Do Natural Disasters Modify Risk Preferences? Evidence From a Field Experiment in Vietnam

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Evidence suggests that individual preferences may not be fully stable, and may change after special life events. We use experimental data over 448 households to study precisely how experiencing a disaster – a flood in Vietnam – shapes risk preferences. We allow for different preferences in the gain and loss domains, and for weighted probabilities. We find that the experience of a flood significantly and lastingly affects risk-taking behaviors, but only in the loss domain: Households in villages affected by a flood in recent years exhibit more risk aversion in the loss domain, compared with individuals living in unaffected, otherwise similar, villages. Moreover, Vietnamese households distort probabilities but in a way unrelated to flood experience. Last, we use measures of perceived flood risk to assess whether the change in elicited monetary risk preferences after a disaster is solely attributable to learning, i.e., to a changing perceptions about a background risk. Our results suggest a lasting impact of emotions. (JEL Q54, O12, D81).

Preferences are considered to be stable features characterizing the attitudes of an individual towards possible options.[1] Stability is an important property, that

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[1]See for instance Ariel Rubinstein's Lecture notes in microeconomic theory, in which he describes

allows to extrapolate from estimated preferences. Among the various dimensions of individual preference, attitude to risk is particularly important as most important economic decisions entail risk or uncertainty. However recent empirical research has shown that risk preferences – or at least attitudes – may change after a shock (i.e., an exceptional occurrence, often of high emotional content and stark consequences). The precise way shocks modify preferences towards risk is of more than theoretical interest. Given the high and increasing frequency of natural disasters, important shocks are likely to befall a majority of the world's inhabitants. While such shocks have obvious economic effects, they will also have potentially overlooked, important and long-lasting consequences if they noticeably impact risk preferences and risk behavior. The object of this paper is to assess, thanks to experimental and survey data, the precise impact on risk preferences of experiencing a natural disaster (a flood, in the past five years) in Vietnam. Floods do matter as they cost around 25 percent of average annual income in the region we consider. To better account for advances in the modeling of individual preferences, we allow for a non-expected utility representation – which will turn out to be relevant and important. We also use individual measures of perceived risk. This allows us to assess whether measured changes in risk aversion over monetary outcomes go beyond changes attributable to new perceptions as to a background (disaster) risk. By controlling for this risk perception effect, and differentiating gains and losses, we can better assess the impact of other elements associated to a disaster experience, presumably and foremost emotions.

Dynamic inconsistency due to preference changes, over time, are at the core of an influential literature, following Laibson (1997). But regarding preferences over risk and time only, stability is still perceived as the norm – as for personality traits in psychology, some of which are related to patience and risk-taking. Some recent research shows that these preferences tend indeed to be highly stable over time: Wolbert and Riedl (2013) report stability of discount factors, risk aversion and

"preferences as the mental attitude of an individual (economic agent) toward alternatives" (p. 19), and numerous graduate textbooks.

probability weighting parameters for up to ten weeks, and Meier and Sprenger (2014) report stability of discount factors over a period of two years. However Andersen et al. (2008) find only a limited stability of risk aversion parameters, and Zeisberger, Vrecko and Langer (2012) find, using a Prospect Theory framework, that one third of their subjects exhibit significant instability over a period of only one month. The potential instability of risk preferences has been mostly studied in the context of intense or specific shocks, a context of particular interest in itself. Some recent empirical research explores the impact of experiencing natural disasters, e.g., floods, earthquakes or volcanic eruptions, on risk attitudes (Eckel, El-Gamal and Wilson 2009, Andrabi and Das 2010, Li et al. 2011, Cameron and Shah 2012, Cassar, Healy and von Kessler 2011, Callen 2011, Ali Bchir and Willinger 2013) and time preferences (Li, Li and Liu 2011, Callen 2011, Cassar, Healy and von Kessler 2011, Ali Bchir and Willinger 2013). Changes in trustiness are also documented (Andrabi and Das 2010, Castillo and Carter 2011, Cassar, Healy and von Kessler 2011).[2] Though causality is difficult to establish, several of these studies suggest that exposed individuals have their preferences lastingly changed. The literature is not fully conclusive however: Callen (2011) and Voors et al. (2012) find no significant impact of disasters[3] (cf. Section I).

Theoretical research also suggests reasons for non-stable preferences. A rich literature attempts to capture evolutionary processes behind the long-term selection of preferences (Robson 2001, Robson 2007): preferences are viewed as endogenously determined by the environment with which people interact. Hence a potential impact of traumatic events, that modify the environment. Experiencing a natural disaster may change the way the cognitive and the emotional systems are involved in decision-making (Loewenstein et al. 2001). Due to the trauma, individuals may put a higher weight on emotions, inducing changes in

[2] The impact of other traumatic events, such as civil wars or wars, on preferences has also been investigated, see e.g., Voors et al. (2012) and Callen et al. (2014).

[3] More precisely, Callen (2011) documents an absence of change in household risk preferences after a tsunami in Sri Lanka in 2004; Voors et al. (2012) show that natural disasters (drought and excess rainfall) in Burundi do not significantly impact individual preferences.

preferences.[4] Recent neurological research (Kandasamy et al. 2014) shows that risk preferences can also be affected by an elevated level of cortisol in the blood, provided this level remains elevated for at least a few days. Since cortisol levels raise in periods of stress, experiencing a disaster can have immediate effects on risk-taking.

Our knowledge of the precise way in which preferences change – if they do – after a disaster remains limited. Risk preferences are complex, and may change in a number of ways, to reflect different ways of evaluating uncertain gains and losses. A disaster experience may potentially modify one's willingness to mix good and bad outcomes, one's fear of making losses, or likelihood of overweighing small probability events, etc. In addition, disasters are highly emotional events. Our precise survey data helps obtaining insights as to the long-term impact of such emotions, in the loss and gain domains, controlling for modified risk perception. This is of interest in view of the existing literature in psychology that studies the immediate impact of induced emotional states and moods.[5]

The potential change in risk preferences after a disaster is of interest to policy-makers: First, risk preferences have been shown to be related to important decisions, including the adoption of self-protection and self-insurance strategies (Dionne and Eeckhoudt 1985). Knowing how past natural disaster experience shapes risk preferences could help design more efficient prevention, protection and emergency policies. This is especially important given the high social cost of natural disasters.[6] Second, due to climate change, an increase in the intensity and in the frequency of extreme events, such as natural disasters (IPCC 2007) is expected. More households might be affected in the next decades, and in a more dramatic way, by natural disasters. Third, changes in individual behaviors after a natural disaster have been documented for various contexts including in-

[4] See Eckel, El-Gamal and Wilson (2009) on the impact of the Katrina hurricane.

[5] cf. Yuen and Lee (2003), Campos-Vazquez and Cuilty (2014) and Drichoutis and Nayga (2013) among others.

[6] According to Munich Re, the world's largest reinsurance firm, the worldwide cost of natural disasters in 2012 has been \$160 billion. This figure represents approximately 0.22% of the world GDP.

come and international financial flows (Yang 2008), migration decisions (Paxson and Rouse 2008, Boustan, Kahn and Rhode 2012) or fertility and education investments (Baez, de la Fuente and Santos 2010). Determining if these behavior changes can be attributed to modifications of risk preferences may provide some insights for designing public policies in these different contexts. Moreover, knowing the exact way in which preferences may change is needed to forecast the economic consequences of such changes.

Our approach . — Our paper contributes to the emerging literature which assesses the link between natural disasters and individual preferences. We investigate whether, and how, experiencing a flood may affect risk-taking. The questions we address are the following: Do floods modify individual preferences with respect to a monetary risk? If they do, in what precise way are preferences affected? In particular, are preferences affected differently for gains and for losses? Is the way in which individuals take into account the probability of gains and losses affected by the experience of a disaster? Are the effects of disasters on preferences lasting over time? Last, are the observed preference changes fully explained when considering that flooding is a background risk, and that individuals modify their perception of this risk after experiencing a flood?

Our approach is novel on two main grounds: we allow for preferences derived from Prospect Theory (PT), and our detailed survey data allows us to control for the impact of perceived (background) risk on behavior.

Most existing empirical studies constrain preferences to follow the commonly used Expected Utility (EU) model. A novelty of our approach is that we allow for different preferences in the gain and loss domains, and for distortions in perceived probabilities. With this PT framework, we can provide a more precise description of the impact of experiencing a disaster on risk preferences, isolating different dimensions of preferences. This is relevant in view of the literature in neuroscience, (Levin et al. 2012, Hsu et al. 2009)[7] and it turns out to be very important in our study. We also use measures of the perceived flood risk to control for the possibility that changes in elicited preferences may be due solely to beliefs updating with respect to a background risk (the risk of flood occurrence).

We investigate the impact of flooding thanks to detailed data on households in Vietnam.[8] We use field experimental data collected in Spring 2012 on a sample of households located in the Nghe An Province. We play standard risk games (using real money) with representative, randomly selected individuals and test if households living in villages that have been exposed to floods exhibit more risk-taking behavior. We assess if these behaviors can be attributed to changes in preferences (controlling for a range of other factors, including involvement in social networks). Interestingly, no significant impact is found for risk preferences in the *gain* domain. But for the *loss* domain, we find that individuals in villages that suffered a flood in the past years, exhibit more risk aversion than individuals living in otherwise similar villages that did not experience this type of disaster. We use three measures of flood experience (being flooded, evacuated or injured due to a flood), but also two different measures, that account for the impact of changing perceptions as to the risk of flood in monetary choices. Our results thus contribute to the empirical literature which has shown that, depending on the structure of individuals preferences, the presence of background risk (flood) may lead to more or less cautious behaviors.[9] We also assess the role played by past flood experience on probability weighting. We find that Vietnamese households underestimate low probabilities and overestimate high probabilities, but these

[7]Levin et al. (2012) show that decisions under risk appear to involve different psychological processes, and may rely on different neural structures, in the gain domain than in the loss domain. Hsu et al. (2009) measure neural responses when participants evaluate monetary gambles, and obtain that the activity in the striatum is non linear in probabilities, which appears in line with non-expected utility models.

[8]Vietnam is the world's seventh most exposed country to natural disasters (WorldBank 2005). Over the past 20 years, natural disasters have resulted on average each year in 650 deaths, in damage on 340,000 ha of paddy (rice) and in a total destruction of 36,000 houses (WorldBank 2010). Within natural disasters, flood is the single most important cause of loss, accounting for 49 percent of total economic losses. Floods are expected to generate higher social losses in the future due to climate change, and Vietnam has been identified as one of the fifth worst affected countries by climate change (WorldBank 2005).

[9]See Gollier and Pratt (1996), Quiggin (2003) and Beaud and Willinger (2013) for theoretical analyzes of the impact of background risk on risk-taking behavior.

distortions are *unrelated* to flood experience. Last, we consider the impact of the time lag since the occurrence of a flood, and of the aid received from various sources, on preferences.

The remainder of the paper is organized as follows. Section I presents the relevant literature we rely on. Section II describes the experimental design used for eliciting individual risk preferences. We discuss our data sources in Section III, and our identification strategy and results in section IV. Section V presents robustness checks and Section VI concludes.

I. Background

The literature that explains why behavior may change after a disaster can be sorted according to whether preferences actually change or simply appear to change due to modified beliefs. In a third part, we review the empirical evidence about the impact of disasters on natural preferences.

A. Natural Disasters and Changes in Individual Preferences

A first possible reason for disasters to affect preferences is related to the *risk-as-feelings* hypothesis proposed by Loewenstein et al. (2001). The *risk-as-feelings* hypothesis states that feelings and emotions are important driving factors of decision-making under uncertainty. It relies on modern paradigms in psychology and neuroscience which indicate that decision-making under risk involves two types of mechanisms: First, people tend to adopt a cognitive approach which integrates the likelihood of possible outcomes into some form of expectation-based calculus to come to a decision. Representations of cognitive approaches include the Expected Utility and the Prospect Theory models, which have been extensively used for analyzing decision-making under risk in the past decades. Second, decision-making also involves emotions and affect through the use of the experiential system, Slovic et al. (2004). Although rational decision-making requires a proper integration of both modes of thought, cognitive-based and emotionbased decision-making have distinct determinants, and can be likened to two systems, system 2 and system 1 (Loewenstein et al. 2001). As a result, emotional reactions to risky situations might diverge from the cognitive assessment of those risks. Changes in individual preferences after a natural disaster may result from a change in the way the cognitive and the emotional systems are involved in decision-making. After having experienced a trauma, individuals may put a higher weight on emotions (Eckel, El-Gamal and Wilson 2009).[10] Determining if the changes in individual preferences are permanent or temporary remains however an open question.[11]

An alternative reason why natural disasters may affect individual preferences is linked to the environment: Preferences may be endogenously determined by the environment with which people interact. This is in line with the cultural theory of risk developed by anthropologists and sociologists (Douglas and Wildavsky 1982), for which risk perception is the result of social and cultural influences.[12] Evolutionary models of preference selection provide a way for rationalizing the link between natural disasters and individual preferences in the long-term. In this type of models, there is an equilibrium match between individual behavior and the environment (Robson 2001, Robson 2007). Evolutionary arguments have been used to explain the selection of time preferences (Robson 2007) and risk preferences (Netzer 2009). A limit of evolutionary arguments is that they are likely to operate primarily in the long run. The optimizing agent's model pioneered by Becker and Mulligan (1997) offers another interesting direction since it allows for

[10] Eckel, El-Gamal and Wilson (2009) rely on this type of argument to explain the risk-taking behaviors observed on a sample of evacuees after the Katrina hurricane.

[11] Long term mental and physical health consequences of disasters have been documented in other disciplines, but not with respect to possible risk preference changes. Neria, Nandi and Galea (2008) review for instance the existing literature on post-traumatic stress disorder (PTSD), one of the most commonly studied post-disaster psychiatric disorder. Examining the body of research conducted after disasters in the past three decades, they conclude that the burden imposed by PTSD on persons exposed to disasters is quite substantial.

[12] The cultural theory relies on the idea that individuals belong to different social structures and that the social context of individuals shapes their values or attitudes. Socialized cognitive patterns work then like filters in the evaluation of information about risks. According to this perspective, the most important predictors for risk perception are not individual cognitive processes, but socially shared worldviews in relation to the "culture" individuals belong to.

voluntary short-term adaptation of preferences.[13]

Lastly, preference shifts following a natural disaster may have a neurobiological basis. The genetic code of individuals is fixed at birth. But it has been shown that traumatic events such as natural disasters may have long-lasting effects on behavior by influencing the *expression* of genes known to affect brain chemicals implicated in decision-making, a process known as methylisation (van IJzendoorn et al. 2010). In particular, trauma have been shown to influence the expression of the gene regulating the transportation of serotonin (Caspi et al., 2003), a neurotransmitter linked to risk taking (Kuhnen and Chiao 2009).

Additionally, recent research shows that exposure to elevated cortisol levels, as after experiencing a disaster, is associated to reduced risk-taking (Kandasamy et al. 2014). Under a double-blind and placebo control protocol (to ensure that the effects were not due to a psychological reaction to the treatment), Kandasamy et al. (2014) use lotteries to elicit risk aversion parameters, and assess probability distortions. They report more risk aversion in subjects whose cortisol levels have been raised for several days (conversely, an accute but short elevation has no significant effect). They also find that, under cortisol, males exhibit more probability distortions (in the direction of higher sensitivity to small-probability events), but not females. A disaster being a stressful event, it is associated to a rise in cortisol, so one would expect more risk aversion. It is not clear however how lasting such an hormonal effect would be, the duration of the study by Kandasamy et al. (2014) being limited to eight days.

B. Natural Disasters as Background Risks

The experimental tasks used to elicit risk preferences do so for monetary risks, given an (unknown to the experimenter) environment with which the subject interacts. An apparent change in preferences, as measured for a given (mone-

[13]Becker and Mulligan (1997) consider endogenous time preferences, allowing individuals to make costly efforts to increase their appreciation of the future. The logic in this model could potentially be applied, with adequate adjustments, to risk preferences.

tary) risk, may actually be due to a change in the individual's perception of the other risks present in her environment. Changes in individuals' risk perception after a natural disaster have been highly documented, especially in the context of flood risk (Bubeck, Botzen and Aerts 2012, Ho et al. 2008, Knuth et al. 2014).[14] A change in risk-taking behaviors after a flood could thus reflect a change in perceived background risk. A natural disaster may constitute a shock that contains new information, causing a rational update in estimates of background risk (Cameron and Shah 2012). Depending on the structure of individuals preferences, the change in background risk may then lead to more or less cautious behaviors (Gollier and Pratt 1996, Quiggin 2003, Beaud and Willinger 2013).

Under the Expected Utility paradigm (EU), Gollier and Pratt (1996) have shown that for utility functions satisfying the condition of "risk vulnerability", adding an actuarially neutral risk to initial wealth leads to a more cautious behavior for a risk averse individual.[15] In contrast, Quiggin (2003) has demonstrated that for the wide class of risk-averse generalized expected utility preferences exhibiting constant risk aversion, a higher background risk can actually have an opposite effect by increasing the propensity of a decision-maker to select riskier choices. Recently Beaud and Willinger (2013) have extended this analysis to Prospect Theory (PT) preferences. They show that, depending on his reference point, an individual with PT preferences may behave either in a more or a less cautious way in the presence of background risk. No consistent pattern thus emerges from the literature.

When the background risk, as in our case, is flooding, the consequences are not only financial but also emotional and physical (health and injuries). The theo-

[14] Ho et al. (2008) study the change in disaster risk perception after experiencing a disaster. They focus on floods and landslides, but also include earthquakes, fires, environmental pollution and contagious diseases. They obtain that flood is the disaster after which the perception of risk increases the most. Knuth et al. (2014) show that the experience of a disaster is the main predictor of the perception of a disaster risk. And as for Ho et al. (2008), flood is the disaster for which the impact of experience on risk perception is the strongest.

[15] So far, existing empirical investigations of the risk vulnerability conjecture are not fully conclusive. Lee (2008) and Lusk and Coble (2008) report little evidence evidence, contrary to Harrison, List and Towe (2007), Guiso and Paiella (2008) and Beaud and Willinger (2013).

retical literature mostly considers additive (Gollier and Pratt 1996, Eeckhoudt, Gollier and Schlesinger 1996) or multiplicative risks. An exception, in the EU paradigm, is the analysis by Malevergne and Rey (2009), who characterize risk vulnerability for bivariate utility functions (which allows to better account for health and emotional states) and an actuarially unfair background risk (as is flooding).

Observing more or less cautious behaviors after a natural diaster may then result from i) a change in risk preferences, ii) a change in background risk or iii) a change in both.[16] This raises some important identification issues, that we will address in the empirical part of this paper. We will argue that the variables that have been used previously for measuring background risk (natural disaster exposure) might not be fully satisfactory. We will use measures directly based on individual expectations about the flood risk. As we will show, this leads to different results.

C. Empirical Evidence

To our best knowledge, Eckel, El-Gamal and Wilson (2009) were the firsts to use experiments to establish a link between a natural disaster (the Katrina hurricane in US) and individual risk preferences. They focus exclusively on the short term impact of Katrina on evacuee's risk preferences. Surprisingly, the evacuees exhibit risk-loving behavior, a feature which is explained by the emotional state of the respondents shortly after the hurricane. Using a hypothetical risk game, Andrabi and Das (2010) find, to the contrary, that individuals living closer to the 2005 Pakistani earthquake fault line are significantly more risk averse. In China, Li et al. (2011) examine the impact of snow-hit and a major earthquake in 2008 on individual risk preferences using hypothetical lottery games. They show that people are not always more risk averse after a disaster. Their results suggest some differentiated impacts on preferences in the loss and in the gain do-

[16] A change in wealth or income may also explain more or less cautious behaviors.

mains. Similar findings are also mentioned in Page, Savage and Torgler (2012) on a sample of homeowners in Brisbane (Australia), who have experienced a flood in 2011. Cameron and Shah (2012) have investigated the relationship between natural disasters (earthquake and flood) and individuals' risk-taking behavior using data from experiments conducted in Indonesia in 2008. They find that individuals in villages that suffered a flood or earthquake in the past three years make choices that exhibit higher levels of risk aversion compared to similar individuals in villages that did not experience a disaster. The impact of natural disasters on risk aversion is however found to be mitigated when households have access to insurance mechanisms such as remittances from people outside the home village. Cassar, Healy and von Kessler (2011) estimate trust, trustworthiness, risk aversion and time discounting for a sample of households in Thailand affected in different degrees by the 2004 Asian tsunami. They show that, four and a half years after the disaster, preferences are significantly different for the subjects who lived in the areas hit the hardest by the tsunami. In particular, individuals affected by the disaster are substantially more trusting and more risk-averse, as well as moderately more trustworthy. Callen (2011) analyzes individual (time and risk) preferences of workers in Sri Lanka after the 2004 Asian tsunami. This article provides different evidence on the impact of experiencing a natural disaster for risk and for time preferences: Sri Lankan workers affected by the tsunami are indeed more patient than unaffected workers. But Callen (2011) documents no change in worker risk preferences after the tsunami. Ali Bchir and Willinger (2013) consider the volcanic threat in Peru. They find that poor households are more risk seeking and more impatient in exposed areas than in unexposed areas, but not high income households. For households in Burundi, exposed to of violent conflicts, Voors et al. (2012) report that shocks such as drought and excess rainfall do not significantly impact risk preferences (while exposure to conflict does).

Except for Li et al. (2011), all the above papers use EU models for eliciting risk preferences with lottery games. Yet since the works of Allais and Ellsberg in the 1950s, psychologists and economists have provided substantial evidence that individuals do not necessarily behave according to the EU framework. One may argue that differences in decision-making observed after a natural disaster may not be imputed solely to a different curvature of the utility function but also to other modifications of individual preferences such as probability weighting. Our experimental design will allow us to assess these potential effects of natural disasters on individual preferences using a non-expected utility framework.[17]

II. Experimental Design

This section first explains how individual risk preferences have been specified. We then discuss our experimental protocol and risk preference elicitation method.

A. Risk Preference Specification

A large literature, in experimental economics and more recently in neuroscience (Levin et al. 2012), supports the view that risk preferences differ in the gain and in the loss domains. Flood experience may then have a different impact on risk preferences in these two domains, for Vietnamese households. To address this possibility, we assume that respondents's preferences follow the prospect theory (PT) framework (Kahneman and Tversky 1979, Tversky and Kahneman 1992). Under PT, individuals have sophisticated preferences that encompass reference dependence and probability weighting. Outcomes are considered as either gains or losses, with respect to a labile reference point, and individuals behave differently for gains and losses. Moreover, preferences are non linear in probabilities, to account for the fact that individuals distort probabilities into decision weights[18]

Therefore, in PT, risk behavior arises from the interplay of utility curvature, probability weighting, and reference dependence:

[17]The article by Callen et al. (2014) on the relationship between violent trauma and economic risk preferences in Afghanistan documents a specific preference for certainty, in violation of EU.

[18]The hypothesis of non linearity in probabilit.ies has received additional support from brain analysis using functional magnetic resonance imaging (Hsu et al. 2009): the activity in the striatum when subjects evaluate monetary gambles is non linear in probabilities.

$$u(y) \equiv \begin{cases} y^{\alpha} & \text{if } y > 0 \\ 0 & \text{if } y = 0 \\ -(-y)^{\beta} & \text{if } y < 0, \end{cases} \tag{1}$$

where α and β are two parameters representing the curvature of the utility function, respectively for the gain and the loss domains. Note that, due to empirical considerations, no loss aversion parameter is included.[19]

Under PT, the objective probabilities are distorted by a probability weighting function, $\omega(.)$.[20] The probability weighting function is strictly increasing from the unit interval onto itself and satisfies $\omega(0) = 0$ and $\omega(1) = 1$. Its specification has been widely discussed. We follow Gonzalez and Wu (1999) by assuming a linear relationship between the log of the weighted odds and the log probability odds:

$$\omega(p) \equiv \frac{p^{\gamma}}{p^{\gamma} + (1-p)^{\gamma}} \tag{2}$$

where γ is the parameter controlling the curvature of the probability weighting function. This parameter can be interpreted as an index of likelihood sensitivity, with $\gamma = 1$ in the absence of probability distortion ($\omega(p) = p$). The usual assumption, backed by a substantial amount of empirical evidence, is that $\gamma < 1$. This gives the weighting function an 'inverse S-shape', and characterizes an overweighing of low probability events and an underweighing of high probability events. If $\gamma > 1$, the function takes the less conventional 'S-shape', with convexity for

[19] In Tversky and Kahneman (1992) a loss aversion parameter is specified. The use of our simplified form has been dictated by empirical considerations. Our pilot experiment has indeed revealed that Vietnamese households had some difficulties manipulating lotteries involving both gains and losses, which are required for identifying loss aversion. Bruhin, Fehr-Duda and Epper (2010) also use a similar sign-dependent power function arguing that it is the best compromise between parsimony and goodness of fit in the context of prospect theory.

[20] Tversky and Kahneman (1992) consider different probability weighting functions, one for the gain domain and the other for the loss domain. However, in most empirical applications they are the same.

smaller probabilities and concavity for larger probabilities. At the extreme, when γ is very high, probabilities tend to be perceived as either 0 or 1.

With the above functional forms, risk preferences are characterized by three parameters: α and β represent the curvature of the utility function in the gain and in the loss domains respectively, and γ reflects the curvature of the probability weighting function.

B. Risk Tasks

We use incentivized lottery tasks to measure the risk preferences of households. Our approach is based on the experiment initially proposed in Eckel and Grossman (2002) (hereafter EG).[21] The EG task presents respondents with a limited set of gambles, lotteries with a 50/50 chance of winning a low prize or a high prize; they are then asked to choose the lottery they prefer. The lotteries are designed to be increasing in expected payoff and risk (standard deviation). An important advantage of this design is that it is simple enough to be easily understood by subjects outside the usual convenient sample of university students. This is very important in our context since many of our participants have received little or no education.

[Table 1, about here]

We extend the EG basic framework in several directions. First, we do not restrict individuals to play 50/50 chance lotteries: We use two additional tasks involving 40/60 and 20/80 chances of winning a low or a high prize. By varying probabilities, we can assess if subjects use non linear probability weights. Second, we introduce the possibility of making losses in order to elicit decisions both in the gain and in the loss domains. This is particularly important in our context since we expect households who have experienced a flood to have different risk-taking

[21] As mentioned by Dave et al. (2010), the EG task is in fact very similar to the one initially proposed by Binswanger (1980). The EG task has been used by, among others, Engle-Warnick et al. (2009), Dave et al. (2010) and Castillo et al. (2010), Eckel, El-Gamal and Wilson (2009) and Cameron and Shah (2012).

behaviors in these two domains. Lastly, we increase the number of lotteries in the gain domain from 5 to 9 in order to measure risk preferences in a more precise way.

Table 1 presents the five risk tasks completed by each individual. Tasks 1-3 involve only gains whereas tasks 4 and 5 involve only losses. The expected payoffs and standard deviation of payoffs decrease with the lottery number, so that a risk averse individual should select a lottery in the bottom of each task. The least risky, or 'safest' lotteries are lotteries 8 and 9 for tasks 1-3, and lottery 5 for tasks 4 and 5. We also report in the last column in Table 1 the risk aversion coefficient intervals implied by choosing a specific lottery in each task (assuming a CRRA utility function).

C. Risk Preference Elicitation

We use lottery choices to generate individual-specific intervals for each of the three parameters (α, β, γ) – cf., Tanaka, Camerer and Nguyen (2010), Liu (2013) or Harrison et al. (2013).

In Table 1, each lottery in tasks 1-5 can be written as $(X_{H,k}, X_{L,k}; p_{H,k})$, where $X_{H,k}$ and $X_{L,k}$ are the high and the low payoffs in lottery k, and $p_{H,k}$ is the probability of the high payoff. The utility derived from lottery k is $\omega(p_{H,k}) \cdot X^{\alpha}_{H,k} + \omega(1 - p_{H,k}) \cdot X^{\alpha}_{L,k}$. If lottery k is chosen, it means that it is preferred to lotteries $k-1$ and $k+1$, which translates into a system of equations that allows us to identify the parameters. Note that, in all five tasks, for subjects preferring the first (respectively the last) lottery, one can only infer an upper (respectively a lower) bound on the parameter to be estimated.

Task 1 involves only gains and equiprobabilities ($p_{H,k} = .5$). As a result, individual decisions depend only on α, the curvature of the utility function in the gain domain. If lottery k is chosen, it is preferred to lotteries $k-1$ and $k+1$, which translates into:

$$X^{\alpha}_{H,k} + X^{\alpha}_{L,k} > X^{\alpha}_{H,k-1} + X^{\alpha}_{L,k-1} \tag{3}$$

$$X^{\alpha}_{H,k} + X^{\alpha}_{L,k} > X^{\alpha}_{H,k+1} + X^{\alpha}_{L,k+1}. \tag{4}$$

This system of equations determines an interval $[\underline{\alpha}_k, \overline{\alpha}_k]$ for each preferred lottery k. The same logic will be applied to the other parameters to be estimated.

Tasks 4 and 5 only involve losses and equiprobabilities ($p_{H,k} = .5$). Individual decisions thus only depend on β, the curvature of the utility function in the loss domain. Applying the same logic as above to lottery k, $k = 1, \ldots, 5$, one obtains:

$$-(-X_{H,k})^{\beta} - (-X_{L,k})^{\beta} > -(-X_{H,k-1})^{\beta} - (-X_{L,k-1})^{\beta} \tag{5}$$

$$-(-X_{H,k})^{\beta} - (-X_{L,k})^{\beta} > -(-X_{H,k+1})^{\beta} - (-X_{L,k+1})^{\beta}. \tag{6}$$

This system of equations determines an interval $[\underline{\beta}_k, \overline{\beta}_k]$ for each preferred lottery k. For subjects preferring the first or the last lottery, only an upper or a lower bound for β can be inferred. Two intervals for the curvature of the utility function in the loss domain are elicited since we have two tasks and hence two observations per subject. This allows us to assess the stability of preferences across tasks.

Tasks 2 and 3 involve non-equiprobable lotteries in the gain domain. They allow us to identify a lower and an upper bound for the curvature of the probability weighting function (parameter γ), conditionally on the lottery choice in Task 1. As above, if lottery k is the preferred one, it is preferred to lotteries $k-1$ and

$k+1$:

(7) $(p_{H,k})^{\gamma} \cdot X_{H,k}^{\alpha} + (1-p_{H,k})^{\gamma} \cdot X_{L,k}^{\alpha} > (p_{H,k-1})^{\gamma} \cdot X_{H,k-1}^{\alpha} + (1-p_{H,k-1})^{\gamma} \cdot X_{L,k-1}^{\alpha}$

(8) $(p_{H,k})^{\gamma} \cdot X_{H,k}^{\alpha} + (1-p_{H,k})^{\gamma} \cdot X_{L,k}^{\alpha} > (p_{H,k+1})^{\gamma} \cdot X_{H,k+1}^{\alpha} + (1-p_{H,k+1})^{\gamma} \cdot X_{L,k+1}^{\alpha}$

This system of equations determines an interval $[\underline{\gamma}_k, \overline{\gamma}_k]$ depending on the preferred lottery k and conditionally on the preferred lottery in Task 1.

III. Data

We use data from a household survey we conducted with face-to-face interviews in the Nghe An province of Vietnam in 2012. This section describes the design of the questionnaire and concludes with a statistical analysis of household flood experience in our sample.

A. Questionnaire Development

From June 2011 to December 2011, several meetings involving research team members, water experts or local representatives (farmers, politicians and households) have been organized in the Nghe An Province. After a pilot study in December 2011 on 30 households, the questionnaire has been reshaped (especially for clarity) and the final survey (with face-to-face interviews) took place from April 4th to June 10th 2012, a period during which no flood or natural disaster was recorded in the Nghe An province.

The survey is structured into seven sections, not all of which are used in this article. We use

i) socio-demographic questions on household's income, housing characteristics and family structure,

ii) questions on the respondent's experience with flooding, flood damage and evacuation due to flood threats,

iii) and lottery games with monetary incentives, to elicit risk preferences, using the five lottery tasks described above (see online Appendix).

B. Sampling Strategy

The Nghe An Province is located in the central part of Vietnam, one of the regions of Vietnam which is the most exposed to floods. This province has a complicated topography with mountains and hills in the East and rivers and streams with a descending slope from the Northwest to the Southeast. The type of flood risk significantly differs according to location: In the mountains, households face flashflood risks with associated risks of landslides. In coastal areas, people are directly affected by typhoons and tropical storms. Finally, people located along rivers or living in delta river areas are affected by floods resulting from river overflows.

[Figure 1, about here]

Our sampling strategy has been the following. First, 14 districts (out of 17 in the Nghe An Province) have been selected based on geographical location (coastal area, plain area, mountain area). Following discussions with local representatives of the Ministry of Agriculture and Rural Development, two representative villages/communes have been targeted within each district (there are 417 villages/communes in the Nghe An Province). Finally, within each village/commune 16 households have been randomly selected from the village/commune listing of registered citizens. Our sampling stratification based on geographical location allows us to have in our data all types of flood which may affect the population in the Nghe An Province. Household random selection guarantees that our sample is representative of this population. Our sample is made of 448 households observed in 28 villages/communes from 14 district in the Nghe An province. [22]

Socio-demographic characteristics in the sample In our sample, the head of the household is 49.8 years old on average. The average household size is just above 4 and 16.7 percent of households have at least one child younger than three. The average household income in 2011 was VND 32.5 million per year (US$1560) – which is lower than the average for the Nghe An province in 2010 (VND 48 million, or US$2300). Farming (or fishing) is the main occupation for 79.2 percent of household heads. Employees represent 5.6 percent of our sample and retired households, 5.1 percent. Last, 30.6 percent of household heads have attended at least high school.

C. *Instructions and incentives for the Risk Tasks*

An important concern in risk preferences elicitation through lottery games is the extent to which subjects understand the instructions. Even if we have selected particularly simple tasks, the experiment could be complex to understand, especially with field subjects in a developing country. As many of our participants have received little or no education, we have provided all experimenters with clear and visual instructions to make it easier for illiterate subjects to understand the consequences of any decisions they made in the games. Moreover, before starting the risk tasks, we tested comprehension by asking test questions. Instructions for the experimental tasks are available in the online Appendix. To illustrate the chances of winning/losing money, we used ten balls numbered from 1 to 10. These balls were put into a bag, and subsequently stirred.

The lottery games are incentivized, allowing respondents to earn real money based on their answers. A respondent's payoff is determined in the following way: Each respondent was given a show-up fee of VND 85 000 (US$4.08), ensuring a strictly positive payoff even in case of losses in the lottery games. We randomly

[22]Some households refused to participate to the survey but they represent fewer than 10 percent of the households contacted.

selected one of the five risk tasks to be implemented with real money: Five numbered balls were put into a bag and a random draw of a ball determined the task to be implemented. Then, ten balls were put into the bag and the preferred lottery of the household was played. The average gain obtained by respondents in the lottery game was VND 37 800 (US$1.8) and it varied from VND -84 800 (US$-4.1) to VND 94 200 (US$4.5) in our sample. Including the show-up fee the average monetary gain was VND 122 800 (US$5.9) which represents 4.5 percent of the average monthly household income. Out of the 448 households interviewed, 370 households completed the risk tasks. This subsample is not significantly different from the global sample in terms of socioeconomic characteristics (including age, income or family size) nor of household flood experience.

D. Measuring Household Flooding Experience

We demonstrate that the cost of flooding is significant in our sample, which supports our view that floods are catastrophic events.

[Table 2, about here]

As mentioned previously, the Nghe An province is exposed to flooding. In Table 2, we present data about households' past experience with floods. To address the multi-dimensional nature of *flooding experience*, three variables have been used: flooding, evacuation and injuries. In our sample, 40.4 percent of households report that their house has been *flooded* at least once in the past 5 years (among these house-flooded households, 76.5 percent have been flooded for the last time in 2011). Second, 20.3 percent of respondents have been *evacuated* from their home due to a flood, at least once in the last 5 years (this type of flood experience may be considered as a traumatic event). A third important dimension of flood experience is its potential impact on health[23]: 4.9 percent of

[23]In a household survey carried out in Cao Lanh (Dong Thap Province of Vietnam), 75 percent of respondents were able to identify an impact of flooding on their health (USSH 2002). The most direct health impacts of flooding were deaths and injuries caused by the existence of floodwater in or around people's homes as stressed in Few, Tran and Hong (2004).

the respondents report that one member of the household has been *injured* due to a flood at least once in the past 5 years.

Concerning the *economic impact* of floods, 76.1 percent of households consider that flooding has represented a significant expenditure over the previous 5 years. To assess the actual cost of flooding, we asked respondents 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 2.[24] The average annual cost of flood damage caused to agricultural (and fishery) production is VND 3.5 million, i.e., 14.8 percent of household income on average. The average annual cost for flood damage caused to houses and house contents is slightly lower: VND 2.6 million per year (9.3 percent of the annual household income). Considering only households who reported a strictly positive damage due to flooding, we get an average damage to houses and house contents equal to VND 3.7 million per year. Damage to health ranks third, with a cost of only 1.2 percent 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 drastically increases to 23.98 percent of annual income. This indicates very high medical expenditures related to flooding. If we combine agricultural, house and health damage, the average annual cost of flood is VND 6.4 million per year, or 25.26 percent of the average annual household income. This is in line with Navrud, Tuan and Tinh (2012) who found, on a sample of Vietnamese households located in the Quang Nam Province, an average flood damage of approximately 20 percent of annual income.

[24]The flood costs reported by households are subjective. Additionally, respondents may overestimate or underestimate their real flood expenses for strategic or psychological reasons, or simply because this information is not easily available. Flood costs reported here should thus be treated with caution. We use robustness checks for these measures in our econometric analysis, cf. Section V.

IV. Individual Risk Preferences and Flood Experience

This section first provides evidence that flood exposure is random, by showing that our sample is balanced on retrospective variables and on fixed variables which should not be altered by flood exposure. We then present evidence of changes in risk preferences induced by a flood experience.

A. Identification Strategy

Following Cameron and Shah (2012), our empirical strategy consists in regressing our risk attitude measures on the household flood experience measures, while controlling for household, individual, and geographic characteristics fixed effects. We claim that this captures the causal effect of flood on risk attitudes since the natural disaster is an unexpected shock.[25]

[Table 3, about here]

However, if people who have been affected by a flood are different, on relevant characteristics, from these who have not been affected, this approach will suffer from a selection bias (Cameron and Shah 2012). More specifically, more risk-averse households may decide to live in an area where the likelihood of being flooded is lower. They may also be more likely to relocate to a safer area after having experienced a first traumatic flood. For these reasons, we could observe a correlation between risk preferences and being affected by a flood. If wealthier households live in areas with a low flood risk and if risk preferences are related to income, we could observe a positive correlation between flood experience and risk aversion that has nothing to do with a causal relationship.

To examine this issue, we present in Table 3 the mean and standard deviation of different individual or household characteristics according to their flood experience. Most of differences are not significantly different. Gender, education and

[25]Similar identifying assumptions have been used by Page, Savage and Torgler (2012) for flood risks and by Callen (2011) and Cassar, Healy and von Kessler (2011) for Tsunami risks.

household size, which are among the strongest and most consistent predictors of risk preferences across studies, appear not to statistically differ across samples. There is no indication of a selection effect. In particular, none of the differences is significant for households reporting flood injuries (the most traumatic flooding experience). Households who experienced a flood in the past five years are not different from those who did not. Thus, we can compare the risk preferences of households affected by a flood with those of unaffected households to determine the causal effect of experiencing a flood on risk preferences.

B. Preferred Lotteries and Flooding Experience

This subsection considers the preferred lotteries in the five risk tasks and provides a preliminary econometric analysis of choices in these tasks, when no parametric assumptions on utility functions are made.

[Table 4, about here]

Table 4 documents the percentage of respondents who prefer each lottery, for each task. Results are presented for all households, for households whose house has been flooded at least once in the past 5 years, for households who have been evacuated at least once from their home in the last 5 years and for households who have suffered from at least one injury in the last 5 years. We also report results according to flooding intensity in the past 5 years, separating households reporting a water elevation in their house greater than 100 cm at least once, and households who have been flooded more than 8 days per year.

Table 4 calls for a few comments. First, the distributions of preferred lotteries appear to often be bimodal with a particularly high proportion of respondents choosing one of the extreme lotteries. For the 'gain' tasks (tasks 1-3), approximatively 50 percent of respondents choose an interior lottery (lotteries 2-8). Depending on the task, between 27.6 percent and 32.1 percent of respondents prefer the riskiest lottery (lottery 1) whereas between 17.9 percent and 27.6 percent prefer the safest one (lottery 9). This indicates a high heterogeneity of risk preferences in the gain domain. It is even more important in the loss domain (tasks 4 and 5) since approximatively 25 percent of respondents prefer the riskiest lottery (lottery 1) whereas a little more than 50 percent prefer the safest one (lottery 5).

At this stage of the analysis, flood experience appears to have a significant impact on the preferred lottery, especially in the gain domain. Respectively 37.5 percent, 31.5 percent and 18.9 percent of households having experienced at least one house flooding over the last five years prefer the safest lottery (lottery 9) in tasks 1, 2 and 3, compared to only 15.4 percent, 23 percent and 17 percent for households who have not experienced house flooding. However, since these differences might be imputed to characteristics of respondents (income, family size, etc.), the next subsections will address in detail the impact of experience on risk choices.

[Table 5, about here]

Table 5 presents the results of discrete choice models where the dependent variable is a dummy variable equal to 1 if an individual selects one of the two least risky, 'safest', lotteries (lotteries 8 and 9) in the tasks with gains, or the least risky lottery (lottery 5) in the tasks with losses. Since each subject participated in five tasks, we use panel estimation with unobserved individual effects modeled using a random-effects specification.

Our explanatory variables include socioeconomic characteristics of the household (age, gender, income, education), a dummy variable for tasks in the loss domain, a variable measuring a household's expectation about future flood damage and a variable measuring household participation to social and informal networks.

Respondents were asked to rank the flood damage they expect for their household in the next 10 years, on a scale going from 1 (no losses and no damage) to 10 (critical damage and losses). We argue that this variable provides a valid measure of personal background risk perception, which is known to be an important determinant of decision-making under risk (Gollier and Pratt 1996, Quiggin 2003). We discuss another variable that has been used in the literature (Cameron and Shah 2012), and contrast the results obtained with the different measures in Section V.

Since informal networks play an important role in risk management in developing countries (Townsend 1994), they should be included as a potential determinant of decision-making under risk. Measuring social network participation at the household level is challenging however due to a high level of heterogeneity. We use as a proxy the number of institutions/organisations each household belongs to. Each respondent selected the organizations to whom he belonged within a list of twenty (including the Communist Party, religious groups, labor unions, professional associations, veteran associations) to which he could add a name if needed. The intensity of social connections is captured by the number of institutions/organisations each household belongs to (on average 2.7). While 14.51 percent of households don't belong to any organization, 15.85 percent report a high level of social interactions (at least 5 different organizations).

Several results from Table 5 are worth being pointed out.

i) *Flood experience* is a strong predictor of choosing the safest lotteries. All coefficients of variables measuring flood experience are positive. Being flooded is significant at 1 percent, being evacuated at 5 percent. The intensity of flooding also matters since the likelihood of choosing the safest lotteries increases with the average duration of floods at 5 percent (flood elevation is almost significant at 10 percent). These preliminary results suggest that behaviors in lottery tasks are affected by individual flood experience.

ii) Interestingly, households exhibit significantly *different behavior in the loss and gain domains*. We find that households are much more likely to select the safest lotteries in the loss domain than in the gain domain. This result, which confirms the need to consider different parameters in these two domains, is in line with the literature on risk preferences.

iii) Our measure of *expectations* about future flood damage has a significant and negative coefficient: Respondents who expect a high future flood damage have a lower likelihood of selecting the safest lotteries. An interesting interpretation is that this variable measures background risk. The negative relationship we obtain is then difficult to understand within an expected utility framework. Within an expected utility framework and under some assumptions, Gollier and Pratt (1996) have shown that an increase in background risk leads to more risk-aversion, in contradiction with our finding. Our result is however compatible with non expected utility behaviors. Quiggin (2003) has for instance shown that for a non-expected utility including probability weighting, adding more background risk can actually increase the propensity of a decision-maker to select riskier choices – as in our sample. For prospect utility, Beaud and Willinger (2013) show that a higher background risk has an ambiguous effect on risk-taking.

iv) Household income is highly significant in all the models considered. Respondents with a high income are less likely to select the safest lotteries in the experimental tasks, so risk-aversion seems to be decreasing in wealth (as for farmers in China (Liu 2013) or Ethiopia (Yesuf and Bluffstone 2009)). The type of professional occupation also matters. Being highly dependent on agricultural activities is associated with more risky choices – possibly due to self-selection into a riskier activity, or increasing risk tolerance due to contextual effects. Conversely, the individual characteristics of the respondent (age, gender, education) appear not to be significant.[26]

v) Households with a large *social network* are also more likely to select the safest lotteries. Informal networks play an important risk diversification role in developing countries, which would intuitively lead to more risk taking. However, two effects go in the opposite direction, and seem to dominate in our sample: a

[26]For comparison, Tanaka, Camerer and Nguyen (2010) report that gender (as here), ethnicity and income (contrary to here) were non significant in explaining risk preferences for a sample of Vietnamese households.

matching and a selection-bias effects. Households who are more risk-averse can be viewed as 'safer' and more attractive connections, making it easier for them to math with others; They are also likely to invest more effort in developing their informal networks.

C. Interval Regressions of Individual Preference Parameters

Let us now consider some explanatory models for the three parameters (α, β and γ) that describe risk preferences according to our PT specification. The dependent variables are the intervals for α, β and γ that subjects implicitly choose when they select their preferred lotteries in the five risk tasks. All models are thus estimated using regressions with interval censoring (interval regression).[27] Table 6 first presents estimates assuming homogenous risk preferences across individuals. In the second part of this table we introduce different measures of flood experience while, in the last part, we control for individual characteristics of the respondent or the household.

[Table 6, about here]

In the homogenous preference model presented in panel A, the coefficients for the curvature of the utility function are positive and significant in both the gain and the loss domains: the utility function is concave for gains and convex for losses. This *S-shape* of the utility function reflects a diminishing sensitivity to changes away from the reference point, taken to be zero. More importantly, we find that Vietnamese households appear to have *domain-specific* risk preferences. Indeed, the coefficient measuring utility curvature in the gain domain is significantly greater than the one for the loss domain ($p < 0.0001$): A given payoff change will result in a greater utility change in the gain domain than in the loss domain. This result implies that Vietnamese households may adopt different be-

[27]Interval regression was first used in the context of experimental data by Coller and Williams (1999) for discount factor elicitation. It has been recently used for risk preferences by Harrison and Rutström (2008).

haviors in the gain and in the loss domains. Those different behaviors would have not been captured by an expected utility model with a single risk aversion parameter. In what follows, we will assess if flood experience has a uniform impact on risk preferences in both domains or, to the contrary, a differentiated impact.

The third part of panel A provides some evidence of probability distortions. Coefficient γ is significantly different from one ($p < 0.0001$): respondents do not use linear probability weighting in risk tasks. The probability weight estimates is 1.14, indicating that respondents underestimate low probabilities and overestimates high probabilities. This S shape of the probability weighting function is quite unusual in the literature. However, Tanaka, Camerer and Nguyen (2010) and Liu (2013) obtain a similar pattern on a sample of Vietnamese households and Chinese farmers, respectively. Since flood is, mathematically, a rather low probability event, our result suggests that Vietnamese households will tend to underestimate its probability. This result has important policy implications: Launching education campaigns to raise public awareness about floods and their frequency may be effective in fostering preparation and prevention in Vietnam.

Panel B relates to the heterogeneous risk preference model in which the three parameters α, β and γ, are only impacted by flood experience. i) First, although flood experience significantly shapes the utility function in the loss domain (being flooded and evacuated are significant at 10 percent and 1 percent, respectively), no significant impact is found in the gain domain. This differentiated impact may help reconciliating previous works in the literature; some indeed report a significant impact of natural disaster on risk preferences (Eckel, El-Gamal and Wilson 2009, Andrabi and Das 2010, Li et al. 2011, Cameron and Shah 2012, Cassar, Healy and von Kessler 2011, Callen 2011) while others find no impact (Callen 2011, Voors et al. 2012, Ali Bchir and Willinger 2013).

ii) Second, households who have been flooded or evacuated are more risk averse in the loss domain (the estimated coefficients of these two variables are negative).

iii) Third, we find no impact of flood experience on probability weighting. Vietnamese households underestimate low probabilities and overestimate high probabilities, but these distortions are unrelated to flood experience.

We already mentioned that the underestimation of low probabilities may lead to insufficient prevention. In addition, the fact that this under-weighing is not related to flood experience may raise another issue: The absence of a significant relationship between flood experience and perceived probabilities is rational if flood events are independent. But if they are correlated, some updating should occur after experiencing a flood. Then our last result could reflect mistaken or even irrational beliefs. In that case, education and informational campaigns about flood risks could be quite valuable for an additional reason than the one discussed above.

The estimates of the heterogeneous risk preference model controlling for individual characteristics, are consistent with the findings above. Risk preferences in the gain domain are almost not affected by flood experience. Only households reporting a maximal water elevation in their house greater than 100 cm at least once in the last 5 years appear to be more risk averse in the gain domain. Risk preferences in the loss domain are much more impacted since being flooded or evacuated are significant, together with reporting an average duration of flood greater than 8 days per year. Households having experienced flooding tend to be more risk averse in the loss domain. Only a few characteristics of respondents appear to be significant for explaining utility curvature in the gain and in the loss domains. Older respondents appear to be less risk averse in the gain domain – a rather unusual result (von Gaudecker, van Soest and Wengstrom 2011, Dohmen et al. 2012) – but no significant impact is found in the loss domain. A positive relationship between income and utility curvature is found in the loss domain – suggesting that richer households are less risk averse in that domain. Households engaged in agricultural activities – that are inherently risky – are also less risk averse; as mentioned, this is possibly due to habituation or to self-selection into those activities. Lastly, probability weighting is not affected by any of the respondent's characteristics, which suggests highly homogenous preferences with respect to this parameter.

V. Complementary analyses

In this section, we further investigate preference changes and conduct some robustness analyzes by considering additional control variables. We assess in particular the impact of a different measure for background risk, of time preferences and of financial and material support received by households after a flood.

A. Background Risk

As discussed previously, the theoretical impact of adding a background risk on risk-taking behaviors strongly depends upon the form of the risk preferences (Gollier and Pratt 1996, Quiggin 2003).

Using a household's expectation about future flood damage as a proxy for the background risk, we have shown that respondents who expect a high future flood damage (high background risk) have a lower likelihood of selecting the safest lotteries. We here explore the robustness of this result by considering an alternative measure of the background risk.

Cameron and Shah (2012) use the village mean number of earthquakes and floods as a proxy for background risk. If flood risk perception has indeed been shown to be influenced by early disaster experiences, several other factors including socio-demographic characteristics, knowledge about hazards, institution trust, or feelings and emotions play an important role in shaping flood risk perception (Bubeck, Botzen and Aerts 2012). For this reason, we believe that background risk perception cannot be fully assessed through past disaster experience, and that our measure of expectations about future flood damage constitutes a better measure. It is however interesting to assess whether our results change with another measure. Aside from testing for robustness, there are two main reasons justifying to replace individual flood experience variables by village-level averages. First, reported individual flood experience measures may be strategically altered if respondents believed that the survey could be used by policy-makers. Second, the risk behavior of an individual who has not been directly affected by a flood in the past five years could still be modified if a large proportion of his neighbors has been affected. Interestingly, witnessing the effects of a flood on neighbors is likely to trigger less emotional upheaval than experiencing it oneself, even though the informative content of the event is quite similar.

Following Cameron and Shah (2012), we re-estimate our models, replacing the individual flood experience measures by village-level averages. Village-level mean flood exposure provides an alternative measure of background risk. We posit that the occurrence of a flood induces a change in the perception of background risk, and use mean exposure as a proxy for this perception.[28]

[Table 7, about here]

We find that the village-level measure of background risk has an impact neither on the curvature of the utility function in the gain domain, nor on the probability weighting parameter, see Table 7.[29]

We find however a significant and negative impact on the curvature of the utility function in the loss domain: a higher village-level background risk is associated with a lower propensity to choose the riskier lottery. This result strongly differs from the one we obtain with our individual, expectations-based measure. A possible explanation is that the village-level variable does not integrate the same emotional content as personal experience. One's personal experience, due to its emotional valence, may affect the way one updates one's beliefs about risk based on the prevalence of floods at the village level. If this is the case, the village measure would very imperfectly correlate with the change in risk perception, and

[28] While village experience is an objective measure, the change in individuals' background risk perception that it induces may remain quite personal.

[29] In Table 7, flood experience is measured by the fact that a household has been flooded at least once in the last 5 years. Results for being evacuated or injured are available from the author upon request.

this would explain why we observe a different impact when using the two measures. None of the variables which were significant with the individual measure of background risk is impacted by the inclusion of the village-level measure.

B. Time Preferences

A potential concern is that we do not control for time preferences whereas risk and time preferences might be correlated within individuals (Dohmen et al. 2010). If they are indeed correlated, our risk aversion results could be biased due to the omission of individual time preferences (Cameron and Shah 2012). We thus include individual discount factors in the regressions as an additional control variable.[30] The discount factor in never significant in the regressions, see Table 7. Moreover our main results about risk aversion are unchanged. The omission of time preferences therefore appears unproblematic.

C. Temporary Versus Permanent Change in Preferences

Determining if observed preference changes following natural disasters are temporary or permanent remains an opened question. And the answer may depend upon the context. Eckel, El-Gamal and Wilson (2009) report for instance that that changed risk preferences appear to attenuate within one year while Cameron and Shah (2012) and Callen (2011) document effects respectively up to two and a half years, and nine years after exposure. Cassar, Healy and von Kessler (2011) report that preferences in Thailand are significantly different for the respondents who lived in areas hit the hardest by the 2004 tsunami, four and a half years after.

[30]In our survey individual time preferences are elicited trough hypothetical questions using a double referendum format. Each household has been asked if he prefers VND 1,000,000 today or VND 1,400,000 in one year from now. If VND 1,000,000 today was preferred then the household was proposed VND 1,600,000 in one year. If the delayed option was preferred in the first question, the household was asked to choose between VND 1,000,000 today or VND 1,200,000 in one year. This double referendum format results in classifying individual time preferences into four categories for the discount rate ($[0, 20\%]$, $[20\%, 40\%]$, $[40\%, 60\%]$ and $> 60\%$). A large majority of subjects have a discount rate greater than 60% (68 percent of our sample). The discount rate belongs to $[0, 20\%]$ only for 3.5 percent of our sample. We have then considered the lower bound of individual discount rates as a potential explanatory variable of risk preference parameters.

For each type of flood experience (being flooded, evacuated or injured) we asked each individual the month and year when the last event occurred. This gives us some measures of the time-lag with the flood event. Since the Nghe An province has been affected by particularly strong floods in 2011, the average time lags are very similar for the three types of flood experience: a year and a month for being injured, a year and two months for being flooded or evacuated. As a result we retained only the time lag for being flooded in our estimates.

As shown in Table 7, the time lag is never significant in our estimated models which would suggest that the shift in risk preferences after a flood persists over time, without significant attenuation over the relevant time period.

D. Aid Received by Households After a Disaster

Another issue is that some households having experienced a flood may have received some form of aid (either formal or informal) whereas other may not. This may create a problem for two reasons. First, receiving some aid might create an income effect which is not necessarily included into income data reported by respondents. Second, receiving some aid may modify individual preferences. Cameron and Shah (2012) find for example that receiving help from others – whether friends or institutional sources – made people more trusting in the long run. Similar findings are reported by Andrabi and Das (2010) after an earthquake in Pakistan.

To address these issues, we asked each household if he received any form of aid (financial or material) after having experienced a flood. Aid from local authorities is reported by 62.97 percent of households. This figure drops to 47.02 percent for national authorities and to 48.35 percent for aid from social networks (family, friends, neighbors, community associations and NGOs). In case of flood, Vietnamese local authorities are indeed in charge of relief distribution to flood victims. We find a significant impact on individual risk preferences of receiving aid from local authorities or from social networks. Household having received some aid from social network appears to be *less risk averse* in the gain domain. A similar impact is found for aid received from local authorities in the loss domain.

We also find that receiving aid after a flood shapes in a significant way probability weighting, with a differential impact depending upon aid provider. Households having received aid from local authorities distort probabilities in a very limited way whereas the S-shape of the probability weighting function is exacerbated for households benefitting from aid from social networks. This impact may have to do with the perception of households about their ability to face adverse events. It is however difficult to asses, as aid from local authorities and from social networks differ in two important dimensions: First, local authorities intervene in case of a flood but not in case of private adverse events, contrary to social networks; Second, aid from local authorities does not impose significant costs, contrary to aid from social networks, that entails reciprocity, reimbursement and providing for less favored members, when one benefits from 'good times'. The fact that social networks insure households, by attenuating both large losses and large gains, may make exceptional events less important. This would correspond to this exacerbating of the S-shape function for probabilities.

VI. Conclusion

Modifications of individual behaviors following natural disasters have been documented for various contexts of decision-making including income and international financial flows (Yang 2008), migration decisions (Paxson and Rouse 2008, Boustan, Kahn and Rhode 2012), and fertility and education investments (Baez, de la Fuente and Santos 2010). Although causality might be difficult to establish (due to mobility and selective migration in particular), some recent studies suggest that these modifications may be related to the fact that individuals exposed to natural disasters have their (risk) preferences lastingly changed. The precise impact of a disaster on preferences is the object of our study.

We have studied whether flood occurrence affects risk-taking for Vietnamese households, within a non-expected utility setting (prospect utility). We have gathered experimental data (in 2012 in the Nghe An Province), implementing standard lottery games (using real money) with randomly selected individuals; This has allowed us to test if households living in villages that have been exposed to floods exhibit different types of risk preferences.

We first find that flood experience significantly shapes risk preferences in the loss domain, households who have been flooded or evacuated being more risk averse in that case. Flood experience has however no significant impact in the gain domain. This differential impact in the loss and gain domains may help explain why some previous works report a significant impact of natural disasters on risk preferences (Eckel, El-Gamal and Wilson 2009, Andrabi and Das 2010, Li et al. 2011, Cameron and Shah 2012, Cassar, Healy and von Kessler 2011, Callen 2011) while others do not (Callen 2011, Voors et al. 2012). It suggests that a large part of the impact of disasters on preferences may come from emotions. Psychological and neurological studies indeed indicate that emotions are more intensely triggered, and more lasting, for losses than for gains. A reason for different risk preferences in the gain and in the loss domains may come from anticipation of regret. Rational individuals could anticipate a stronger emotional impact for losses than for gains.[31] Our results are thus of interest for psychologists, who stress the role of emotions in preference changes.

Second, we find no impact of flood experience on probability weighting. Vietnamese households underestimate low probabilities and overestimate high probabilities, but interestingly, these distortions are unrelated to flood experience. We have argued that our findings may have important policy implications: they imply that education and informational campaigns about flood risks could be quite valuable, in order to foster prevention despite behavioral biases in probability weighting.

[31] For instance, Coricelli et al. (2005) show with fMRI analyses that activation of the orbitofrontal cortex is much larger for negative comparisons between an obtained gain and the potential gain expected, than for positive comparisons.

We also contribute to the empirical literature which assesses the impact of background risk on risk-taking behaviors. So far, the existing empirical investigations of the risk vulnerability conjecture are not fully conclusive. Our empirical analysis reveals that the measure used for background risk plays a crucial role. With the measure we favor, because it is based on individual expectations, a higher background risk is associated with more risk taking. We obtain an opposite result with a measure based on local (village) experience, a result in line with the risk vulnerability conjecture. This may be viewed as an additional indication that emotions, that are more intense for losses than for gains, play an important role. For both measures, flood experience retains its significance in risk preferences. This indicates that the impact of flood on preferences is not limited to a change in background risk perception.

Our results also highlight that receiving aid make individuals more risk-taking. Interestingly, receiving aid also impacts the way individuals assess probabilities, but in a very different way depending on the source of aid: aid from local authorities limits probability distortions while aid from social networks, perhaps due to expected contributions in good times, amplifies the S-shape of the probability weighting function.

Last, we also observe no attenuation of the impact of floods when the time lag since the last occurrence increases, at least in the time range represented in our data. Given this persistence, it is particularly important to take into account the indirect effects of disasters via risk behavior.

Table 1—Definition of risk tasks

Task Number	Domain	Lottery Number	Payoff (high)	Prob. (high)	Payoff (low)	Prob. (low)	CRRA interval*
1	Gain	1	94,200	0.5	3,600	0.5	$-\infty$;0.13
1	Gain	2	93,600	0.5	3,800	0.5	0.13;0.17
1	Gain	3	90,000	0.5	6,000	0.5	0.17;0.20
1	Gain	4	85,200	0.5	9,000	0.5	0.20;0.40
1	Gain	5	81,000	0.5	10,800	0.5	0.40;0.64
1	Gain	6	73,200	0.5	13,200	0.5	0.64;0.87
1	Gain	7	66,000	0.5	15,000	0.5	0.87;1.10
1	Gain	8	63,000	0.5	15,600	0.5	1.10;1.32
1	Gain	9	59,400	0.5	16,200	0.5	1.32;$+\infty$
2	Gain	1	87,500	0.6	10,000	0.4	$-\infty$;0.22
2	Gain	2	82,500	0.6	15,000	0.4	0.22;0.27
2	Gain	3	77,500	0.6	20,000	0.4	0.27;0.45
2	Gain	4	74,000	0.6	23,000	0.4	0.45;0.77
2	Gain	5	71,000	0.6	25,000	0.4	0.77;0.81
2	Gain	6	67,500	0.6	27,500	0.4	0.81;0.89
2	Gain	7	64,000	0.6	30,000	0.4	0.89;1.15
2	Gain	8	61,000	0.6	32,000	0.4	1.15;1.37
2	Gain	9	58,000	0.6	34,000	0.4	1.37;$+\infty$
3	Gain	1	60,000	0.8	7,000	0.2	$-\infty$;0.15
3	Gain	2	59,000	0.8	10,000	0.2	0.15;0.29
3	Gain	3	58,000	0.8	13,000	0.2	0.29;0.50
3	Gain	4	57,000	0.8	15,000	0.2	0.50;0.77
3	Gain	5	56,000	0.8	16,500	0.2	0.77;0.84
3	Gain	6	55,000	0.8	18,000	0.2	0.84;0.92
3	Gain	7	54,000	0.8	19,500	0.2	0.92;1.40
3	Gain	8	53,000	0.8	20,500	0.2	1.40;1.51
3	Gain	9	52,000	0.8	21,500	0.2	1.51;$+\infty$
4	Loss	1	-4,000	0.5	-84,800	0.5	$-\infty$;0.07
4	Loss	2	-8,000	0.5	-80,000	0.5	0.07;0.24
4	Loss	3	-9,600	0.5	-76,000	0.5	0.24;0.81
4	Loss	4	-10,400	0.5	-72,000	0.5	0.81;1.10
4	Loss	5	-11,200	0.5	-68,800	0.5	1.10;$+\infty$
5	Loss	1	-12,500	0.5	-50,000	0.5	$-\infty$;0.3
5	Loss	2	-16,000	0.5	-45,000	0.5	0.30;0.58
5	Loss	3	-19,000	0.5	-40,000	0.5	0.58;0.76
5	Loss	4	-20,500	0.5	-37,500	0.5	0.76;0.96
5	Loss	5	-22,000	0.5	-35,000	0.5	0.96;$+\infty$

Note: This table describes the five experimental tasks used to elicit prospect theory preferences of households. All payoffs are expressed in Vietnamese Dongs (VND). The official exchange rate is 1 US$ for VND 20,833 on April 2013.

*: Implied interval assuming a constant relative risk aversion utility function.

Table 2—Household flood history and cost of flooding in the last 5 years

Variable	Mean	SD
Panel A. Household flood history in the last 5 years		
House flooded at least once (0,1)	0.404	0.491
Respondent evacuated at least once (0,1)	0.203	0.403
One household member injured at least once (0,1)	0.049	0.216
Panel B. Cost of flooding (annual mean based on the last 5 years)		
Flooding has represented a significant cost (0,1)	0.761	0.427
House cost (VND million)	2.636	6.543
Agricultural cost (VND million)	3.536	7.720
Health cost (VND million)	0.249	1.320
Total cost (VND million)	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

Note: SD is the standard deviation. Due to missing answers, flood costs reported in Panel B have been computed on a sub-sample of 407 households.

TABLE 3—T-TESTS OF EQUALITY DEPENDING ON HOUSEHOLDS FLOOD EXPERIENCE

Variable	Household flooded			Household evacuated			Household injured		
	Yes	No		Yes	No		Yes	No	
	Mean	Mean	P-value	Mean	Mean	P-value	Mean	Mean	P-value
Age of household's head (years)	51.15	48.96	0.09	52.32	49.22	0.05	47.05	49.99	0.32
	(13.87)	(13.23)		(14.24)	(13.28)		(12.55)	(13.57)	
Household's head has attended high school (0,1)	0.31	0.30	0.89	0.30	0.31	0.83	0.41	0.30	0.28
	(0.46)	(0.46)		(0.46)	(0.46)		(0.50)	(0.46)	
Number of household's members	4.21	4.19	0.90	4.25	4.18	0.70	4.32	4.19	0.70
	(1.56)	(1.47)		(1.64)	(1.47)		(2.06)	(1.48)	
Main occupation of household's head is agriculture (0,1)	0.71	0.85	0.00	0.60	0.84	0.00	0.86	0.79	0.40
	(0.46)	(0.36)		(0.49)	(0.37)		(0.35)	(0.41)	
Child under 3 years in the household (0,1)	0.20	0.18	0.70	0.20	0.19	0.84	0.32	0.18	0.14
	(0.43)	(0.42)		(0.40)	(0.43)		(0.57)	(0.41)	
Holds a health insurance (0,1)	0.42	0.45	0.49	0.34	0.46	0.03	0.41	0.44	0.77
	(0.49)	(0.50)		(0.48)	(0.50)		(0.50)	(0.50)	
Holds a life insurance (0,1)	0.03	0.06	0.20	0.05	0.05	0.77	0.09	0.05	0.35
	(0.18)	(0.24)		(0.23)	(0.21)		(0.29)	(0.21)	
Number of years in current housing (years)	36.84	30.33	0.00	35.31	32.36	0.18	28.86	33.17	0.29
	(19.39)	(17.79)		(18.93)	(18.63)		(14.78)	(18.88)	
Household's head is male (0,1)	0.86	0.90	0.17	0.87	0.89	0.65	0.82	0.88	0.35
	(0.35)	(0.30)		(0.34)	(0.32)		(0.39)	(0.32)	
Number of organization memberships	2.95	2.51	0.06	3.02	2.61	0.13	2.32	2.71	0.45
	(2.41)	(2.33)		(2.30)	(2.38)		(2.21)	(2.38)	
Household has received remittances in the past year (0,1)	0.05	0.04	0.81	0.05	0.04	0.68	0.05	0.05	0.97
	(0.22)	(0.21)		(0.23)	(0.21)		(0.21)	(0.21)	
A household member works abroad (0,1)	0.09	0.04	0.02	0.12	0.05	0.01	0.09	0.06	0.57
	(0.29)	(0.20)		(0.33)	(0.21)		(0.29)	(0.24)	

Note: Standard deviations are in parenthesis.

Table 4—Distribution of subjects per preferred lottery in the five risk tasks (in percent)

		Lottery Number								
		Most risky							Least risky	
	N	1	2	3	4	5	6	7	8	9
Task 1 (gain)										
All households	370	20.8	11.6	13.5	10.0	12.7	7.3	8.7	5.7	9.7
Households with house flooded	153	21.6	9.2	13.1	7.8	13.7	7.8	7.8	5.9	13.1
Households evacuated	79	24.1	8.9	12.7	11.4	10.1	7.6	7.6	5.1	12.7
Households injured	19	42.1	10.5	10.5	5.3	0.0	10.5	5.3	5.3	10.5
Flood elevation $\geq$ 100 cm	33	18.2	6.1	6.1	12.1	18.2	12.1	3.0	9.1	15.2
Flood duration $\geq$ 8 days	65	23.1	9.2	16.9	6.2	9.2	7.7	7.7	3.1	16.9
Task 2 (gain)										
All households	370	15.7	24.9	16.0	7.6	4.9	6.0	8.9	4.9	11.4
Households with house flooded	153	17.7	19.6	13.7	7.8	5.2	6.5	9.2	5.2	15.0
Households evacuated	79	15.2	21.5	15.2	7.6	5.1	6.3	7.6	5.1	16.5
Households injured	19	21.1	26.3	15.8	10.5	10.5	5.3	5.3	5.3	0.0
Flood elevation $\geq$ 100 cm	33	21.2	9.1	12.1	9.1	3.0	3.0	12.1	6.1	24.2
Flood duration $\geq$ 8 days	65	18.5	21.5	18.5	6.2	6.2	4.6	1.5	6.2	16.9
Task 3 (gain)										
All households	370	18.7	14.1	14.6	14.3	13.8	9.7	3.8	8.1	3.0
Households with house flooded	153	17.7	12.4	15.7	12.4	15.0	8.5	3.3	11.1	3.9
Households evacuated	79	15.2	11.4	15.2	17.7	15.2	7.6	3.8	12.7	1.3
Households injured	19	15.8	15.8	10.5	15.8	21.1	10.5	0.0	0.0	10.5
Flood elevation $\geq$ 100 cm	33	15.2	6.1	12.1	15.2	18.2	9.1	6.1	15.2	3.0
Flood duration $\geq$ 8 days	65	15.4	10.8	13.9	12.3	20.0	4.6	6.2	12.3	4.6
Task 4 (loss)										
All households	370	15.1	17.8	21.1	23.8	22.2				
Households with house flooded	153	14.4	16.3	19.0	22.2	28.1				
Households evacuated	79	11.4	13.9	19.0	26.6	29.1				
Households injured	19	5.3	31.6	10.5	31.6	21.1				
Flood elevation $\geq$ 100 cm	33	15.2	9.1	21.2	39.4	15.2				
Flood duration $\geq$ 8 days	65	15.1	17.8	21.1	23.8	22.2				
Task 5 (loss)										
All households	370	11.9	22.4	24.1	16.2	25.4				
Households with house flooded	153	11.8	17.7	26.8	12.4	31.4				
Households evacuated	79	6.3	13.9	25.3	16.5	38.0				
Households injured	19	0.0	10.5	36.8	10.5	42.1				
Flood elevation $\geq$ 100 cm	33	15.2	15.2	18.2	21.2	30.3				
Flood duration $\geq$ 8 days	65	12.3	12.3	30.8	15.4	29.2				

Note: N is the sample size. *All households* corresponds to the full sample. *Households with house flooded*, *Households evacuated* and *Households injured* respectively correspond to households whose house has been flooded at least once in the last 5 years, to households who have been evacuated at least once from their home in the last 5 years and to households who have suffered from at least one injury in the last 5 years. *Flood elevation $\geq$ 100 cm* is the subsample of households reporting a water elevation in their house greater than 100 cm at least once in the last 5 years and *Flood duration $\geq$ 8 days* corresponds to households reporting that their house has been flooded more than 8 days per year on average in the last 5 years. All figures are in percent. For instance, in Task 1, 20.8 percent of the respondents (370 households) declare to prefer lottery 1. If we restrict the sample to households reporting that their house has been flooded at least once in the last 5 years (153 households), this percentage increases slightly to 21.6 percent.

Table 5—Logit models for explaining the choice of selecting the safest lottery in risk tasks

	Models				
	(1)	(2)	(3)	(4)	(5)
Annual income (VND million)	-0.01**	-0.01**	-0.01**	-0.01**	-0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share of income coming from agriculture	-0.58**	-0.58**	-0.71**	-0.68**	-0.65**
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)
Age of respondent (years)	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Respondent is female (0,1)	-0.05	0.01	-0.01	-0.07	-0.02
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Respondent has attended high school (0,1)	-0.05	-0.07	-0.12	-0.11	-0.12
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
Number of organization memberships	0.09*	0.10**	0.10**	0.10**	0.10**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Future flood damage (index 1–10)	-0.16***	-0.15***	-0.15***	-0.16***	-0.16***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Task in loss domain (0,1)	0.81***	0.81***	0.81***	0.81***	0.81***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Household flooded at least once (0,1)	0.69***				
	(0.21)				
Household evacuated at least once (0,1)		0.58**			
		(0.25)			
Household injured at least once (0,1)			0.23		
			(0.47)		
Water elevation in house greater than 1 meter (0,1)				0.55	
				(0.35)	
Household flooded more than 8 days per year (0,1)					0.61**
					(0.26)
Constant	-0.64	-0.64	-0.58	-0.45	-0.52
	(0.60)	(0.60)	(0.61)	(0.61)	(0.60)
Panel-level variance component (log)	0.52**	0.55***	0.58***	0.56***	0.55***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
Standard deviation of residuals	1.30***	1.31***	1.33***	1.32***	1.31***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Share of variance due to panel-level variance component	0.34***	0.34***	0.35***	0.35***	0.34***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Log likelihood	-789.56	-792.10	-794.79	-793.69	-792.18
P-value for Wald test (H_0 is all coefficients are null)	0.001	0.001	0.001	0.001	0.001

Note: This table reports panel estimation with unobserved individual effects modeled using random-effects where the endogenous variable is equal to l if the respondent selects one of the two least risky lotteries in the risk tasks with gains or the least risky lottery in the risk tasks with losses. (1), (2), (3), (4) and (5) indicate models where flooding experience is captured by different variables computed in the last 5 years: being flooded at least once, being evacuated at least once, being injured at least once, having a water elevation in house greater than 1 meter and having housing flooded more than 8 days per year on average.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE 6—INTERVAL REGRESSION FOR PROSPECT THEORY PARAMETERS

	α Utility curvature in the gain domain					β Utility curvature in the loss domain					γ Probability weighting				
Panel A. Homogenous preferences															
Constant	0.55***					0.31***					1.14***				
	(0.03)					(0.02)					(0.04)				
Standard deviation of individual effect						0.34***					0.46***				
						(0.03)					(0.05)				
Standard deviation of residual	0.57***					0.37***					0.70***				
	(0.02)					(0.02)					(0.02)				
Log likelihood	-896.1					-1204.9					-1469.2				
Panel B. Heterogenous preferences without exogenous variables															
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Flood experience	-0.08	-0.01	0.17	-0.15	-0.06	-0.09*	-0.17**	-0.14	-0.04	-0.10	0.02	-0.10	0.13	-0.04	0.03
	(0.06)	(0.08)	(0.15)	(0.11)	(0.08)	(0.05)	(0.06)	(0.11)	(0.08)	(0.06)	(0.08)	(0.09)	(0.17)	(0.13)	(0.10)
Constant	0.58***	0.55***	0.54***	0.56***	0.56***	0.35***	0.35***	0.32***	0.32***	0.33***	1.13***	1.16***	1.13***	1.14***	1.13***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Standard deviation of individual effect						0.34***	0.34***	0.34***	0.34***	0.34***	0.46***				
						(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)				
Standard deviation of residual	0.57***	0.57***	0.57***	0.57***	0.57***	0.57***	0.37***	0.37***	0.37***	0.37***	0.46***	0.45***	0.45***	0.45***	0.46***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Log likelihood	-895.3	-896.1	-895.4	-895.1	-895.8	-1203.0	-1200.2	-1204.0	-1204.8	-1203.6	-1469.1	-1468.5	-1468.9	-1469.1	-1469.1
Panel C. Heterogenous preferences with exogenous variables															
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Annual income (VND million)	-0.00	0.00	-0.00	-0.00	-0.00	0.00**	0.00**	0.00***	0.00**	0.00**	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share of income coming from agriculture	0.03	0.04	0.05	0.03	0.04	0.13**	0.12*	0.15**	0.14**	0.14**	-0.10	-0.12	-0.10	-0.10	-0.10
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Age of respondent (years)	0.01**	0.00**	0.00**	0.01**	0.00**	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Respondent is female (0,1)	0.05	0.05	0.06	0.07	0.05	0.07	0.06	0.06	0.07	0.07	-0.05	-0.06	-0.05	-0.05	-0.05
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Respondent has attended high school (0,1)	0.07	0.08	0.08	0.07	0.08	-0.04	-0.04	-0.03	-0.03	-0.02	0.04	0.03	0.04	0.04	0.04
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Number of organization memberships	-0.00	-0.00	-0.00	-0.00	-0.00	0.01	0.01	0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Future flood damage (index 1–10)	0.02	0.01	0.01	0.02	0.02	0.02	0.02*	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Flood experience	-0.09	-0.01	0.19	-0.19*	-0.08	-0.10**	-0.17***	-0.17	-0.06	-0.10*	0.02	-0.12	0.12	-0.03	0.03
	(0.06)	(0.08)	(0.15)	(0.11)	(0.08)	(0.05)	(0.06)	(0.11)	(0.08)	(0.06)	(0.08)	(0.09)	(0.17)	(0.13)	(0.10)
Constant	0.17	0.17	0.16	0.13	0.16	-0.06	-0.05	-0.07	-0.08	-0.08	1.27***	1.29***	1.27***	1.27***	1.28***
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Standard deviation of individual effect						0.33***	0.33***	0.33***	0.33***	0.33***	0.45***	0.45***	0.45***	0.45***	0.45***
						(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Standard deviation of residual	0.56***	0.57***	0.57***	0.56***	0.57***	0.37***	0.37***	0.37***	0.37***	0.37***	0.70***	0.70***	0.70***	0.70***	0.70***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log likelihood	-891.8	-892.9	-892.1	-891.4	-892.4	-1195.6	-1193.6	-1196.5	-1197.6	-1196.5	-1468.2	-1467.4	-1468.0	-1468.2	-1468.2

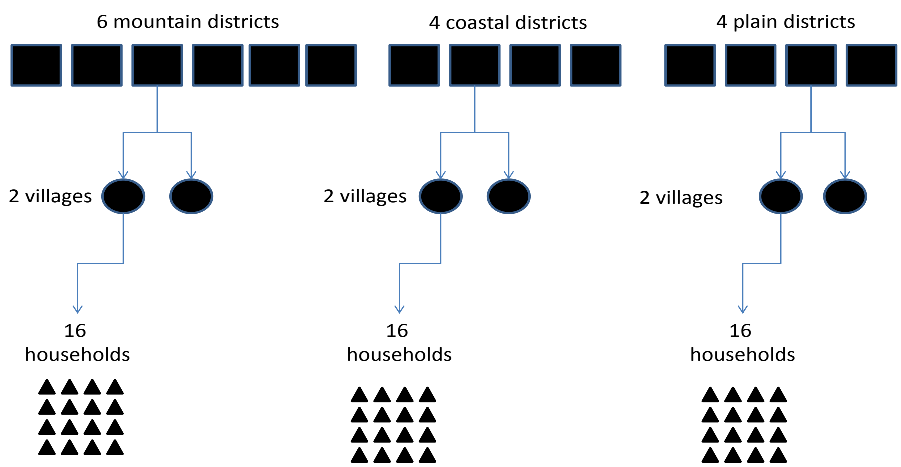
Note: This table reports interval regression estimations (for parameter α) and interval regression panel estimations with unobserved individual effects modeled using a random-effects specification (for parameters β and γ). (1), (2), (3), (4) and (5) indicate models where the flood experience is respectively measured by different variables computed over the last 5 years: being flooded at least once, being evacuated at least once, being injured at least once, having a water elevation in house greater than 1 meter and having housing flooded more than 8 days per year on average.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 7—Robustness checks for prospect theory parameters

	α Utility curvature in the gain domain				β Utility curvature in the loss domain				γ Probability weighting			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Annual income (VND million)	0.00	-0.00	-0.00	-0.00	0.00***	0.00**	0.00**	0.00***	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share of income coming from agriculture	0.05	0.03	0.04	0.02	0.11*	0.13**	0.13**	0.16**	-0.11	-0.09	-0.10	-0.05
	(0.09)	(0.09)	(0.09)	(0.09)	(0.06)	(0.06)	(0.06)	(0.07)	(0.11)	(0.10)	(0.10)	(0.10)
Age of respondent (years)	0.00**	0.01**	0.00**	0.00*	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Respondent is female (0,1)	0.05	0.05	0.06	0.06	0.06	0.07	0.07	0.07	-0.05	-0.05	-0.06	-0.08
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)	(0.08)	(0.08)
Respondent has attended high school (0,1)	0.08	0.07	0.07	0.04	-0.04	-0.04	-0.04	-0.03	0.03	0.04	0.04	0.08
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)	(0.08)	(0.08)
Number of organization memberships	-0.00	-0.00	-0.00	0.00	0.01	0.01	0.01	0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Future flood damage (index 1–10)	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02*	0.00	-0.00	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Share of households flooded at least once (village-level)	0.05				-0.29***				-0.07			
	(0.12)				(0.09)				(0.14)			
Household flooded at least once (0,1)		-0.09	0.16	-0.09		-0.10**	-0.09	-0.09*		0.02	-0.13	0.02
		(0.06)	(0.21)	(0.06)		(0.05)	(0.15)	(0.05)		(0.08)	(0.26)	(0.08)
Individual discount factor		-0.07				-0.14				0.22		
		(0.22)				(0.16)				(0.26)		
Time lag since the last flood (months)			0.00				0.00				-0.00	
			(0.00)				(0.00)				(0.00)	
Aid received from national authorities after flood (0,1)				-0.03				0.01				0.03
				(0.08)				(0.06)				(0.09)
Aid received from local authorities after flood (0,1)				0.11				-0.11*				-0.29***
				(0.08)				(0.06)				(0.10)
Aid received from social network after flood (0,1)				-0.14**				-0.05				0.16**
				(0.07)				(0.05)				(0.08)
Constant	0.15	0.20	-0.13	0.21	0.04	0.00	-0.07	-0.05	1.31***	1.18***	1.46***	1.24***
	(0.19)	(0.20)	(0.30)	(0.18)	(0.14)	(0.16)	(0.22)	(0.14)	(0.23)	(0.25)	(0.37)	(0.22)
Standard deviation of individual effect					0.33***	0.33***	0.33***	0.33***	0.45***	0.45***	0.45***	0.43***
					(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Standard deviation of residual	0.56***	0.56***	0.56***	0.56***	0.37***	0.37***	0.37***	0.37***	0.70***	0.70***	0.70***	0.70***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Log likelihood	-892.8	-891.8	-891.0	-889.1	-1192.1	-1195.2	-1195.6	-1192.1	-1468.1	-1467.8	-1468.0	-1461.9

Note: This table reports interval regression estimation (for parameter α) and interval regression panel estimations with unobserved individual effects modeled using a random-effects specification (for parameters β and γ). (1) indicates a model in which individual flood experience has been replace by a village-level measure. (2) indicates a model including a measure of individual time preferences. (3) indicates a model with a measure of the time lag since that last flood. (4) indicates a model with three measures of aid received by a household after a flood.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure 1. Sampling strategy



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