishing damage to their house and house contents, damage to agricultural production and damage to health (all medical expenses due to flooding for any member of the household). The cost of flooding is reported in Table 3.[10] The average annual cost of flood damage caused to agricultural (and fishery) production is 3.5 million VND representing 14.8% of household

[9] 76.5% of them report that they had been flooded for the last time in 2011.

[10] Notice however that flood costs reported by households correspond to a subjective assessment. It may be the case that, when reporting their costs, subjects overestimate or underestimate their real flood expenses for strategic reasons or simply because this information is not easily available. Moreover, they do not include non-monetary costs such as those related to anxiety or distress. Flood costs reported here should then be treated with caution.

income on average. The average annual cost for flood damage caused to houses and house contents is slightly lower. It represents on average 2.6 million VND per year or 9.3% of the annual household income. Considering only households having reported damage strictly due to flooding, the average damage to houses and house contents increases to 3.7 million VND per year. Damage to health ranks third in terms of cost. Those expenses only represent 1.2% of the annual household income. If we restrict the sample to households in which at least one member has been injured due to flooding, this percentage increases to 23.98%. This indicates high medical expenditure in case of injury or disease related to flooding. If we combine agricultural, house and health damage caused by flooding, we get an average annual cost of damage equal to 6.4 million VND per year which represents 25.26% of the average annual household income. This is in line with (Navrud, Tuan, and Tinh 2012) who found, in a sample of Vietnamese households located in the Quang Nam Province, that the average flood damage represented approximately 20% of their annual income. The high economic impact of flooding on Vietnamese households is corroborated by the fact that 8.9% of households plan to move to another area where the flood risk is lower. Moreover, 32.3% considered the risk of flooding in choosing their housing location. It should, however, be stressed once again that the cost reported by households corresponds to their subjective ex-post assessment of flood damage which may differ from the actual cost.

A potential driver of household preferences for some specific flood insurance schemes could be the household's confidence level in the ability of various institutions to efficiently provide flood insurance. This is to some extent related to the issue of the credibility of insurers discussed (Petrolia, Landry, and Coble 2013). In the questionnaire, we asked each respondent to indicate his/her level of trust

in various insurance providers using the following question: "In many countries, households can use insurance to reduce the impact of flooding on their lives. Flood insurance is usually provided by different institutions (state-owned firms, private firms, NGOs, local cooperatives). For each institution, please indicate whether you are confident that this institution could efficiently provide flood insurance. Use a scale from 1 (not at all confident) to 10 (very confident)." In fact, respondents seem to be more confident when the flood insurance is provided at a local level though a local cooperative. Indeed, the average confidence score is 6.912 in that case compared to 4.769 and 4.477 for private-owned firms and NGOs respectively. State-owned firms rank second with a confidence level equal to 6.382.

4.2 Individual choices and status quo responses in the CE

We now move to the results of the CE. In Table 4, we report the frequency of program choices in the CE experiment. As discussed previously, each household had to complete 8 choice sets. In each choice set each respondent selected his/her preference among three possible programs (A, B and No insurance). Programs A and B were chosen in 20.51% and 25.17% of cases respectively. The status quo option (No insurance) ranks first with 54.32%, which is not unusual is this kind of stated preference analysis (Scarpa, Willis, and Acutt 2007). Although rational choice explanations can be provided, the disproportionate number of respondents choosing the status quo option may have a variety of psychologically explications, such as misperceived sunk costs, regret avoidance or mistrust. This is the well-known *status quo bias* in decision-making, first documented by (Samuelson and Zeckhauser 1988). In specifying the random utility model, we will address this

issue by including an alternative specific constant (ASC) in order to capture unobservable influences beyond attributes present in the choice sets (Hoyos 2010).[11]

[Table 4, about here]

When a status quo option is available in the choice sets in a CE, it may be selected repeatedly by a significant proportion of respondents. In our case 117 households (26.12% of our sample) chose the status quo in the 8 proposed choice sets. It is then important to make the distinction between "true zero bids" which correspond to respondents having indicated that they are not willing to pay because they are truly averse or indifferent to the good for which a WTP is solicited and "false zero bids" which correspond to respondents having reported a zero WTP even though their true valuation for the good in question is positive, (Hanley, Wright, and Alvarez-Farizo 2006). To make the distinction between "true zero bids" and "false zero bids" we first asked if each respondent agreed or not with the following sentence "Given my current economic situation, I cannot pay for flood insurance". Among the 117 households who always chose the status quo option, 82 considered that they could not afford flood insurance. Second, we asked whether or not they agree with the following sentence "I don't need any flood insurance". 61 households among the 117 agreed. Combining the two questions leads to 93 households who can be qualified as "true zero bids" and 24 as "false zero bids". Specific treatments will be implemented in the following paragraphs for this particular respondent group.

[11] A question which remains to be assessed is whether the ASC really captures the average effect on utility of all factors not included in the model, or whether it is associated with a behavioral assumption and interpreted as the utility of the status quo alternative, (Meyerhoff and Liebe 2009).

4.3 Conditional Logit (CL) models

Assuming a type I extreme value distribution for $\epsilon's$ in Equation (1) leads to the CL model. The CL model is the basic model used in CE studies. It offers a good starting point by allowing us to assess average individual preferences (Train 2009). We start with a basic specification in which the indirect utility derived from a flood insurance program is simply a linear function of all attributes of that program and of the ASC, which is equal to 1 one when the "No insurance" program is selected and to zero otherwise. Omitting indexes for simplicity, the specification of the indirect utility function becomes:

$$V = ASC \cdot (\alpha) + TypeAgri \cdot (\beta) + TypeHealth \cdot (\gamma) + MonthlyPayment \cdot (\zeta) + ProvState \cdot (\eta) + ProvNGO \cdot (\mu) + MaxCoverage \cdot (\zeta) + C \cdot (\kappa) \quad (2)$$

where $TypeAgri$ and $TypeHealth$ are dummy variables equal to 1 for agricultural and health insurances respectively (reference category is house insurance), $MonthlyPayment$ is a dummy variable equal to one if a monthly payment is possible, $ProvState$ and $ProvNGO$ are dummy variables equal to 1 if the provider of the insurance program is respectively a state-own firm or an NGO (reference category is private-owned firm), $MaxCoverage$ is the maximum level of insurance coverage (in million VND) and C is the insurance premium (in million VND).

Table 5 gives the estimate of the CL model with this basic specification of the indirect utility function. The overall fit of the model measured by MacFadden's ρ^2 is correct (0.114), and the model predicts 69.55% of choices correctly. We reject at 1% the null hypothesis of all coefficients being equal to zero. Most of the

coefficients are significant and all the signs are as expected a priori. We also test the independence of the irrelevant alternatives (IIA) property using the (Hausman and McFadden 1984) test. In all cases, we find that the IIA cannot be rejected at the 99% level. Therefore, the CL model is appropriate to our dataset.

[Table 5, about here]

The sign of the cost coefficient indicates that the effect on utility of choosing a choice set with a higher payment level is negative, which is an expected result (hypothesis H1).

The positive and significant sign of the ASC coefficient indicates strong preferences for the status quo alternative. Preferences for the status quo could be due to doubts over the ability of Vietnamese authorities to effectively implement flood insurance programs as described in the choice sets. Alternatively, it could be that individuals chose the status quo because they view the flood insurance choice as too complex. However, in the debriefing section, only 10.26% of respondents who repeatedly chose the status quo reported that the choice experiment was not clear enough.[12] The high level of significance for the ASC coefficient indicates in any case a strong status quo effect that we will explore more deeply in the following paragraphs.

The positive and significant sign of $TypeHealth$ indicates that respondents are more likely to select an insurance which covers medical expenses due to flood occurrence, compared to house damage or agricultural losses (hypothesis H2). This is in line with the findings of the survey on flood health impacts in Vietnam

[12] As a robustness check, we re-estimated the model first by excluding all respondents who always selected the status quo option and, second, by removing the 24 households identified previously as "false zeros". Estimates of the CL model are not statistically different from those presented in Table 5.

(USSH 2002) in which 75% of the respondents identified an impact of flooding on the prevalence of disease and ill-health.

The probability of an insurance scheme being chosen increases with the fact that the insurance scheme is provided at the state level (in comparison to being provided either by an NGO or a private firm). The level of coverage has no significant impact. Offering monthly payments does not increase the probability of an insurance scheme being chosen. This provides no evidence of liquidity constraints impacting on flood insurance choices (hypothesis H4).

To account for heterogeneity in the sample we estimate the CL model by including various respondent-specific characteristics as interactions with either the ASC or the attributes of the flood insurance programs. The former captures heterogeneity in choosing the status quo vs. the proposed flood insurance programs and the lattercaptures heterogeneity in the different attributes. The specification of the indirect utility function becomes in this case:

$$\begin{aligned} V_i = {} & ASC \cdot (\alpha_1 + \alpha_2 \cdot Z_i) + TypeAgri \cdot (\beta_1 + \beta_2 \cdot Z_i) + TypeHealth \cdot (\gamma_1 + \gamma_2 \cdot Z_i) \\ & + MonthlyPayment \cdot (\zeta_1 + \zeta_2 \cdot Z_i) + ProvNGO \cdot (\mu_1 + \mu_2 \cdot Z_i) \\ & + ProvState \cdot (\eta_1 + \eta_2 \cdot Z_i) + MaxCoverage \cdot (\zeta_1 + \zeta_2 \cdot Z_i) + C \cdot (\kappa_1 + \kappa_2 \cdot Z_i) \end{aligned} \tag{3}$$

where Z_i is a vector of respondent-specific social, economic and attitudinal characteristics. After extensive testing of the various possible interactions, we end up with the CL model presented in Table 6. Interaction variables have been selected based on their economic meaning, their significance level and by trying to keep the model as parsimonious as possible.[13]

[13] See Appendix A for the definition of each variable.

Compared to the basic specification, the goodness of fit of the CL with interactions is slightly higher (MacFadden's ρ^2 is 0.124). Using a Hausman specification test, we reject the null hypothesis that the estimated parameters in the basic CL model and in the CL model with interactions are the same ($p<0.001$).

All interaction variables introduced into the model are significant. In their survey of the literature on flood mitigation, (Bubeck, Botzen, Suu, and Aerts 2012) mention that previous experience of a hazard is usually found to be statistically significantly related to the adoption of private mitigation measures. Here, we find a significant and positive sign for the interaction variable between the ASC and being evacuated due to flooding in the previous 5 years (hypothesis H3).[14] This might be surprising since we would have expected a priori a lower preference for the status quo option (no insurance) for evacuated households. However, since 40.4% or the respondents report that they have been evacuated from their home at least once in the last 5 years due to flood, it may be possible that being evacuated is not viewed as a traumatic event. On the contrary having been evacuated without having experienced any kind of loss due to a flood may give respondents the feeling that they don't need any form of insurance to cover this risk ("inoculation hypothesis" in psychology).

It has been shown that the probability of buying flood insurance is related to individual risk preference.[15] To measure the individual risk preference of households, we have used lottery games (with monetary incentives). More specifically, we adapted the task initially proposed in (Eckel and Grossman 2002).[16] An im-

[14] Other variables representing respondents' experience of flooding have been tested (respondent's house flooded, member of the household injured). Interaction terms with flood insurance attributes have been introduced into the CL model but they were never significant.

[15] In the Netherlands, (Botzen and van den Bergh 2012) have shown that risk averse individuals are more likely to insure against flood risks.

[16] The task we use is presented in Supplementary Material: Lottery task.

portant advantage of the (Eckel and Grossman 2002)'s task is that it is simple enough to be easily understood by subjects drawn from outside the usual convenient sample of university students. Assuming CRRA utility, risk preferences are then estimated by maximum likelihood following (Harrison and Rutström 2008). This provides a unique CRRA coefficient for each household of our sample, which is used as an explanatory variable in the CL model. Interestingly, we find that highly risk-averse respondents positively value a high level of insurance cover.

The level of confidence in the ability of institutions to provide flood insurance efficiently appears to be a significant determinant of respondents' choice (hypothesis H4). A high confidence level in the state (variable ConfidenceState) is associated with a high respondent's utility if the provider is a state-owned firm. Similarly, high confidence in NGOs (variable ConfidenceNGO) results in a high utility in the case of insurance provided by an NGO. This stresses the fact that trust and confidence in institutions may play an important role in the process of insurance adoption in Vietnam. This result is in line with (Fatti and Patel 2012) who show that household flood risk perceptions in South Africa are highly influenced by historically distrustful relationships with the local government.

In line with the expected utility theory, the probability of adopting an insurance should be related to respondents' expectations concerning future floods and future flood damage. Different variables have been tested, including a dummy variable if the respondent expects more flooding in the next 10 years and a categorical variable representing the respondent's expectation concerning future damage due to flooding.[17] Only the latter appeared to be significant when cross-referenced

[17] The exact question we used is: "In the next 10 years, could you tell me what damage you think that floods will create for your household , on a scale from 1 (no loss and no damage) to 10 (critical damage and loss)".

with the level of cover. We find that respondents expecting higher future damage have a lower valuation for the maximum insurance cover, a result which is, *a priori*, counter-intuitive. One possible explanation is that households expecting high future flood damage may rely on other mitigation and adaption strategies such as relocation in less flood-prone areas.[18]

Lastly, to more deeply analyze the link between credit constraint and insurance adoption, the dummy variable for monthly payment is cross-referenced with household income. We find a significant positive relationship indicating that wealthy households are more likely to adopt insurance if monthly payments are available (hypothesis H4). Since the low-income households in our sample are mainly farmers, they may prefer a one-time annual payment, possibly just after the harvest.

4.4 Random Parameter Logit (RPL) model

Building on the existing literature, we then use a random parameter logit (RPL) model which accounts for unobserved, unconditional heterogeneity (Train 1998). The RPL is also attractive because it is not subject to the undesirable IIA assumption. In the RPL model, the random utility gained by individual i from choosing program j in a particular choice task k is written:

$$U_{ijk} = V(X_{ijk}|\beta_i) + \epsilon_{ijk} \tag{4}$$

where β_i is a vector of utility coefficients (for observed variables X_{ijk}) representing the individual's tastes. The coefficient vector varies with respondents with a

[18] 9% of the surveyed households have declared that they plan to move to another area where the flood risk is lower than the current risk. If we restrict the sample to households expecting the most critical damage and loss due to future flooding, this percentage increases to 14.5%.

specified density function $f(\beta)$ and is assumed to be independent of the density of $\epsilon's$. Assuming a type I extreme value distribution for $\epsilon's$ leads to the RPL model, which must be estimated by maximum simulated likelihood since individual's taste parameters are unobserved (Train 1998).

As for the CL models, we consider a basic RPL model and an RPL model in which interaction variables have been included. Estimates of the RPL models by maximum simulated likelihood are reported in Table 6.[19]

[Table 6, about here]

In the basic specification, all parameters, with the exception of the flood insurance premium, have been assumed to be independent and normally distributed.[20] The insurance premium is included here as a fixed effect parameter. Thus, preferences for the price of the flood insurance program are assumed to be homogeneous, that is, the marginal utility of money is assumed to be constant over the sample. Such a specification allows for the estimation of WTP for different insurance schemes. Following (Train 2009), the distribution simulations are based on 1000 Halton sequence draws.

The introduction of random preference variation improves the model significantly ($\chi^2_{(7)} = 2171.607$, p<0.0001). Compared to the CL models, the model fit measured by MacFadden's ρ^2 improves considerably to 0.180. All coefficients of the standard deviation parameters are highly significant, with the exception of

[19] Notice that we have also estimated a latent class (LC) model as an alternative way to account for preference heterogeneity. We find that the variables which affect segment membership in the LC model are quite similar to be the ones included in the RPL model with interactions. Estimates of the LC model are available from the authors upon request.

[20] We have conducted some robustness tests on these two assumptions. We have in particular considered correlated random parameters and log-normal distributions. Estimates of the main parameters of interest were quite similar. When correlation was introduced, the only noticeable change was an increase in the coefficient of $TypeAgri$. These additional estimates are available from the authors upon request.

the monthly payment coefficient. This suggests a high level of heterogeneity in our data. The log-likelihood ratio test rejects at 1% the null hypothesis that all the standard deviations are equal to zero. Hence, the model is appropriate for analysis of the data set presented in this paper. All signs of the flood insurance program attributes remain the same in the CL and RPL basic specifications, with the exception of the monthly payment variable.

A common feature for all flood insurance attributes is that the magnitudes of the coefficients for standard deviations are greater than the mean coefficients. This indicates a large heterogeneity among the respondents for the flood insurance attributes. This is particularly the case for the $TypeAgri$ attribute which indicates a remarkable variation in preferences for agricultural flood insurance. This may be easily understood if agricultural flood insurance is positively valued only by respondents reporting crop, livestock or fish production as their main occupation. In fact the estimated coefficient for $TypeAgri$ is positive for only 48.7% of the households. As with the CL model, we find here that health insurance is highly valued by respondents, especially when it is provided by a state-owned firm. Hence, the coefficient for $TypeHealth$ and $ProvState$ are positive for 68.5% and 73% of the households respectively. In contradiction with the CL model, the coefficient of $MonthlyPayment$ is positive and significant indicating a preference for monthly payment of the insurance premium.

Next, we included in the RPL model some respondent-specific characteristics such as interactions with the ASC or the attributes of the flood management programs. As mentioned in (Revelt and Train 1998), the specification with interaction captures preference variation in terms of both unconditional taste heterogeneity (random heterogeneity) and individual characteristics (conditional heterogeneity).

Estimation of the RPL model with interactions is presented in columns 4 and 5 in Table 6. As expected, introducing interactions between respondent-specific characteristics and attributes results in a loss in the significance of the main attribute effects, but this loss appears to be limited in our case. Coefficients of $TypeAgri$ and $TypeAgri \times OccupFarmer$ suggest that the agricultural flood insurance is only positively valued by respondents involved in agricultural activities. Again we find that confidence in the institutions providing flood insurance programs appears to be an important driver of flood insurance adoption (hypothesis H4).

4.5 Willingness To Pay (WTP)

The interpretation of coefficient estimates in the indirect utility functions is not straightforward except for the significance. A more convenient way is to present the results in terms of marginal willingness to pay (WTP) for a change in the attribute in question. For a given attribute, denoted by Att, the marginal WTP is defined as:

$$WTP_{Att} = \frac{\partial V / \partial Att}{\partial V / \partial C} \tag{5}$$

which corresponds to minus the marginal rate of substitution between the attribute considered and the cost of the program.

[Table 7, about here]

In Table 7 we report the marginal WTP obtained for the attributes of our CE. For the CL model, the associated confidence intervals are obtained using the parametric bootstrapping technique proposed by (Krinsky and Robb 1986) with 1000 replications (similar intervals have been obtained with the Delta and Fieller

methods). For the RPL models, they are based on the unconditional parameter estimates through simulation (Hensher, Rose, and Greene 2005).[21]

As expected, RPL models provide more precise estimates of WTP. The range for the 95% confidence interval for the WTP associated with flood insurance covering medical expenses (TypeHealth) is divided by five when passing from the CL basic model to the RPL model with interaction. This provides further evidence of the need to control for the high level of heterogeneity in individual preferences.

The highest marginal WTP is found for health insurance. Using the RLP model with interactions, it is equal to 0.894 million VND which represents 2.75% of the average annual household income. The WTP for insurance covering agricultural losses is never significant, whatever the model considered. Nevertheless, if we compute it with the RPL model with interactions specifically for a farmer (and not at the sample mean), we obtain a WTP equal to 0.035 million VND significantly different from zero at 10%. This may indicate the existence of a (limited) demand for flood insurance from Vietnamese farmers (hypothesis H1). Again using the RPL model with interactions, we find a significant positive WTP for insurance provided by a state-owned firm (0.888 million VND) or by an NGO (0.118 million VND). Lastly, it should be stressed that the ranking of attributes (in terms of WTP) remains globally consistent across estimation methods. This might be viewed as an indication of the robustness of our results.

[21] In models with interactions presented in Table 5–6, the coefficient for the price attribute is positive. Taking into account the cross-effect with the CRRA parameter, we get a negative impact of the price on individual's utility.

4.6 Welfare Analysis

Since the CE method is consistent with utility maximization and demand theory, it is then possible to derive some compensating surplus measures (CS) for any flood insurance program described by a specific set of attributes.

[Table 8, about here]

We consider here six different flood insurance scenarios based on the type of risk covered and the level of coverage, see Table 8. For each type of insurance (agricultural, health and house) we define two difference insurance schemes. The *High* scheme corresponds to a high level of cover and a high risk premium. The *Low* scheme corresponds to a low level of cover and a low risk premium. In defining flood insurance programs, we assume that monthly payments are always possible and that the provider is a state-owned firm.

For the CL model, the CS associated with the above scenarios are equal to the difference between the welfare measure under the status quo and the six flood insurance scenarios.[22] For the RPL model, the CS for each individual are obtained using unconditional parameter estimates through simulation (Hensher, Rose, and Greene 2005). The compensating surplus obtained from the CL basic model and from the RPL models (with and without interactions) for the six different flood insurance scenarios are presented in Table 9.

[Table 9, about here]

[22] Notice that in our case the welfare associated with the status quo situation (no flood insurance) is equal to zero. Formally the welfare in the status quo should be computed from the coefficient of the ASC but in such a case all the proposed flood insurance scenarios would have resulted in a reduction in compensating surplus. Following Adamowicz et al. (1998), we assume that the welfare change can be calculated on the basis of attributes alone. Hence we ignore the status quo bias discussed in the previous sections of this article. This might be a reasonable strategy if respondents' preference for the status quo situation is essentially driven by psychological motives.

Interestingly, the CS are all positive. Implementing flood insurance policies might result in welfare improvements in Vietnam. The CS is the highest in the case of flood insurance covering medical expenses. Using the RPL model with interactions, we find that the CS associated with insurance covering medical expenses is valued at between 1.612 and 1.728 million VND (between 5.0% and 5.3% of the respondents' average annual income). The ranking of flood insurance scenarios remains consistent for the CL and RPL models and the obtained CS are quite similar. For a given type of flood insurance, we find that respondents always prefer the *Low* scenario which would mean that they are not ready to pay for a high level of cover.

5 Conclusion and policy implications

A choice experiment has been employed to estimate how Vietnamese households value flood insurance mechanisms in the Nghe An Vietnamese Province. Using different econometric specifications (conditional logit model and random parameter logit model), we have computed the willingness to pay (WTP) for different flood insurance programs. We have identified the relationships between the WTP and different attributes of insurance schemes (type of risk covered, level of cover, insurance provider, billing frequency, insurance premium) with a specific focus on heterogeneity in terms of households' preferences.

We have found a strong preference for the status quo option (no insurance), a result which is not unusual in the environmental valuation literature and which may be explained by the well-known status quo bias in decision-making (Samuelson and Zeckhauser 1988). From a policy perspective, the strong preference for the sta-

tus quo calls for a careful assessment of respondents motivations for not adopting any of the proposed flood insurance policies. Hence, respondents' preference for the status quo situation could be driven by different factors including psychological motives (fear of novelty for example), cognitive difficulties in manipulating flood insurance programs or protest answers to the CE.

We do, however, document the fact that flood insurance may be an effective option for Vietnamese households. Hence, 29.24% of respondents in our survey included flood insurance as one of their four preferred policies for managing flood risk. Moreover, in the CE, 73.88% of the respondents selected at least one program with a flood insurance (within eight choice sets they had to complete). These results call for a careful design of flood insurance policies. We have shown in particular that the confidence level in the ability of institutions to provide flood insurance efficiently appears to be a significant determinant of respondents' decision to buy a flood insurance program. Since a household may have different levels of confidence in flood insurance providers (state-owned firms, NGOs or privately-owned firms), a portfolio of providers should be considered when implementing flood insurance on a large scale. Households would then select their preferred provider and one might expect an increase in the flood insurance adoption rate.

Our results also reveal some very different levels of willingness to pay for flood insurance policies depending on the type of risk covered. First, in all models considered, the WTP for flood insurance covering agricultural losses is found to be non-significant. This may help in understanding why past attempts at implementing agricultural flood insurance have failed until now in Vietnam. It may also help in understanding why only farmers receiving a 100% subsidy have subscribed to the flood insurance proposed in the pilot program launched by the Vietnamese

government in June 2012. Second, in all models we have considered, health consequences of floods rank first in terms of willingness to pay. The willingness to pay is equal to 0.894 million VND which represents 2.75% of the average annual household income. This is surprising given the fact that Vietnamese households report relatively low average medical expenses due to floods (less than 1.2% of their annual income). One explanation could be a higher level of household risk aversion for health risks, possibly since self-protection measures are more limited compared to agricultural production or house risks. Our results thus suggest scope for extending health insurance policies in order to cover medical expenses resulting from floods.

Lastly, in order to increase the likelihood of flood insurance adoption, one may consider the option of bundling different flood insurance policies in order to benefit from the complementarities which may exist between them. Public authorities may for instance propose a flood insurance jointly covering damage to health and damage to homes and home contents. A formal analysis of this type of insurance scheme would however require a modication to the design of the CE presented here, and to the econometric model. We leave this for future research.

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Table 1 Attributes and levels used in the CE

Attribute description	Attribute levels	Status no
Insurance type	Health, Agricultural, House	None
Insurance provider	State-owned firm, Private-owned firm, NGO	None
Maximal annual insurance cover		None
– *for health insurance*	5, 10 (million VND)	
– *for agricultural insurance*	5, 10, 15 (million VND)	
– *for house insurance*	5, 10, 15, 20, 40 (million VND)	
Annual insurance premium*		None
– *for health insurance*	2%, 4%, 6%	
– *for agricultural insurance*	2%, 4%, 6%	
– *for house insurance*	2%, 4%, 6%, 8%, 10%	
Monthly payment	Yes, No	None

* In the choice sets, the insurance premium is presented as a monetary value (VND). For each type of insurance, the risk premiums correspond to the percentage provided in this Table multiplied by the maximal annual insurance cover.

Table 2 Main household socio-economic characteristics

Variable	**Mean**	**Std. Dev.**
Age of head of household (years)	49.848	13.519
Household income (million VND)	32.488	33.004
Number of household members	4.199	1.509
Dummy if there is a child under 3 years old	0.190	0.420
Dummy if one household member is older than 60	0.449	0.752
Dummy if household's head has attended high school	0.306	0.461
Dummy if main occupation of head of household is agriculture	0.792	0.406
Dummy if main occupation of head of household is employee	0.056	0.23
Dummy if head of household is retired	0.051	0.221
Dummy if main occupation of head of household is own business	0.058	0.234

Table 3 Household flood history and cost of flooding in the last 5 years

Variable	Mean	Std. Dev.
Household flood history		
House flooded at least once in the last 5 years	0.404	0.491
Respondent evacuated at least once in the last 5 years	0.203	0.403
One household member injured at least once in the last 5 years	0.049	0.216
Respondent has considered risk of flooding to choosing housing location	0.323	0.468
Respondent plan to move to another location due to flood risk	0.089	0.285
Cost of flooding*		
Flooding has represented a significant cost in the last 5 years	0.761	0.427
House cost (million VND)	2.636	6.543
Agricultural cost (million VND)	3.536	7.720
Health cost (million VND)	0.249	1.320
Total cost (million VND)	6.421	11.137
House cost (% of income)	9.287	22.198
Agricultural cost (% of income)	14.798	27.642
Health cost (% of income)	1.170	7.370
Total cost (% of income)	25.256	37.022

* Due to missing answers, flood costs have been computed on a sub-sample of 407 households.

Table 4 Frequency of individual choices

Choice	**Frequency (%)**
Insurance A	20.51%
Insurance B	28.15%
No insurance	54.32%
Insurance A for all choice sets	0.45%
Insurance B for all choice sets	2.90%
No insurance for all choice sets	26.12%

Table 5 CL models

	Basic model		**Interaction model**	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
ASC	1.346***	(0.101)	1.298***	(0.104)
TypeAgri	-0.019	(0.076)	-0.495***	(0.142)
TypeHealth	0.670***	(0.082)	0.727***	(0.083)
ProvState	0.705***	(0.070)	-0.032	(0.144)
ProvNGO	-0.011	(0.077)	-0.634***	(0.140)
MonthlyPayment	-0.066	(0.060)	-0.172**	(0.076)
MaxCoverage	-0.005	(0.005)	-0.177**	(0.081)
C	-0.501***	(0.105)	2.209	(1.667)
ASC ×Evacuated	–	–	0.383***	(0.111)
TypeAgri×OccupFarmer	–	–	0.616***	(0.145)
ProvState×ConfidenceState	–	–	0.117***	(0.019)
ProvNGO×ConfidenceNGO	–	–	0.134***	(0.025)
MonthlyPayment×Income	–	–	0.003**	(0.001)
MaxCoverage×HighFutureDamage	–	–	-0.018***	(0.005)
C×CRRA	–	–	-1.068*	(0.646)
MaxCoverage×CRRA	–	–	0.071**	(0.031)
N	10752		10752	
Log-likelihood	-5361.924		-5301.222	
χ^2	$\chi^2_{(8)}$: 1379.559		$\chi^2_{(16)}$: 1500.962	
MacFadden's ρ^2	0.114		0.124	

Significance levels : * : 10% ** : 5% *** : 1%

Table 6 RPL models

Variable	Basic model Coefficient	(Std. Err.)	Interaction model Coefficient	(Std. Err.)
Coefficients				
C	-1.203***	(0.191)	5.730	(3.870)
ASC	2.463***	(0.377)	2.499***	(0.402)
TypeAgri	-0.083	(0.230)	-2.177***	(0.509)
TypeHealth	1.838***	(0.277)	2.044***	(0.303)
ProvState	1.585***	(0.208)	0.478	(0.454)
ProvNGO	0.211	(0.176)	-0.566*	(0.343)
MonthlyPayment	0.366**	(0.151)	0.163	(0.218)
MaxCoverage	-0.016	(0.012)	-0.376**	(0.177)
ASC ×Evacuated	–	–	1.434**	(0.626)
TypeAgri×OccupFarmer	–	–	2.604***	(0.529)
ProvState×ConfidenceState	–	–	0.199***	(0.067)
ProvNGO×ConfidenceNGO	–	–	0.172***	(0.063)
MonthlyPayment×Income	–	–	0.005	(0.004)
MaxCoverage×HighFutureDamage	–	–	-0.047***	(0.015)
C×CRRA	–	–	-2.926*	(1.526)
MaxCoverage×CRRA	–	–	0.154**	(0.069)
Coefficient standard deviations				
ASC	5.308***	(0.401)	5.911***	(0.471)
TypeAgri	2.482***	(0.280)	2.523***	(0.265)
TypeHealth	3.814***	(0.402)	3.900***	(0.428)
ProvState	2.591***	(0.254)	1.593*	(0.831)
ProvNGO	-1.209***	(0.309)	-1.127***	(0.371)
MonthlyPayment	0.594	(0.373)	-0.755	(0.494)
MaxCoverage	0.071***	(0.011)	0.000	(0.014)
ASC ×Evacuated	–	–	-3.436***	(0.615)
TypeAgri×OccupFarmer	–	–	0.383	(0.836)
ProvState×ConfidenceState	–	–	0.313***	(0.095)
ProvNGO×ConfidenceNGO	–	–	0.099	(0.077)
MonthlyPayment×Income	–	–	0.003	(0.003)
MaxCoverage×HighFutureDamage	–	–	-0.008	(0.022)
C×CRRA	–	–	0.703***	(0.106)
MaxCoverage×CRRA	–	–	0.011**	(0.005)
N	10752		10752	
Log-likelihood	-2327.58		-2274.039	
χ^2	$\chi^2_{(7)}$:2171.607		$\chi^2_{(15)}$: 2179.706	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 7 Marginal WTP (in million VND) for flood insurance attributes

	CL basic		RPL basic		RPL interactions	
Attribute	Est.	CI (95%)	Est.	CI (95%)	Est.	CI (95%)
ASC	2.798	(1.867;4.732)	2.066	(1.993;2.139)	2.209	(1.986;2.432)
TypeAgri	-0.091	(-0.539;0.197)	-0.067	(-0.090;-0.044)	0.067	(-0.001;0.135)
TypeHealth	1.285	(0.802;2.208)	1.527	(1.484;1.569)	0.894	(0.756;1.031)
ProvState	1.332	(0.870;2.243)	1.306	(1.279;1.332)	0.888	(0.827;0.948)
ProvNGO	0.015	(-0.324;0.369)	0.169	(0.162;0.176)	0.140	(0.118;0.163)
MonthlyPayment	-0.076	(-0.357;0.206)	0.308	(0.306;0.310)	0.064	(0.049;0.079)
MaxCoverage	-0.007	(-0.039;0.012)	-0.014	(-0.014;-0.013)	-0.003	(-0.004;-0.003)

Table 8 Definition of flood insurance scenarios

Scenario name	Type	Provider	Max. cover. (million VND)	Risk premium (million VND)	Monthly payment
Health^{H}	Health	SOF	10	0.2	yes
Health^{L}	Health	SOF	5	0.1	yes
House^{H}	House	SOF	20	0.4	yes
House^{L}	House	SOF	10	0.2	yes
Agri^{H}	Agri.	SOF	15	0.3	yes
Agri^{L}	Agri.	SOF	10	0.2	yes

Note: SOF for state-owned firm.

Table 9 Compensating surplus for different flood insurance scenarios (in million VND)

Scenario name	CL basic	RPL basic		RPL interactions	
	Av.	Av.	(Std. dev.)	Av.	(Std. dev.)
Health^H	2.274	2.801	(2.446)	1.612	(0.083)
Health^L	2.301	2.971	(2.450)	1.728	(0.082)
House^H	0.729	0.869	(2.027)	0.552	(0.032)
House^L	0.989	1.208	(1.996)	0.785	(0.033)
Agri^H	0.765	1.105	(1.482)	0.602	(0.034)
Agri^L	0.898	1.275	(1.452)	0.718	(0.034)

A Definition of variables

Table A.1 Name and definition of variables used in the empirical application

Variable	Definition
Attributes of the CE	
$TypeAgri$	Dummy variable equal to 1 if insurance cover agricultural losses
$TypeHealth$	Dummy variable equal to 1 if insurance cover medical expenses
$TypeHouse$	Dummy variable equal to 1 if insurance cover house damage
$ProvState$	Dummy variable equal to 1 if insurance provided by a state-owned firm
$ProvNGO$	Dummy variable equal to 1 if insurance provided by a NGO
$ProvPriv$	Dummy variable equal to 1 if insurance provided by a private firm
$MaxCoverage$	Maximum cover in case of flood damage (in million VND)
$MonthlyPayment$	Dummy variable equal to 1 if monthly payment is possible
C	Annual insurance premium (in million VND)
Respondent's characteristics	
$Income$	Household's annual income in 2011, counting all sources including wages, salaries, pensions, dividends and other incomes (in million VND)
$OccupFarmer$	Dummy variable equal to 1 if respondent's main activity is agriculture
$Evacuated$	Dummy variable equal to 1 if respondent has been evacuated or advised to evacuate from his/her house because of the threat of flooding (0/1)
$Injured$	Dummy variable equal to 1 if a member of the household has been injured by a flood event in the last 5 years (0/1)
$ConfidenceState$	Respondent's level of confidence in a state-owned firm to efficiently provide a flood insurance (1 to 10, with 1 for not at all confident and 10 for very confident)
$ConfidencePriv$	Respondent's level of confidence in a private-owned firm to provide flood insurance efficiently (1 to 10, with 1 for not at all confident and 10 for very confident)
$ConfidenceNGO$	Respondent's level of confidence in an NGO to provide flood insurance efficiently (1 to 10, with 1 for not at all confident and 10 for very confident)
$HighFutureDamage$	Dummy variable equal to 1 if respondent's expectation of future damage due to flooding is 8, 9 or 10 on a scale going from 1 to 10 (with 1 for no losses and no damage to 10 for critical damage)
$CRRA$	Constant relative risk aversion coefficient of the respondent elicited through lottery games with monetary incentives.