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Attitudes toward Flooding Risks in Vietnam: Implications for Insurance

Truong Cong Thanh Nghi

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EEPSEA Philippines Office, WorldFish Philippines Country Office, SEARCA bldg., College, Los Baños, Laguna 4031 Philippines; Tel: +63 49 536 2290 loc. 196; Fax: +63 49 501 7493; Email: admin@eepsea.net

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Front cover photo: Phu Huu commune, An Phu district, An Giang province. Photo by Truong Cong Thanh Nghi

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Attitudes toward Flooding Risks in Vietnam: Implications for Insurance

Truong Cong Thanh Nghi
School of Economics
University of Economics Ho Chi Minh City

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Comments should be sent to: Ms. Truong Cong Thanh Nghi
School of Economics, University of Economics Ho Chi Minh City
1A Hoang Dieu Street, Phu Nhuan District, Ho Chi Minh City
Tel: +84 8 38448222
Fax +84 8 38453897
E-mail: tct.nghi@ovs-vietnam.org

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EXECUTIVE SUMMARY

This study used the experimental method to elicit abstract risk attitudes on and preferences for uncertainties based on the context of flooding in the Mekong Delta, Vietnam. In contrast to the common assumption that farmers are risk averse, our results showed that farmers are, on the average, risk neutral. Moreover, although farmers are ambiguity averse toward Ellsberg-type uncertainty, they are not averse to flooding uncertainty. We also found that farmers systematically underestimate the probability of flooding. The results of the study provide possible explanations for the low take-up of insurance.

1.0 INTRODUCTION

Uncertainty occupies a central position in our lives. It affects the outcome of investments, success in our careers, and our health. Being relatively rich, however, provides shelter against many uncertainties. The poorest people in the world are exposed to a wider range and magnitude of risks, and they have no cushions to soften the blow of the worst outcomes. Weather shocks often wipe out their harvest and their income. Weather shocks also destroy livelihoods, destroy health, and claim many lives, and thus make regular life impossible. Moreover, the effects of weather shocks can often be felt in subsequent generations. Maccini and Yang (2009) showed that higher-than-average rainfall in Indonesia during a given year considerably improves the lifetime health and economic outlook of girls born in that year due to increased crop yield, which leads to increased household income and food availability.

In this research report, we looked at the relationship between risk attitudes on and preferences for betting on particular types of uncertainty over others, in the specific context of flooding in the Vietnamese Mekong Delta. In addition, we disentangled the separate effect of subjective probabilities of flooding and the willingness to bet on them, or *source preference* (Abdellaoui et al. 2011). In doing this, we added to the literature in development economics, insurance, and decision making in several ways. On one hand, we brought direct evidence on why micro-insurance take-up may be low in some cases. This may in turn help to develop better communication and sales strategies for such risk management instruments. Likewise, we added to the decision-making literature by bringing evidence on the validity of the source function argument from an applied real-world context. Finally, we added to the debate in behavioral economics in general by linking the preferences and beliefs of subjects to their real-world behavior (Karlan 2005; Sutter et al. 2011).

A crucial element in any strategy that aims to allow the world's poor to find their way out of poverty is to provide them with safeguards against external shocks that can affect their income, wealth, and livelihoods. Index-based micro-insurance has been hailed as one such solution. By insuring specific crops, this type of insurance is circumscribed and affordable, shelters the insured from the potential loss of their harvest, and thus smoothes out the income fluctuations. Index-based micro-insurance is designed to provide quick payouts in order to avoid long transition periods for damage assessment that often cannot be bridged using the limited savings of the affected households. Being based purely on an index, this type of micro-insurance is not bureaucratic and leaves no room for moral hazard, since the insurance will pay out regardless of actual damages.

It has thus been somewhat puzzling that insurance take-up has been exceedingly low in places where such insurance has been offered, even though the policies were generally subsidized and offered below actuarially fair levels. A number of potential causes have been indicated, ranging from insufficient information on availability, to financial literacy issues that hinder the intended beneficiaries from understanding how insurance works; from liquidity constraints to risk attitudes (Cole et al. 2013). Where these explanations have been tested and the supposed causes of low uptake have been removed, the results have often disappointed. Although several of the explanations were found to play a role, their quantitative effect was often limited and insurance uptake was still low after the intervention.

In the context of flooding in Vietnam, we took a fresh look at the incidence of risk and uncertainty attitudes. In our opinion, existing studies did not go far enough. On one hand, risk attitudes can be very different across different domains. Existing studies have often used gambles with known probabilities, often over monetary gains, and have related the preferences measured to insurance uptake—generally with no success. However, the situation faced by farmers is best modeled as uncertainty, a situation where no precise probabilities are known (Knight 1921; van de Kuilen and Wakker 2011), and which takes place over losses. Moreover, different sources of uncertainty may be treated very differently by people, depending on how familiar they feel about the situation; thus, farmers would react differently about the risk of flooding from the river they live by, and risk deriving from currency exchange markets to which they are likely to have very little exposure (Abdellaoui et al. 2011). Finally, there are two ways by which such uncertainties may influence the uptake of insurance. One is through the willingness to bet on uncertain events as previously discussed. The other is through the extent to which one's subjective probability estimates happen to coincide with objective probabilities used to calculate the insurance premium. A farmer may then be unwilling to buy insurance against an adverse event because (1) he estimates the probability correctly, but behaves in a risk-seeking way toward this event; (2) he acts in a risk-neutral or even risk-averse way, but underestimates the probability of the adverse event taking place; or (3) a combination of the two, such that either the underestimation of the probabilities or the willingness to bet are so strong as to dominate the relation.

2.0 SOURCE FUNCTION APPROACH

For a long time, the decision-making literature has focused mainly on risk. This was indeed convenient, since the normative principles for decision making under risk were axiomatized early on (Von Neumann and Morgenstern 1947); this has opened the way for all kinds of tests and has made it relatively easy to explain empirical violations. Similar axioms for normative decision making under uncertainty were developed shortly thereafter (Savage 1954). Nevertheless, the study of uncertainty never took off as a separate strand of decision theory research. Instead, the discovery by Ellsberg (1961) that people tend to violate these normative principles by expressing a strong preference for known probability events over normatively equivalent unknown probability events triggered a flood of papers on ambiguity aversion. This gave rise to studying preferences for known probabilities over unknown probabilities with urns, which hold to this day.

This historical accident had several unfortunate consequences. For one, the fact that ambiguity aversion had been discovered in the laboratory made the concept theoretically stiff and difficult to apply to real-world situations. Indeed, most early literature attempting such a generalization was highly speculative. In addition, in its most famous version, Ellsberg (1961) had used urns offering 50–50 prospects over gains, which then determined the dominant research paradigm. Although there are some early exceptions to this rule, it was not until the early 1990s that this started to change more systematically, and researchers started to look at different probabilities and outcome domains (Hogarth and Einhorn 1990). Shortly thereafter, Heath and Tversky (1991) started looking at different sources of uncertainty, such as the temperatures in one's hometown versus a faraway place, or between topics one was a self-declared expert in and topics in which one was not, and found that people preferred to bet over relatively familiar sources of uncertainty rather than relatively unfamiliar ones. This opened the door for associations with phenomena such as the home bias, whereby people tend to have much larger holdings in domestic stock rather than foreign stock, which may be sub-optimal from a risk diversification point of view.

From here, it was only a small step to the development of the source preference idea, which was first formalized by Fox and Tversky (1998). In subsequent years, this approach was further developed (Kilka and Weber 2001). Wakker (2010) made a theoretical case, which states that beliefs should be represented in probability judgments, whereas preferences should be represented in weights; a third step could then be used to transform decision weights depending on the source of uncertainty. The source function approach (Abdellaoui, Baillon, Placido, and Wakker 2011; henceforth referred to as ABPW) lets people have different preferences according to the source where the uncertainty stems from. Risk, the case in which probabilities are known, thus only represents a special case. This case is a good representation of some real-world processes—most notably state lotteries, in which probabilities can be calculated exactly— or long-established medical procedures, for which many past observations exist. However, a more frequent case is the one where probabilities are not known precisely and can only be approximated to a certain extent. Knight (1921) indicated such situations as the true origin of entrepreneurial profits (see also Keynes).

In cases of true uncertainty, there are two elements that describe behavior—subjective probability estimates and willingness to be on them (i.e., source preference). The former may differ from objectively observable probabilities for several reasons. In some cases, there may not be enough past observation to obtain meaningful or stable objective probabilities at all, so that the latter will only become known ex-post. Alternatively, not all past information may be available to the individual making the estimation. Or again, people may have cognitive limitations that systematically distort their recall of past events. Abdellaoui, L'Haridon, and Paraschiv (2011) found that subjects had suffered from a recency bias, overweighting recent observations relative to more remote ones even in an environment as short-lived as a laboratory experiment. This may in turn go some way toward reconciling typical findings in the classical decision theory literature, in which the small probabilities given are typically overweighted and the findings in the literature on decisions are based on experience, which finds a tendency toward underweighting probabilities that are not given but need to be discovered (Hertwig et al. 2004). To the extent that subjective probabilities may be distorted and may underestimate objective probabilities in such tasks, the difference may lie in their probability estimation rather than in their weighting.

3.0 FLOODING IN THE MEKONG DELTA

3.1 Overview of the Flooding Situation in the Mekong Delta

The Vietnamese Mekong Delta is the most downstream of the Mekong River where the Mekong River empties into the Southeast Sea. It lies on flat terrain, with an average height of 0.7–2.0 meters above sea level. As it approaches Vietnam, the Mekong River divides into two branches: the Tien River and the Hau River, which flow to the sea via nine river mouths, including Tieu, Dai, Ba Lai, Ham Luong, Co Chien, Cung Hau, Dinh An, Ba Thac, and Tranh De. The Mekong Delta is the largest agricultural region in Vietnam.

The flooding season in the Mekong Delta can be divided into three periods (SIWRP 2011):
Early flood season (July–August): The water level on the Mekong River increases gradually, and the rivers flow into the fields via canal systems.
High-level flood period (September–October): The water levels on the Tien and Hau rivers reach their peak (exceeding 4.0 m at Tan Chau and 3.8 m at Chau Doc). These floodwaters flow into the Mekong Delta from two directions: (a) perpendicular from the main river courses and (b) directly from the Vietnam–Cambodia border region.
Recession period (November–December): The flood water levels fall when the flow from Cambodia decreases.

The floods in the Mekong Delta are determined by three factors (Le et al. 2007):

1. Large water discharges; long and heavy rainfall occurs in the Mekong Delta itself
2. High tides that lead to high water levels in the rivers
3. Canal system prevents easy drainage

3.2 Dangerous Floods and the Economic Consequences of Flooding

According to the classifications defined by the National Center for Meteo-Hydrological Forecasting, there are three warning levels for flooding in the Mekong Delta. These correspond to three types of floods: low levels of flooding, average flooding, and major flooding. The exact warning water levels are different at different gauging stations (Table 1).

Table 1. Warning levels for four main gauging stations in the Mekong River, Vietnam

Gauging Station	Tan Chau	Chau Doc	My Thuan	Can Tho
Warning Level I	3.5 m	3.0 m	1.6 m	1.7 m
Warning Level II	4.0 m	3.5 m	1.7 m	1.8 m
Warning Level III	4.5 m	4.0 m	1.8 m	1.9 m

According to the classifications defined by the National Center for Meteo-Hydrological Forecasting, a major flood starts above 450 centimeters (cm) as measured at Tan Chau station. Above 450 cm, damage to housing, infrastructure, and agriculture begins to take place. From a level of 480 cm, the flooding can be dangerous enough to cause loss of life. Note that damage can be also caused by low water levels or droughts—these may lead to dikes (where they exist) drying out and to increased presence of pests and lower productivity because more fertilizers have to be used due to the lack of fertilizing sediments. This is, however, not discussed, mainly because insurance for this type of event is not being planned.
Clearly, different farmers may have idiosyncratic risks that affect them at different water levels, either because their land is located at different heights, more or less protected, or because of the activities and crops they specialize in. This issue is addressed below when looking at individual data.

3.2.1 Flood damage

According to Haskoning (2008, 2009), flooding in the Mekong Delta has caused the following types of damage:

1. Direct damage
   - Loss of life and injuries
   - Damage to property: depending on the magnitude and duration of the flood
   - Damage to crops: depending on the depth, timing and duration of the flood. The bigger the flood, the greater the area of cultivation that becomes submerged, leading to bigger losses. However, if flooding occurs after harvesting, then there is no crop damage at all.
   - Livestock, aquaculture and agricultural equipment
2. Indirect damage
   - Cost of illness in humans and livestock related to poor environmental conditions and increased water-borne diseases
   - Income losses due to the disruption of economic activities and/or services because of flooding
   - Higher cost of living due to temporary relocation, the need to purchase food, etc.
   - Costs of temporary relocation and rescue:
     - cost of prevention measures
     - cost of cleaning and sanitation
     - other costs, such as loss in tourism revenue, problems in income distribution and loss of confidence of people in the government

Haskoning (2008, 2009) estimated the value of damages (such as those listed above) due to flooding in the Mekong Delta. The depth damage relationships in two provinces of Dong Thap and An Giang are shown in Figure 1.

Figure 2 shows the distribution of the annual flood damage in two provinces in the Vietnam Mekong Delta. The distribution is calculated based on historical data from 1910. The economic damage from flooding has increased quite dramatically over the past 30–40 years. Although climate change may add to this in the future, so far, the increase in damage has been mostly caused by population growth.

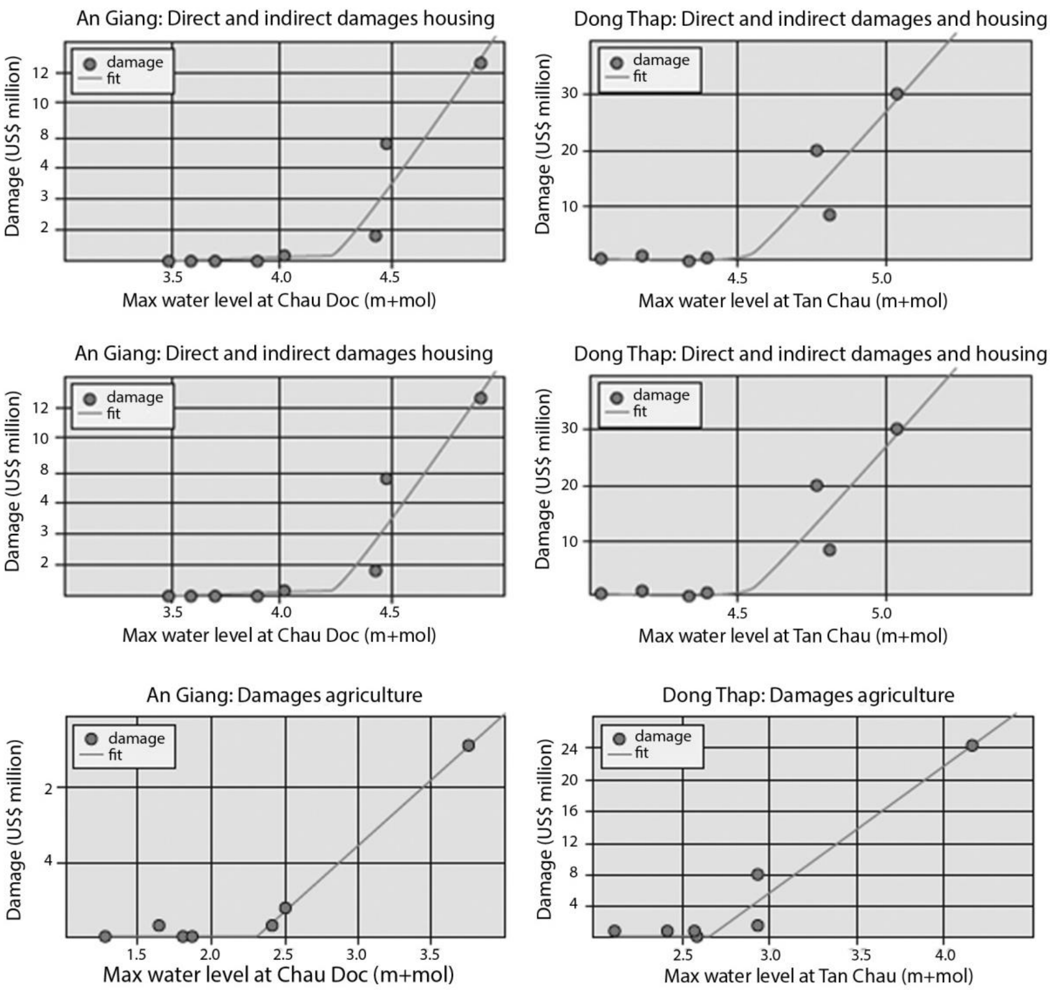

Figure 1. Sectoral flood damage curves for the Mekong Delta

Source: Haskoning (2008)

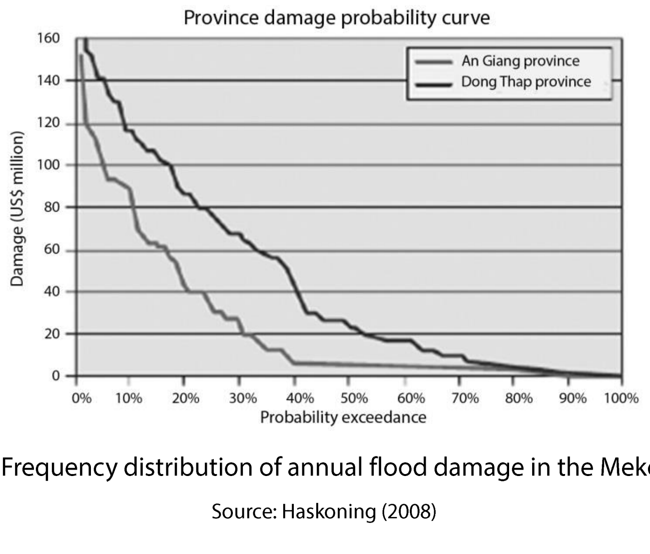

Figure 2. Frequency distribution of annual flood damage in the Mekong Delta

Source: Haskoning (2008)

3.2.2 Flood benefits

Floods also bring benefits, including the following (Haskoning 2009):

1. Fishery: Floodwater provides habitats for fish. Fish are an important resource for the people living in the Mekong Delta. The benefit of catching fish during the flood season amounts to about VND 1–5 million per household (USD 100–300 per household) in normal flood years and about VND 2–12 million per household in major flood years (e.g., 2000, 2001, 2002).
2. Agricultural production: Floodwater brings sedimentation to the flood plain, flushes toxic substances from the cultivated soil, flushes acids from acid sulfate soil areas, kills rats and pests, speeds up the process of plant residue disintegration, improves soil structure, and provides soil fertility. The amount of fertilizers and pesticides applied to the Winter-Spring paddy (November–March) after a big flood is less than that in a normal flood year to a total value of VND 2–3 million per hectare (about USD 100–200 per hectare) but the yield is higher by 0.5–1.0 ton per hectare (t/ha). As a result, floods benefit agriculture by approximately USD 200–300 per hectare.
3. Biodiversity conservation: This is especially beneficial with regard to wetlands.

From these analyses, it is obvious that floods that are too high or too low are not good for the local people. If the water level is too high, then serious damage will occur; if the water level is too low, then the benefits of flooding will be correspondingly low. The Annual Mekong Flood Report 2005 concluded that the flood brings more benefits than damages when the water level at the Tan Chau station stands between 3.5–4.5 m.

Three great floods in the Mekong Delta recently occurred in successive years—2000, 2001, and 2002—with water levels of 5.06 m, 4.78 m, and 4.82 m, respectively. Between 2003 and 2010, there were no serious floods in the Mekong Delta. In 2010, the maximum water level achieved at Tan Chau station was only 3.2 m, which is 30 cm lower than the first alarm level of 3.5 m. After eight years without a serious flood, the Mekong Delta faced a serious flood in 2011; a maximum water level of 4.89 m occurred at Tan Chau station, which was higher than Warning Level 3. The 2011 flood caused significant damages in the Mekong Delta (Table 2).

Table 2. Damage statistics as of 4 November, 2011

Provinces	Deaths	Evacuation		Damage to Houses			Agricultural Losses	
	Total	Under 16 Years Old	No. of Families Evacuated	Destroyed	Lost Their Roof/ Severely Damaged	Flooded	Rice (ha)	Fish/ Shrimp Cages (Units)
An Giang	18	14	1,151	52	1,379	20,294	5,471	1,149
Dong Thap	20	19	2,433	105	352	27,949	2,063	0
Can Tho	6	6	0	5	25	15,498	109	11
Long An	14	13	1,846	131	141	26,379	826	8,284
Vinh Long	0	0	0	0	0	24,785	44	5,139
Hau Giang	0	0	0	0	0	3,327	545	0
Kien Giang	15	13	578	66	179	6,770	970	0
Total	73	65	6,008	359	2,076	125,002	10,028	14,583

Source: IFRC (2011)

3.3 Dike Systems in the Mekong Delta

Before 1978, Mekong Delta farmers referred to the flood season as *mua nuoc noi*, which means "the period when the water comes and brings natural resources to the fields." During the flood period, farmers often use adaptation strategies such as catching fish, collecting wild vegetables, planting deepwater rice, or evacuating to higher ground. The reality of "living with floods" has been practiced by the local people for a long time (Tran 2010). Since 1978, due to the demands for economic development in the Mekong Delta, the government started to build flood-control infrastructure. The semi-dike or the August dike systems were built to prevent the early August flooding of the summer crops. However, the August dike systems do not allow farmers to cultivate a third rice crop, and they cannot fully protect properties and human lives (Tran 2010). After the huge floods of 2000—the most damaging floods in terms of loss in human life and damages to assets—the strategy and response methods for dealing with heavy floods were quickly reviewed, and the government decided to invest in full-dike systems using the highest water level of the floods of 2000 as the reference. Since then, the full-dike area has been increasing year-on-year.

4.0 THE STUDY SITE

4.1 Description of the Study Site

Our study site is Phu Huu commune, a rural remote commune of An Phu district, An Giang province (Figure 3). It is located at the border of Cambodia and Vietnam, upstream of the Tien and Hau rivers. The natural area of Phu Huu commune is 3,975 ha, and the population is 18,866, most of whom are farmers. The main agricultural products of this commune include rice, corn, peanuts, chili, lotus, and eels.

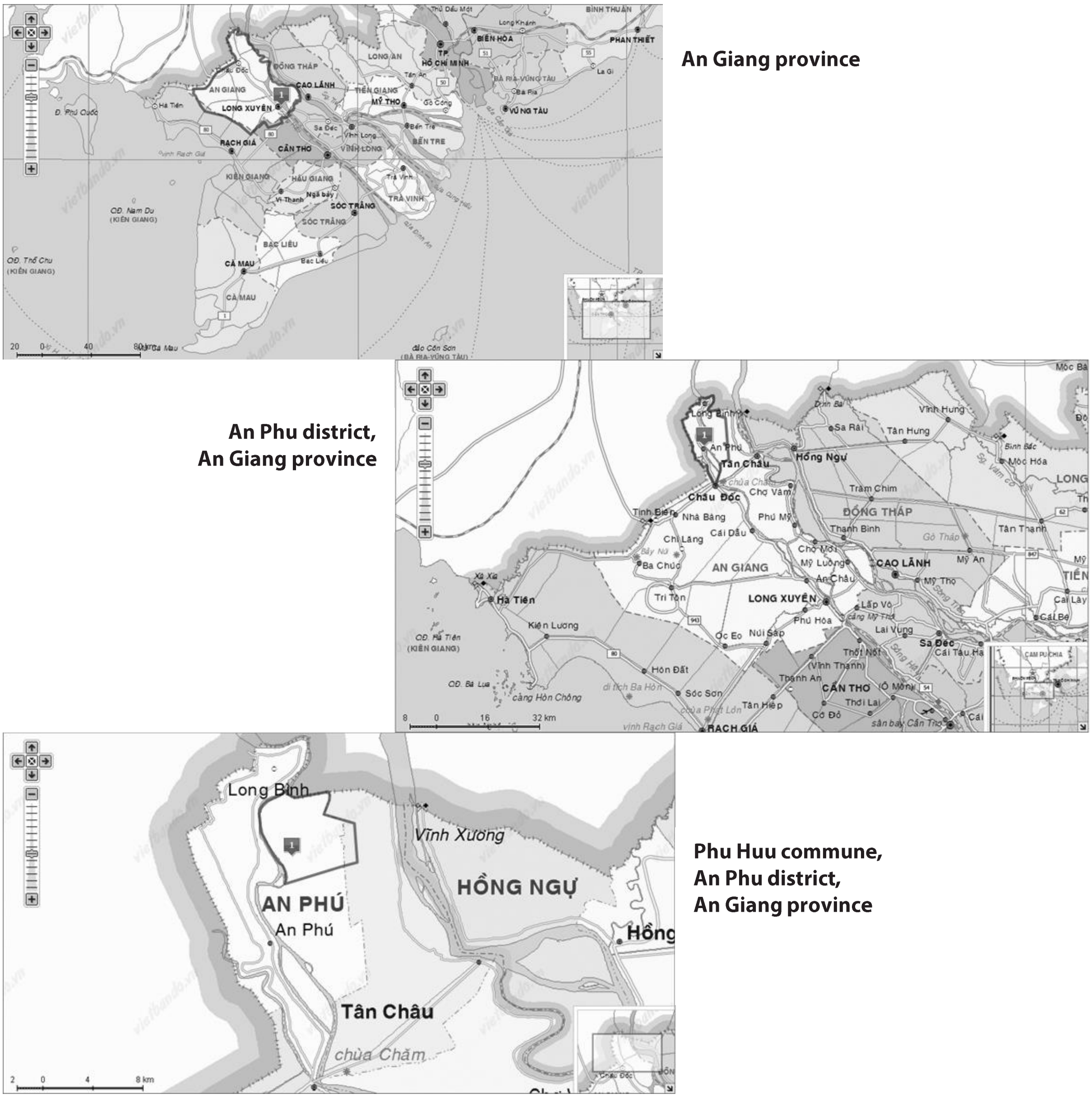

Figure 3. Location of the study site
Source: gis.chinhphu.vn

Table 3 presents the crop seasons at the study site. Rice is the most important agricultural product in this area; but before 2012, the paddy rice fields were not protected by the full-dike system, only by the semi-dike system. At the end of July 2012, the first full-dike system at Phu Huu commune was finished, protecting 1,500 ha of rice fields throughout the whole flood season. This new full-dike system allows farmers to produce a third rice crop (the Autumn–Winter crop). This particular area was chosen because it served as a test case for a pilot for Vietnamese rice crop insurance, which is an area-yield-based insurance. According to Decision No. 3035/QĐ-BTC, approved by the Ministry of Finance and to Circular No. 47/2011/TT-BNNPTNT issued by the Ministry of Agriculture and Rural Development, the critical threshold for this rice crop insurance is 75% of an average of three recent years of area yields. These documents also assign the premium rate for seven provinces participating in the pilot program for rice crop insurance. The government will subsidize up to 100% of the insurance premium.

Table 3. Crop seasons in Phu Huu commune

Months	01	02	03	04	05	06	07	08	09	10	11	12
Double rice crop												
Corn												
Chili												
Peanuts												
Lotus												
Eels												
Fishing												

4.2 The Gauging Station and the Uncertainty Source

The gauging station used in this study is the Tan Chau gauging station. It is the main gauging station upstream of Tien River, and the distance between this station and the study site is about 18 kilometers. We used historical data on peak water levels measured at this gauging station as our main source of uncertainty. Figure 4 shows the peak water levels all the way back to 1926, when the gauging station was first installed by the French colonial regime. Clearly, there is considerable variation in high water levels from year to year.

High water levels (or peak water level) are actually not the only source of uncertainty that may be relevant to farmers. Farmers are just as affected by floods that rise early above a certain level, since this may affect the harvest of the Summer–Autumn rice crop. Also, if the water level falls too late, then this interferes with the planting of the Winter–Spring rice crop. The high winds associated with the high water levels also make fishing difficult and dangerous. In this study, we focus on the peak water levels. The exact dates on which the water level may reach a certain level capable of threatening the harvest could also constitute such a continuous variable. Alternatively, one could use the water level on 30 July, which usually corresponds to harvest time. We decided to use peak water levels because they constitute a continuous variable, which is well-suited to the type of measurements we want to undertake. Also, they are salient and can be used to calculate more general damage—not only to rice harvests, which would be affected by the water level at the end of July, but also to vegetable farming and to fishing.

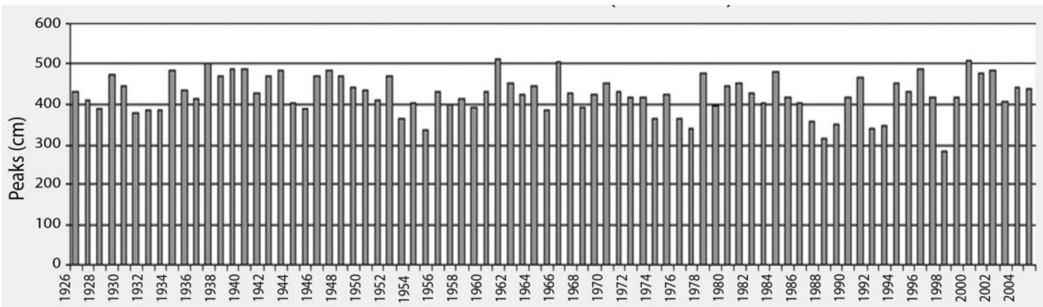

Figure 4. Historical data of flooding intensity

(Source: Le Anh Tuan et al. 2007)

4.3 Risk Management Strategies at the Study Site

4.3.1 The dike system in Phu Huu commune

Before July 2012, Phu Huu commune was protected by the semi-dike system. The annual contribution of each household for consolidating this dike system is VND 40,000. Households can also contribute labor to construct and consolidate the system, especially during the flood season. The height of the semi-dike system is designed to ensure that the second crop can be harvested before floodwaters overflow into field. Since July 2012, part of Phu Huu commune has been protected by the full-dike system. Households in this area contribute a one-off amount of VND 400,000 for building the dike system. The height of the full dikes is based on the flood peaks of 2000 and it allows farmers to plant and harvest a third crop (Autumn–Winter crop), which yields a higher profit than the other two crops do in the year. However, in 2012, not all of the households in the full-dike area invested in the Autumn–Winter crop because they were afraid that the flood of 2012, which was forecasted to be very high, would break the new dike system.

4.3.2 Early warning system

The early warning system in the Mekong Delta, particularly in Phu Huu commune, is not fully developed. However, warnings and forecasts regarding flood levels are distributed widely to farmers via many different channels. Information about flooding is reported by the gauging stations to the Southern Regional Hydro-Meteorological Center. The Hydro-Meteorological Report and Forecast is issued every 10 days every month; when a flood is coming, a Flood Warning Notice is also issued daily. There are three common channels of information:

1. Southern Committee for Flood and Storm Control —> Provincial Committee for Flood and Storm Control —> District Committee for Flood and Storm Control —> Commune Committee for Flood and Storm Control —> households
2. Provincial government —> district government —> local authority —> households
3. Weather and flood forecasts on television and radio —> households

The results from the pilot suggest that these channels are effective in distributing information and in warnings the local residents about floods. All interviewees said that they received information about the water level in the Mekong Delta in time.

4.3.3 Insurance

In 2011, a pilot agricultural insurance program was launched in some provinces of Vietnam; Phu Huu commune was one of the pilot areas for the rice crop insurance. However, the implementation of this insurance was slow, and the farmers in the pilot said that they did not fully understand how the insurance works.

4.3.4 Other risk management strategies

Over a long period of time, farmers in the Mekong Delta have learned many different ways to adapt to floods and to manage the risks of flooding. The risk management strategies mentioned by respondents during the interview (survey) include:

1. *Changing the seed planted*

   Farmers in Phu Huu have shifted from planting rice varieties with a long growing time to rice varieties with a short growing time. This strategy is used to adapt to the risk of early flooding. Rice varieties with short growing time allow farmers to harvest the Summer–Autumn crop sooner than those varieties with a longer growing time, i.e., before the flooding arrives. However, the quality of a short-term rice crop is often lower than that of a long-term rice crop; thus, the price for short-term rice is not as high as that for long-term rice.

2. *Renting land*

   The farmers in the area protected by the semi-dike system rent land in the area protected by the full-dike system, which enables them to cultivate the third crop during the flood season. However, this strategy requires farmers to have the financial ability to rent land.

3. *Leasing land*

   Because the flood of 2011 had come later and had lasted longer than the flood of 2010, the cultivation of the Winter–Spring crop of 2011–2012 in Phu Huu commune was consequently later than that in normal years. This situation forced farmers to consider if they should cultivate the Summer–Autumn crop of 2012 or not because a late Winter–Spring crop leads to a late Summer–Autumn crop; thus, the probability of losing the crop due to early-arriving flooding was higher. To adapt to the risk of early flooding, farmers did not invest in the Summer–Autumn crop of 2012 and leased their land instead.

4. *Migration*

   Farmers in Phu Huu can migrate to Long Xuyen city (the main city of An Giang province) or migrate to other provinces (Binh Duong, Dong Nai, Ho Chi Minh City) during the flood season to earn a living. They can work in the industrial and construction sectors, or sell clothes or lottery tickets. Some farmers migrate to Cambodia to find jobs.

5. *Fishing*

   Fishing is the main livelihood activity in Phu Huu commune during the flood season. The cost of investing in fishing is not high so even poor farmers can adopt this strategy. On average, in one flood season (July–November), each household can catch 800–1,000 kilograms of fish. The average price for fish in this area is about VND 30–50 thousand per kilogram. However, this strategy is very risky when flooding is accompanied by strong winds, thunder, and lightning.

5.0 EXPERIMENTAL METHODOLOGY AND SET UP

5.1 Subjects

A total of 207 subjects participated in our study, the overwhelming majority of who were farmers (and some retirees). The mean age of our subjects was 50 years, with a range from 23–87. A total of 97% of our respondents were male. The overwhelming majority of the subjects declared themselves to adhere to Hòa Hảo, a local version of Buddhism, or to be Buddhist. They own an average of 1.14 ha of land (median = 0.83 ha), with a minimum of 0 and a maximum of 6 ha. The median household has an income of about VND 3.6 million a month, which corresponds to a median income per head of VND 833,000, or roughly USD 40 at contemporary exchange rates (USD 104 PPP).

5.2 Definitions and Terminology

The term *risk* is used to refer to the case of known or given probabilities. Risk seeking is thereby found to prevail when a subject weakly prefers a prospect to its expected value, risk aversion if the expected value is weakly preferred to the prospect, and risk neutrality when a subject is both risk seeking and risk averse.

The term *uncertainty* is used in general to refer to cases in which probabilities are unknown; uncertainty aversion, seeking, and neutrality are defined in the same way as risk. When it comes to uncertainty, we distinguish two cases: (1) *abstract* or *Ellsberg-type* uncertainty, where the source of the uncertainty is derived from unknown proportions of balls with different numbers in an urn as used by Ellsberg (1961); and (2) *natural* or *water-uncertainty*, where the source of uncertainty is constituted by historical peak water levels in the Tien River (see below for details). Sometimes, we may also use *uncertainty sources* as an overreaching term, which includes known probabilities or risk as a special case.

Finally, in keeping with most of the traditional literature on uncertainty that studies the latter only in contraposition to risk (Chow and Sarin 2001; Fox and Tversky 1995), we will refer to *ambiguity* whenever we compare uncertainty attitudes to risk attitudes, rather than to a normative benchmark of uncertainty neutrality. Since we have two types of uncertainty, we will also have two types of ambiguity, *Ellsberg-type ambiguity* and *water-ambiguity*. We will speak of ambiguity seeking whenever a subject prefers betting on the source characterized by uncertain probabilities over the pure risk; the other definitions follow from this in the same manner as above.

5.3 Elicitation

In this study, all preferences were elicited from individual interviews. A team of 16 enumerators had been trained. The enumerators subsequently interviewed students in the University of Economics Ho Chi Minh City (HCMC) as practice and training before being brought into the field. The elicitation took place in two separate parts. The first part comprised some general questions about the participants (which served as a warm-up task) and the elicitation of the natural uncertainty attitudes. Then, the participant was dismissed. In the second session, which usually took place later on the same day or the next day, the subjects' abstract risk and uncertainty attitudes were elicited. After this, the questionnaire was administered. The whole process took between 3–4 hours, with the first session somewhat shorter than the second.

5.4 Incentives

Elicitation procedures were incentivized using a random incentive mechanism. The abstract risk and uncertainty elicitation and the natural elicitation part of the experiment were incentivized separately, but payoffs were not made known until the very end of the interviews in order to avoid income effects. The main prize used in the experiment was VND 160,000, or USD 20 PPP, corresponding to about 20% of the average monthly per capita earnings of the median household. The elicitation of abstract risk and uncertainty attitudes and of the flooding uncertainty attitudes were incentivized separately, so that farmers could win this prize twice. The uncertainty was, however, not resolved until the very end of the experiment so as to avoid income effects. Indeed, previous earnings have been found to lead to higher risk acceptance in tasks such as these (Gertner 1993; Thaler and Johnson 1990), so we chose to neither resolve the uncertainty nor pay out the money until the very end of the experiment. This also constituted an additional incentive to come back for the second interview session.

5.5 Measurements

In all the elicitations of risk and uncertainty attitudes, we used certainty equivalents (CE) to measure attitudes toward the various types of risk. A CE is thereby defined as the fixed amount of money that makes the subject indifferent between playing the prospect or obtaining the sure amount. Notice how for losses, where subjects are asked to choose between sure losses that increase in absolute terms and a prospect, this measure exactly mimics an insurance premium. We used certainty equivalent, instead of other measures such as willingness to pay, since the latter has been found to result in biased measurements of ambiguity attitudes (Trautmann, Vieider, and Wakker 2008). Certainty equivalents, on the other hand, provide a measurement that is consistent with other measurement methods such as direct choice, while having the added advantage of providing a measure of the strength of preference or willingness to bet on one's probability estimate. They also constitute the current standard in the literature (e.g., Bruhin, Fehr-Duda, and Epper [2010]). In this experiment, the CE was encoded as the mean of the last sure amount for which the lottery was chosen, and the first for which the sure amount was chosen (and vice versa for losses).
The enumerators were told to enforce one switching point so that multiple switching would not occur in our data.

5.6 Sources of Uncertainty

In the experiment, risk was simply implemented through using a bag with numbered ping pong balls as a chance device. The subjects could examine the contents of this bag at any time if they wanted to. Specifically, abstract uncertainty was implemented following the design of ABPW; the subjects were told that there were eight balls in an urn, bearing the numbers 1–8 inclusive. They were also told that it was possible that one or several of these numbers may be absent, and that others may recur repeatedly instead. Notice how this creates uncertainty or probabilistic vagueness, while the normative probability levels in the urn are identical to those in the risky urn (indeed, the reasoning presented in Raiffa [1961] can easily be extended to this case). For natural uncertainties, we deviate from ABPW by using backward-looking uncertainty rather than true, forward-looking uncertainty. Thus, farmers were asked not to bet on the arrival of the high-water season, but rather on peak water levels from the last 50 years. This was done for several reasons. First, we could avoid the issue of whether farmers would trust us to come back and pay them out. More importantly, we wanted to disentangle miscalibration in probabilities deriving from cognitive limitations from expectations about the future. In particular, the year 2012 (the year in which the study took place) was a Dragon year in the Chinese calendar. Preliminary interviews revealed a common superstition according to which Dragon years are associated with particularly high floods—an association that is not borne out by the data. Nevertheless, we asked about probabilities associated with an early flood in the questionnaire. We will come back to this issue in the results section.

5.7 Abstract Risk and Uncertainty Attitudes

Abstract risk and uncertainty attitudes were elicited using the design employed in the study of Vieider, Chmura, and Martinsson (2012a) and Vieider, Martinsson, and Medhin (2012b). The biggest difference was that instead of letting our subjects fill out the questionnaires by themselves, we used individual interviews to elicit the data. The enumerators were trained and instructed to follow exactly the information provided in the instructions, and not to deviate from their content. In case gross inconsistencies emerged, such as violations of first-order stochastic dominance between subsequent decisions, enumerators were instructed to point out the potential incoherence; if the subject did not see this or did not want to change his answer, however, then they were instructed not to insist and to move on with the interview.

In total, we elicited 44 CEs from each farmer. Table 4 shows the exact prospects used in the experiment. The elicitation process always followed the same order. We started by eliciting CEs for prospects offering 50-50 gambles over different monetary gains. Then, we offered one fixed gain or prize for different probability levels, increasing from 1/8 to 7/8. This was followed by a second part that reproduced the same procedure for monetary losses. Losses always took place from an endowment. Even though this procedure may result in order effects, we found this to be more preferable to the increased noise and confusion that would follow from randomizing the tasks. Etchart-Vincent and L'Haridon (2011) tested whether presenting losses before or after gains made a difference, and found none. They also found no difference between real losses and losses from an endowment.

Table 4. Decision tasks (in '000 VND)

Gains Known Prob	Gains Unknown Prob	Losses Known Prob	Losses Unknown Prob	Mixed Known Prob
1. (1/2: 40; 0)		23. (1/2: –40; 0)		44. (1/2: 160; –z)
2. (1/2: 80; 0)		24. (1/2: –80; 0)		
3. (1/2: 160; 0)		25. (1/2: –160; 0)		
4. (1/2: 240; 0)		26. (1/2: –160; –40)		
5. (1/2: 240; 80)		27. (1/2: –160; –80)		
6. (1/2: 240; 160)				
7. (1/8: 160; 0)	15. (1/8: 160; 0)	28. (1/8: –160; 0)	36. (1/8: –160; 0)	
8. (1/8: 160; 40)	16. (1/8: 160; 40)	29. (1/8: –160; –40)	37. (1/8: –160; –40)	
9. (2/8: 160; 0)	17. (2/8: 160; 0)	30. (2/8: –160; 0)	38. (2/8: –160; 0)	
10. (3/8: 160; 0)	18. (3/8: 160; 0)	31. (3/8: –160; 0)	39. (3/8: –160; 0)	
11. (5/8: 160; 0)	19. (5/8: 160; 0)	32. (5/8: –160; 0)	40. (5/8: –160; 0)	
12. (6/8: 160; 0)	20. (6/8: 160; 0)	33. (6/8: –160; 0)	41. (6/8: –160; 0)	
13. (7/8: 160; 0)	21. (7/8: 160; 0)	34. (7/8: –160; 0)	42. (7/8: –160; 0)	
14. (7/8: 160; 40)	22. (7/8: 160; 40)	35. (7/8: –160; –40)	43. (7/8: –160; –40)	

5.8 Attitudes toward Flood Risks

Attitudes toward natural uncertainties were elicited in two steps following the design of ABPW. First, subjects were asked whether they were familiar with the Tan Chau gauging station. We asked farmers whether they were familiar with this station before starting the experiment, and 80% of respondents declared that they were. They were then presented with some information about the gauging station, including its exact location and the frequency of flood measurements. The respondents were also informed of the water levels corresponding to the different warning levels: 3.0 m, 3.6 m, and 4.2 m. This was done mainly to avoid systematic discrepancies with beliefs regarding water levels as observed in the village and those measured at the station itself. Once all this information was presented, farmers were asked to provide their best estimates of extreme water levels, i.e., the lowest and highest water levels ever observed. This choice was incentivized by paying a fixed amount of VND 32,000 (USD 4 PPP) for each value that came within ±5% of the correct historical value. These values were then used as the endpoints in subsequent elicitation. In order to avoid nonsensical answers, the software was programed to reject all water levels that did not at least have the three warning levels within them. This was taken as a sign of poor understanding or inattention, since these water levels were reported in the initial information. A total of six farmers were excluded because they had trouble understanding this. All the other farmers were quite familiar with the warning levels and immediately fulfilled our minimum criteria for the endpoints.

Once the historically lowest and highest peak water levels had been determined, we began offering bets on water levels between these extremes to obtain measures of subjective probabilities, or better of water levels that would subsequently divide the probability space. To do this, we employed the method developed by Baillon (2008) and by ABPW. This was done to divide the water levels into events corresponding to different water intervals, to which specific subjective probabilities were assigned:

$E_{0–1/16}$	$E_{1/16–1/8}$	$E_{1/8–1/4}$	$E_{1/4–1/2}$	$E_{1/2–3/4}$	$E_{3/4–7/8}$	$E_{7/8–15/16}$	$E_{15/16–1}$

$a_{1/16}$ $a_{1/8}$ $a_{1/4}$ $a_{1/2}$ $a_{3/4}$ $a_{7/8}$ $a_{15/16}$

min water level max

We started by eliciting the water level $a_{1/2}$, which splits the event space into two equal-probability events. To do this, we first offered a choice between a bet paying a prize if the water level (which is to be randomly drawn from historical peak water levels) is above the midpoint between the endpoints elicited, and one that offers the same prize if the water level extracted falls below that midpoint. Depending on the first choice, we then offered another bet.

For example, if the farmer preferred betting on the water level falling above the midpoint, then the midpoint between the last dividing level and the maximum would be taken as a new dividing line between the bets. This would go on for the next five steps so that the water level would move closer to the level of indifference; that is, the water level for which the farmer does not have a strong preference between betting on one or the other option. Once the equal probability split water level has been reached in Step 5, we would then ask the farmer if he had a strong preference for either of the two bets. If he answered no, we would accept that water level and then move on to the next elicitation task. If the farmer said that he still had a definite preference for one or the other, we would go back and start over. If we move on, then the same procedure would be repeated, only that now the question would be whether the farmer would prefer to bet on a water level above or below a given point, conditional on the water level falling below (or above) the point elicited in the first step. This would serve to elicit the water levels $a_{1/4}$ and $a_{3/4}$. The same procedure would be repeated until a point of indifference was reached.

After the subjective probabilities had been determined, the enumerators elicited CEs for betting on the different water levels similar to those obtained for the abstract risk attitudes. Once again, this was done in a specific order: starting with the water level corresponding to the lowest probability of 1/16 for gains, and then moving on to increasingly higher probabilities. Once this had been done for gains, the process was repeated for losses, which again took place from an endowment. However, instead of starting from the low-water level corresponding to a probability of 1/16, for losses, we started from the high-water level corresponding to a probability of 1/16. This is permitted due to the substitutability of equal-probability events, and served the purpose of directly mimicking insurance for low probability floods.

5.9 Indices and Analysis

Given the quantity of information we have, we need to aggregate these data in order to analyze them in a meaningful way. Contrary to ABPW, who decompose attitudes into a utility- and probability-weighting function in the theoretical framework of prospect theory (Kahneman and Tversky 1979; Wakker 2010), we estimate linear best fits for our certainty equivalents, separately for each uncertainty source. We do this for several reasons. First, such linear best fits are theory-neutral, and thus they may find wider acceptance. Second, implications in terms of insurance are more easily discussed if we summarize uncertainty attitudes within one index, instead of having to reassemble such attitudes through utility and weighting functions. Finally, the main advantage of the separation in this context—the possibility to use utility curvature to extrapolate our findings to different stake levels—has been discredited by violations of separability between utility and probability weighting (Hogarth and Einhorn 1990). Indeed, Fehr-Duda et al. (2010) found that as stake sizes increase, the increased risk aversion resulting from this is reflected in probability weighting functions rather than in the utility function using state of the art estimation procedures.[1] This makes extrapolation to different stakes using utility doubtful at best. We thus opt for simple linear best fits for our analysis. Nevertheless, we allow for the parameters thus obtained to differ for gain and loss frames, since framing has been shown to be empirically robust (Kühberger, Shulte-Mecklenberg, and Perner 1999; Tversky and Kahneman 1981; Vieider 2011), as well as being of primary interest for insurance questions.

In order to estimate this linear best fit, we first normalize the certainty equivalents elicited by the highest amount to be won in the gain prospects, and the lowest amount to be lost for the loss prospects. We thus estimate the following relationship at the individual level using maximum likelihood procedures:

$$CE/X = c + s \times EV/X$$

where:

CE	=	elicited certain equivalent;
X	=	highest or lowest outcome in the prospect for gains and losses, respectively;
EV	=	expected value of the prospect;
c	=	intercept of the linear best fit, which can be taken as a measure of absolute risk acceptance (gains) or aversion (losses); and
s	=	slope of the linear best fit, and thus its sensitivity to variations in expected value.

Since the latter varies directly with the probability of winning or losing, it constitutes a measure of probabilistic sensitivity. Notice also how this estimation is identical to the neo-additive probability weighting functions used in ABPW (Chateauneuf, Eichberger, and Grant 2007). The difference is that, while ABPW allow for utility to differ, we set the utility by definition equal to 1, so that the regression line does not represent a weighting function, but uncertainty attitudes more in general.

Even though the two parameters just described fully define the relationship, it is convenient in some cases to use additional indices for analysis. In particular, we need to use these two additional measures: (1) $1\text{-}s\text{-}c$, which is the anti-intercept indicating the distance between 1 and the point where the line hits the axis at $p = 1$, can be used as a measure for risk aversion (gains) or risk seeking (losses) for large probabilities; and (2) $1\text{-}s\text{-}2c$, which summarizes the total area between the regression line and the 45° line and below the latter minus the one above, can be taken as a measure for global uncertainty aversion (gains) or uncertainty seeking (losses). For an in-depth discussion see Abdellaoui et al. (2010).

5.10 The Questionnaire

A large questionnaire was administered at the end of the experiment (although some initial questions on general demographics were asked at the very beginning as a warm-up task). We thus obtained detailed data on the composition of the household, including number of members, gender of members, activities, age, education, etc. We also obtained data on

[1] The same pattern of separability violation is replicated if we use an alternative estimation procedure on the risk data reported in Vieider et al. (2012a, 2012b). The results are available from the corresponding author.

1. income and wealth;
2. land owned, leased, and the use the land was put to;
3. expenditures, migratory behavior, savings, and loans; subjective evaluations of past floods;
4. probability estimates about future flooding;
5. adaptation measures to flooding;
6. measures on the extent to which the floods affect the household and how the household is affected by other sources of uncertainty, such as variation in the prices of agricultural products, droughts, infrastructure, government relief; and
7. data on membership in various organizations, satisfaction levels with regard to various aspects of their lives, etc.

A complete description of the questionnaire is beyond the scope of this section. The variables used in the analysis will be described more in detail as the need arises.

6.0 RESULTS

6.1 Source Functions of Farmers for Gains: Risk, Uncertainty, and Water Levels

We start by looking at the attitudes that farmers have toward the various sources of uncertainty. The functions summarizing these attitudes for gains are shown in Figure 5. For risk, we find risk-seeking behavior for small probabilities ($z = 6.97$, $p < 0.001$),[2] risk aversion for large probabilities ($z = 3.79$, $p < 0.001$), and risk neutrality globally ($z = 0.19$, $p = 0.852$). We also find significant probabilistic insensitivity, with CEs varying less than linearly as the probability of winning —and thus the expected value of the prospect— increases ($z = 4.59$, $p < 0.001$). These results correspond very closely to the results obtained with students (using interviews) in Ho Chi Minh City, which we used as a consistency check, except that farmers tend to display more probabilistic insensitivity. This was to be expected given their lower levels of education. The fact that farmers are risk neutral globally is not very surprising. Indeed, Vietnamese students are risk seeking on a global level. Although this may be a little surprising at first, this is mainly due to the fact that almost all our knowledge about risk attitudes has been obtained from western university students. Vieider, Chmura, and Martinsson (2012b) showed that on a global level, risk seeking or neutrality is very frequent with these kind of stakes, and that risk tolerance bears a strong inverse relation to GDP per capita.

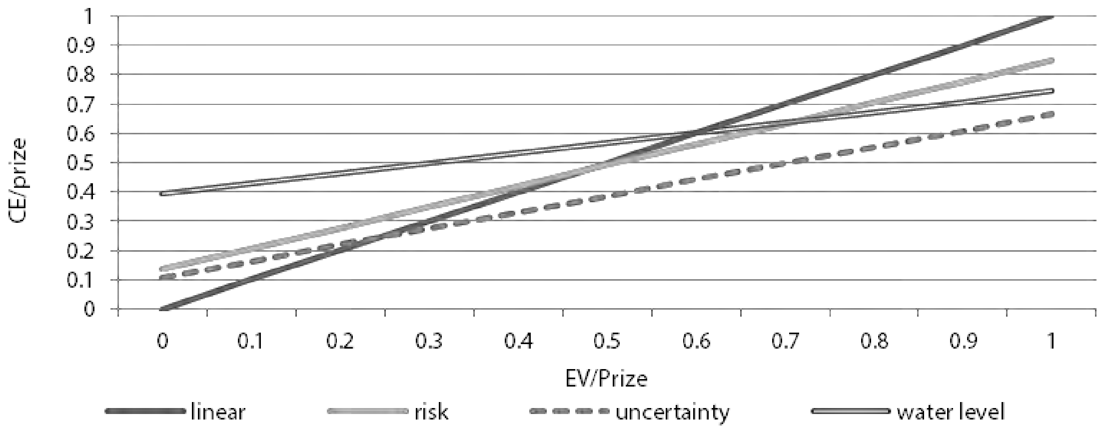

Figure 5. Median attitudes towards uncertainty sources, gains

[2] All tests presented in the text are nonparametric. Where comparisons of samples are concerned, these are Mann-Whitney tests; signed rank tests are used where a variable is compared to a normative benchmark or comparison value. All p-values reported are two-sided unless otherwise specified.

Next, we look at Ellsberg-type, or abstract, uncertainty. In keeping with the decision-making literature, we compare attitudes under uncertainty directly to attitudes under risk, thus discussing ambiguity attitudes. For small probabilities, our farmers are ambiguity neutral, behaving no differently under uncertainty than they do under risk ($z = 0.31$, $p = 0.758$). For large probabilities, on the other hand, our farmers display significant ambiguity aversion ($z = 2.53$, $p = 0.011$), which is also the global tendency ($z = 3.06$, $p = 0.002$).

Finally, we look at source preferences for betting on water levels. Our famers are clearly water-uncertainty seeking for small probabilities ($z = 8.59$, $p < 0.001$), while we cannot exclude water-uncertainty neutrality for very large probabilities ($z = 0.32$, $p = 0.749$). Globally, there is a clear trend toward water-uncertainty seeking ($z = 5.76$, $p < 0.001$). We can also look at the same attitudes in comparison to risk attitudes instead of using a benchmark of uncertainty-neutrality. In this case, we find our farmers to be water-ambiguity seeking for small probabilities ($z = 4.44$, $p < 0.001$), and water-ambiguity neutral for large ones ($z = 1.01$, $p = 0.312$). This, in turn, means that globally they are water-ambiguity seeking ($z = 4.47$, $p < 0.001$) or, in other words, they display a source preference for betting on water levels over betting on risk. Thus, in the gain domain, farmers are ambiguity averse toward Ellsberg-type urns, but display a clear source preference for betting on water levels over risk.

6.2 Source Functions of Farmers for Losses: Risk, Uncertainty, and Water Levels

Being in an insurance context, the source functions above only give us a general indication about preferences. What we should specifically care about is rather the source functions estimated in the loss frame. Figure 6 shows these source functions for losses. Notice how now a positive intercept represents uncertainty aversion and a positive anti-intercept represents uncertainty seeking, contrary to what we observed in the gain domain. This derives from the fact that we followed the convention of weighting losses de-cumulatively (see Wakker 2010), so that attitudes for losses are mirror images of those for gains. For risk, we find farmers to be risk averse for small probabilities ($z = 3.03$, $p = 0.002$), and risk seeking for large ones ($z = 5.15$, $p < 0.001$), with a global tendency toward risk seeking ($z = 4.34$, $p < 0.001$). This again corresponds well to the pattern we observe for students.

We next move on to examining ambiguity attitudes. Contrary to expectations, we find no significant ambiguity aversion for small probability losses ($z = 0.96$, $p = 0.335$). Farmers are, however, averse to Ellsberg-type uncertainty for such small probabilities, i.e., they dislike betting on them, thus accepting sure losses that are larger than the expected loss from playing out the prospect ($z = 3.57$, $p < 0.001$). We also find the expected ambiguity seeking for large probabilities ($z = 2.03$, $p = 0.043$). This effect also predominates globally, with significant ambiguity seeking on average over the probability space ($z = 2.56$, $p = 0.011$).

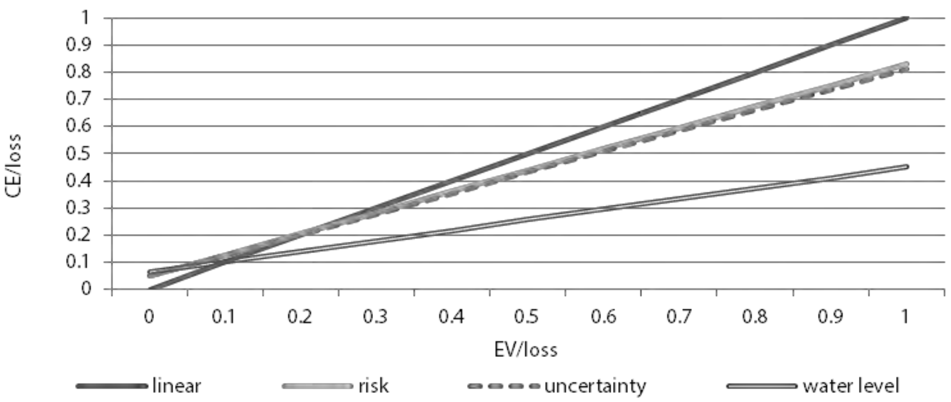

Figure 6. Median attitudes towards uncertainty sources, losses

As far as uncertainty attitudes toward water levels are concerned, we replicate the effect of global water-ambiguity seeking already found for gains (z = 3.74, p < 0.001), meaning that our farmers prefer betting on water levels rather than risk. This effect is very clear for large probabilities (z = 3.28, p = 0.001). For small probabilities, on the other hand, we cannot reject water-ambiguity neutrality (z = 0.97, p = 0.330). While we have, however, seen risk and uncertainty aversion to prevail for this type of probability, we cannot rule out water-uncertainty neutrality (z = 0.05, p = 0.960)—that is, we cannot reject the hypothesis that observations fall to equal parts above and below the expected value of the prospect, given subjective probability estimates (more on the latter below). In this sense, farmers do not display the uncertainty aversion they display for small probability risk and Ellsberg-type uncertainty for water uncertainty. Thus, for losses, we replicate the effect of source preference for water uncertainty already found for gains. Farmers are risk averse as well as Ellsberg-type uncertainty averse for small probabilities, but they are not averse to water uncertainty.

6.3 Subjective Probability Estimates

The source preferences we have seen above for water levels are conditional on subjective probability estimates. That is, we measure the willingness to bet on a given water level, which corresponds to a subjective probability of that water level occurring. A question that is just as important as the one whether farmers have a preference for betting on water levels as a source of uncertainty is to what degree their subjective probability estimates will be accurate. In particular, given the median neutrality or subjective expected value maximization toward losses associated with small probability water levels, the willingness to buy insurance may completely depend on subjective probability estimates. That is, we would expect the median farmer to buy insurance if he overestimates the probability of flooding, and not to buy it if he underestimates this probability; if his estimate is perfectly calibrated, he should be indifferent whether to buy insurance or not.

Figure 7 shows the cumulative probability distribution over different peak water levels. We see immediately that water levels are underestimated for most of the probability space, that is, there is too much probability mass attributed to low water levels once subjective estimates cross the objective probability line just after a water level of 340 cm. Serious floods above 450 cm occur with a probability of about 25%, and very dangerous floods above 490 cm with a probability close to 6%. If we thus take the 1/16 probability associated with the highest water levels, we can directly evaluate the impact of probability underestimation. Our farmers associate a water level of 448 cm or higher with this probability, whereas the true figure is 486 cm or higher, a water level to which our farmers by linear interpolation assign only a probability of roughly 1.7%. We thus easily reject the null hypothesis that the subjective estimate at this level is accurate for the alternative hypothesis that the water level associated with this probability is systematically underestimated (z = –10.17, p < 0.001). We also clearly reject the hypothesis that the endpoint estimate, defined as the highest water level ever observed, is accurate, again in favor of the alternative hypothesis that this value is underestimated (z = –5.01, p < 0.001). We thus have clear underestimation of probabilities in the relevant range.

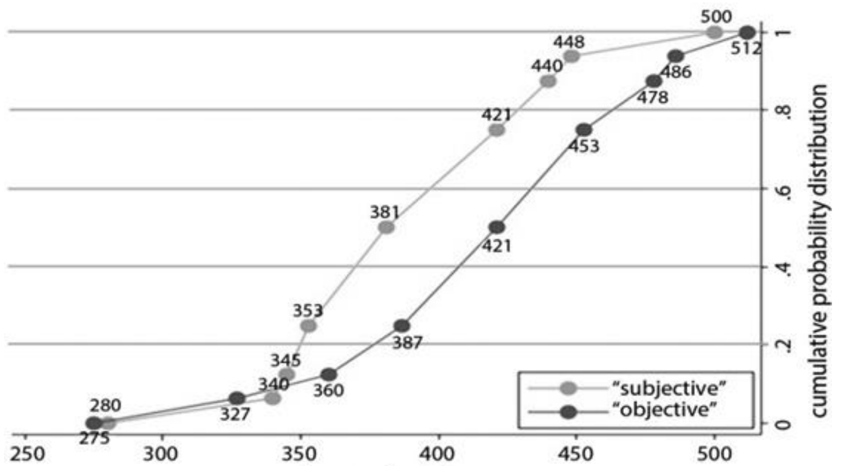

Figure 7. Subjective versus objective probabilities of flooding

There may be several reasons for this systematic underestimate. One obvious reason is that 50 years are a long time to recall. Thus, we look at the same relationship taking objective probabilities going only 30 years back. Given a mean age of our respondents of 50 years (median = 48), the majority should have living memory of these events, so it really becomes an exercise in recall. It turns out that the value corresponding to the 15/16 probability is the same as for the 50-year period. We have, however, a different, lower, maximum water level. Indeed, for the endpoint we can no longer reject the hypothesis that the subjective probability estimate of farmers is accurate ($z = -1.11$, $p = 0.266$). This is not a coincidence. The year in which that flood occurred (Year 2000) is vividly remembered by the farmers—and it happens to be the last Dragon year in the Chinese calendar, which observes a 12-year cycle.

7.0 CONCLUSION

Risk and uncertainty aversion is one potential explanation for the low take-up of insurance. In this study, we looked at specific preferences for uncertainties deriving from water levels in the Mekong, as well as abstract risk and uncertainty attitudes. While our subjects do generally exhibit a source preference for betting on water levels, this does not seem to drive potential low insurance uptake. The latter seems rather to be driven by subjective probabilities attributed to high water, with the probability of flooding being systematically underestimated.

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