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Flood insurance demand and probability weighting: The influences of regret, worry, locus of control and the threshold of concern heuristic

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ABSTRACT

Low-lying densely populated areas can be susceptible to flooding due to extreme river discharges. Insurance may be used to spread flood risk and reduce potential material damages. However, homeowners often purchase insufficient amounts of insurance against natural hazard risks like flooding, which may be due to the way they process probabilities. A common finding from (Cumulative) Prospect Theory is that individuals over-weight low probabilities and under-weight moderate to high probabilities in making decisions under risk. However, very low probabilities typical of flood risks are either significantly over-weighted or neglected altogether. This study aims to examine factors related to flood insurance demand regarding emotions specific to risk, like immediate and anticipated emotions, the threshold level of concern as well as personality traits, like locus of control. In addition, we compare results under real experiment incentives to hypothetical ones with high loss outcomes. Based on data collected from 1041 homeowners in the Netherlands, we find that: an internal locus of control and anticipated regret about potentially uninsured flood losses is related to higher flood insurance demand. The use of the threshold of concern model is related to more probability under-weighting/less probability over-weighting when probabilities of flooding are low. Several policies are suggested to overcome psychological factors related to low demand for flood insurance to improve future flood preparations.

1. Introduction

Flooding is the most costly type of natural hazard worldwide [1,2]. The estimated average damage costs from river floods alone are €110 billion per year globally [3]. Climate change and socio-economic developments, such as increasing population levels in river deltas, are projected to increase flood risks even further [4]. The Netherlands is particularly prone to climate change induced flooding, because most areas in the country are located below sea level or in a zone at risk of river flooding [5]. Expected increases in flood risk require improved flood risk management strategies to adapt to changing risks, like flood protection and financial coverage through insurance.

Insurance can be used by homeowners as a tool to spread flood risks and to obtain financial protection against the potentially high costs from flood events. However, previous research in the U.S. flood insurance market has shown that individuals often do not

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purchase insurance even when premiums are subsidized [6]. This behaviour cannot be explained within an Expected Utility Theory (EUT) framework under sensible levels of individual risk aversion [7].

Cumulative Prospect Theory (CPT) [8] is a popular framework employed to model decision making under risk, as an alternative to EUT [9]. While EUT evaluates outcomes with a utility function over final wealth, CPT evaluates utility over gains and losses relative to a reference point. This way CPT allows for incorporating loss aversion, which reflects the commonly observed notion that losses loom larger than gains in decisions. Moreover, while EUT assumes a linear processing of probabilities, CPT introduces non-linear sensitivity to probabilities through a probability weighting function. Previous research on CPT has shown that individuals are less responsive to probability changes as one moves away from the endpoints of the probability scale at 0 and 1 [10], which is reflected by an inverse-S probability weighting function [11]. Individual risk attitudes are determined by the combination of utility curvature, loss aversion and probability weighting under CPT, which allows for describing a wider diversity of observed individual behaviour than EUT.

Empirical evidence about factors related to the probability weighting function and/or utility curvature include, among others, the influence of the size and spacing of outcomes [12–14], gender [15], age [16,17], mood [18,19], time pressure [20], as well as induced affect and numerical skill [21–25]. Many of these studies elicited preference parameters under neutrally framed decisions, which is useful if the aim is to perform controlled theoretical tests, because specific context framing can add noise to results [26]. However, in the end we are also interested in how individuals make decisions about real risks, such as flood disaster events, which is the focus of the current paper.

CPT has been used frequently to explain results in the previous literature in applications related to natural disasters and water research, e.g., on topics like flood risk [27–30], drought risk [31,32] and climate change policy [33] [34]. utilized CPT risk preference parameters estimated in previous studies under neutrally framed decisions (e.g. Refs. [12,35], to estimate willingness-to-pay for flood insurance under different climate change scenarios for the Netherlands. But to our knowledge, no studies have elicited CPT risk preference parameters based on these decisions directly, i.e., using flood insurance choices.

In this paper we focus on flood risk insurance in the Netherlands. Dikes and levee systems provide a cost-effective solution to prevent flooding in the Netherlands [36], however this protection is incomplete and residual flood risks remain for low-lying densely populated areas. Efforts have been made in recent years to make flood insurance more widely available, but to date this insurance is purchased by only a small fraction of the Dutch population [37]. As a result there are currently no revealed preference measures of flood insurance demand available on a large scale in the Netherlands, like for example exist in the U.S. (e.g., Refs. [38–40]. An alternative to obtain insights into flood insurance demand and its determinants based on actual flood insurance decisions is to elicit stated preferences for insurance.[1] The topic of the current paper is to examine how these preferences relate to heuristic processes, emotions and personality characteristics of the Dutch population.

Decision heuristics are simple rules-of-thumb which can be employed when individuals are presented complex tasks involving probability assessment [41]. An example is the threshold of concern model, which predicts that individuals ignore risks when the perceived probability of that risk is below a subjective threshold level of concern [42]. Anticipated and immediate emotions like regret, worry and mood have also been shown to relate to individual risk judgments and protective decisions [43–46]. Other factors like personality traits, and in particular locus of control can also relate to flood insurance demand [47]. Locus of control reflects beliefs about whether individuals have control over outcomes in their life [48]. Individuals assigned as internal locus of control types attribute outcomes to their own efforts, whereas externals believe that outcomes more often arise due to fate.

It has to our knowledge not been examined yet how CPT risk preference parameters relate to emotions regarding specific risk and insurance products, like worry and regret as well as personality traits like locus of control.[2] This research aims to fill this gap in the context of flood risk and flood insurance. The research is also relevant from a policy perspective because if we have a good understanding of psychological factors which may lead to the under-/over-weighting of flood risks, policymakers can employ tailored strategies to improve individual flood preparedness decisions. A better understanding of why individuals under-/over-weight events like flooding was also suggested as a direction for future research by Ref. [49].

An economic experiment was conducted with a sample of 1041 homeowners in the Netherlands. The experiment elicited certainty equivalents (maximum willingness-to-pay for insurance) for fourteen prospects of probability and loss combinations framed in the context of flooding. We included survey questions to elicit our variables of interest. Based on the experiment data we conduct non-parametric statistical tests of risk attitudes to test our hypotheses, and conduct an exploratory structural model analysis of the CPT preference functionals to examine whether the relationships found are due to probability weighting, utility curvature or random decision making.

We find that internal locus of control and anticipated uninsured flood loss regret are related to more flood insurance demanded. Other factors like the use of the threshold of concern model are related to risk preferences when probabilities of flooding are low.

The paper is structured as follows: Section 2 describes the experiment implementation, design and hypotheses. Section 3 discusses the methods used to test the hypotheses and to conduct an analysis of the relationship between our variables of interest and the CPT preference functionals. Section 4 presents the results of a non-parametric testing of our hypotheses and a parametric exploratory analysis of the flood insurance choices. This is followed by a discussion in Section 5 and conclusion in Section 6.

[1] Although stated preference methods are not used very often in flood risk valuation, some studies have adopted this method recently (e.g., Refs. [27,96].

[2] However, a paper by Ref. [46] examined the relationship between mood and probability weighting in an insurance context.

Table 1
Descriptive statistics.

Variable	Percentage	Frequency
Reside outside dike-ring area in river bed	0.8%	8
Reside in 1/1250 area	48.2%	502
Reside in 1/2000 area	3.8%	40
Reside in 1/4000 area	7.8%	81
Reside in 1/10,000 area	18.3%	190
Reside outside dike-ring area in low risk zone	19.4%	202
Male	52.4%	546
Income less than €1000	4.5%	47
Income is between €1000 and €1499	3.7%	39
Income is between €1500 and €1999	9.5%	99
Income is between €2000 and €2499	14.5%	151
Income is between €2500 and €2999	13.4%	139
Income is between €3000 and €3499	17%	177
Income is between €3500 and €3999	11.6%	121
Income is between €4000 and €5499	16.8%	175
Income is more than €5500	8.9%	93
Higher education	61.7%	642

2. Implementation and experiment design

In Section 2.1 we provide an overview of the way in which the experiment was implemented, as well as some sample descriptive statistics. Our methods for eliciting flood insurance demand are explained in Section 2.2, and the elicitation of as well as hypotheses related to our variables of interest are given in Section 2.3.

2.1. Implementation

The first version of our experiment was pretested using thirty face-to-face household interviews during March 2017 with one trained and supervised interviewer. Adjustments were made to improve the clarity of introduction text and questions based on the pretest, after which we launched a final online pretest resulting in a few small adjustments to the instructions.

An online experiment was then conducted with a sample of Dutch homeowners. We opted for an online experiment because given our study topic, the benefits of higher external validity and better statistical power offered by more respondents, outweighed the disadvantages of potentially lower attentiveness and motivation for individuals participating in online relative to lab experiments. We take measures explained in the next section to avoid responses which display an overall lack of attentiveness.

Our sample consists of 1041 homeowners drawn at random from the consumer panel of Multiscope (www.multiscope.nl). Renters do not pay for structural flood damage to their home, so this sub-group was excluded from participation in the study. All individuals were rewarded “Social Points” for participating, which can be exchanged into gifts via the Multiscope website, and the link to the experiment could no longer be used by the same individual once they had entered their unique information.

Sample descriptive statistics are provided in Table 1. 48% of the sample live in dike-ring areas designed at standards 1/1250, implying that dikes can withstand a 1 in 1250 years flood event. A further 4% of the sample live in 1/2000 areas, 8% live in 1/4000 areas, and 18% reside in dike-rings with the highest protection standard (1/10,000). Moreover, 19% live outside dike-ring areas in land that cannot be flooded by rivers, therefore the probability of river flooding is zero. 1% live outside dike-ring areas in a river bed, therefore the probability of flooding is high although there is no official safety standard. The remaining 2% could not be classified because they provided invalid postcodes. With respect to socio-economic factors, 52% are male, median monthly after tax household income is between €3000 and €3499 and 62% had completed higher education, i.e., they possess either a Bachelor's degree, higher professional education diploma (HBO), Master's degree or PhD.

Due to budget constraints, it is challenging to offer financial incentives for decisions about high-impact losses in economic experiments. A recent review of insurance demand studies by Ref. [50] showed that experimenters frequently implement large losses by only paying one or a few respondents (e.g., Refs. [51–54]. The review concluded that it is unclear whether this method can be used without distorting choices. We aim to examine whether preferences elicited under this procedure are different to those elicited from hypothetical decisions. From the sample of 1041 individuals, 624 were randomly assigned to face real incentives, where one respondent was randomly selected for a large payment (see Section 2.2), whilst no performance-based payment was provided to 417 respondents.

2.2. Eliciting flood insurance demand

Respondents were asked to imagine that they purchased a property worth €240,000 in an area at risk of flooding.[3] Additional text

[3] €240,000 = approximate average purchase price for a home in the Netherlands in the year 2016 [97].

Table 2
Prospects.

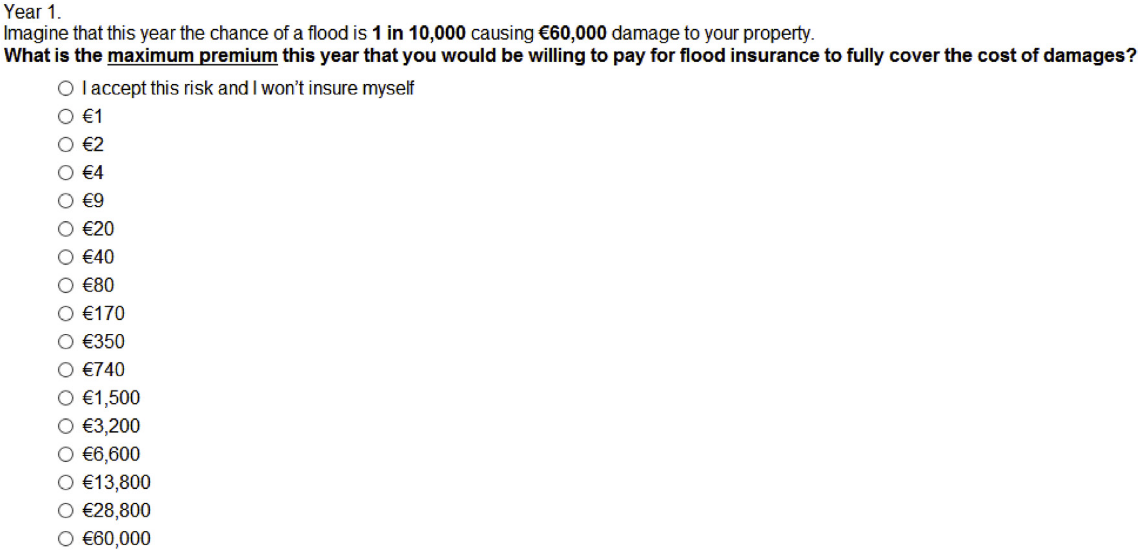
Decision	Probability of worst outcome	Worst outcome	Best outcome
1	1 in 10,000	-€60,000	€0
2	1 in 1000	-€60,000	€0
3	1 in 100	-€60,000	€0
4	1 in 20	-€60,000	€0
5	1 in 4	-€60,000	€0
6	1 in 3	-€15,000	€0
7	1 in 3	-€30,000	€0
8	1 in 3	-€60,000	€0
9	1 in 2	-€60,000	€0
10	3 in 4	-€60,000	€0
11	19 in 20	-€60,000	€0
12	1 in 3	-€30,000	-€15,000
13	1 in 3	-€45,000	-€15,000
14	1 in 3	-€60,000	-€45,000

stated that flood insurance is available, and government compensation will not be granted for uninsured flood damages. We obtained certainty equivalents (maximum willingness-to-pay for insurance) for fourteen two-outcome prospects of probability and loss combinations framed as flood risks, as is a common approach for estimating CPT functionals. Two-outcome prospects were chosen with sufficiently varying outcomes and probabilities to separate attitudes towards outcomes and attitudes towards probabilities (see Refs. [15,55,56] for a similar procedure). Prospects that included one non-zero outcome were ordered ascending in the probability of their worst outcome. Although this method may induce order effects, an advantage is that individuals may find the procedure easier than if prospects were to be randomized [57]. This is important because violations of stochastic dominance may be high in experiments where individuals are unsupervised. Such violations occurred in our experiment when an individual was willing to pay more for flood insurance under a given flood risk than under another flood risk with a higher flooding probability. Table 2 displays the included prospects in their order of presentation.

Changes in flood risk between prospects were attributed to the property being exposed to rising water levels. For instance, in year 1, which was the first flood risk faced by respondents, individuals were asked to “imagine that this year the chance of a flood is 1 in 10,000 causing €60,000 damage to your property”. In year 2, individuals read that “due to higher water levels in this year than the previous one, the chance of a flood is now 1 in 1000 causing €60,000 damage to your property”. Note that cities of high economic importance in the Netherlands, like Amsterdam and The Hague, are protected by dikes with an average annual dike exceedance probability of 1 in 10,000 which is the lowest flood probability in our experiment. For homeowners located on the wrong side of dikes, the annual probability of flooding can reach as high as 1 in 5 [58]. However, flood probabilities are not static, and can be very high at a particular point in time under certain circumstances, for example because of extreme storm conditions, extreme rainfall or extreme peak river discharges. In 1993 and 1995 river floods in some parts of the Netherlands were very likely to occur due to extreme river discharges, which is why the government decided to evacuate around 250,000 people during this event. Hence, we used a storyline of changes in water level conditions to explain why flood probabilities increased at a certain point in time. This approach allowed us to elicit flood insurance demand at various flood probability levels. To our knowledge, the only previous study eliciting demand for flood insurance in the Netherlands under high probabilities of flooding is [59]. According to the authors, these flood risks are not perceived as completely unrealistic by Dutch residents because previous flood experiences were covered extensively in the media, and may play a greater role in formulating public flood risk perceptions than the official safety levels of dikes. The most recent flood event in the Netherlands occurred in 2003 due to a canal dike breach in Wilnis. Rising river water levels are one of the most urgent consequences of climate change facing the Netherlands [60].

Flood insurance decisions took place from an endowed bank balance of €60,000. We assume that individuals incorporated prior endowments into their reference point, isolated from potential losses and willingness-to-pay for insurance, so the latter should be viewed as losses. To elicit certainty equivalents for flood risk, we used a two stage procedure where individuals faced a payment card task and then a willingness-to-pay task.[4] In stage one, individuals were presented a yearly risk of flood damage as well as sixteen ascending values between the extreme values of the prospect, with an additional option to accept the flood risk and remain uninsured. The sixteen values were logarithmically spaced (see Ref. [8] to include risk seeking/neutral/averse options into the elicitation task, which is not possible with equal spacing for large outcomes. According to the values, individuals were asked their maximum willingness-to-pay for flood insurance to fully cover the cost of property damages. To obtain a more refined certainty equivalent, in stage two individuals were again asked what they were at most willing to pay for flood insurance between the value chosen in stage one and the next highest value. Sample decision screens corresponding to the first flood insurance decision are displayed in Fig. 1

[4] Given the online nature of our experiment there is a risk that individuals would be tempted to give up on the experiment after a short time if they perceived the tasks as too difficult. Therefore, we favor the two stage procedure over more complex methods for determining risk preferences like the price list format, where participants make a series of discrete choices. The latter would require a sizeable number of decisions which may have lowered response rates or lead to lower attentiveness. While more theoretically appealing risk preference elicitation procedures exist, collecting valuations directly has advantages (see Zeisberger et al. (2012, pp. 364–365) for a discussion).


Year 1.
Imagine that this year the chance of a flood is **1 in 10,000** causing **€60,000** damage to your property.
What is the maximum premium this year that you would be willing to pay for flood insurance to fully cover the cost of damages?

- ○ I accept this risk and I won't insure myself
- ○ €1
- ○ €2
- ○ €4
- ○ €9
- ○ €20
- ○ €40
- ○ €80
- ○ €170
- ○ €350
- ○ €740
- ○ €1,500
- ○ €3,200
- ○ €6,600
- ○ €13,800
- ○ €28,800
- ○ €60,000

Fig. 1. Flood insurance decision stage 1 screenshot.

(stage 1) and Fig. 2 (stage 2).

We paid one respondent according to one flood insurance decision (both selected at random) under real incentives. A 1% exchange rate was applied to these earnings, so the selected individual could earn €600 should they not experience a loss in the chosen decision. For payment we applied the [61] (BDM) mechanism: a premium for which flood insurance is to be sold is selected at random between the extreme values of the prospect in the chosen decision.[5] That is, the selling price varied between the lowest and highest option of the payment card. If the individual is willing to pay an amount equal to or greater than the premium, then they have purchased insurance at the price of the premium, and otherwise they face the flood risk uninsured. Respondents should make decisions consistent with true preferences according to the BDM procedure, and this was explicitly mentioned in the instructions. For example, insurance valuations lower than true valuations run the risk of not qualifying for insurance. Valuations made greater than true valuations, may end up with insurance and regret making the excessive offer [53]. Due to the potentially complex nature of the BDM mechanism for some individuals, we illustrated the method graphically alongside written instructions.[6]

We omit 57 respondents from the proceeding analysis who chose a maximum willingness-to-pay for flood insurance equivalent to either the highest or lowest prospect values for every decision presented to them. These may be protest responses [62], or reflect an overall lack of attentiveness by individuals.

2.3. Hypotheses of variables related to flood insurance demand and variable elicitation

A series of five-point Likert scale survey questions were presented following the flood insurance decisions in order to elicit the explanatory variables that may be related to flood insurance demand (see Appendix). The selection of variables to elicit in the experiment was based on a review of the literature on psychological determinants of insurance demand under catastrophic risk. We examine the influence of factors related to anticipated and immediate emotions like regret, mood and worry, personality characteristics like locus of control, as well as heuristic processes like individual utilization of the threshold of concern model [63]. defined anticipated emotion as emotion expected to be experienced in the future, while immediate emotion is experienced at the moment of decision making. Immediate emotion can be further sub-divided into incidental influences, like mood which is unrelated to a given decision, and anticipatory emotions, like worry which arises when an individual is considering the consequences of a decision. The potential relation of these factors to flood insurance demand is explained in more detail below.

Our literature review also identified some variables that have been found to influence flood insurance demand and risk perception in other countries that we consider less relevant for the Netherlands, and are hence not used here. In particular, homeowner's trust of flood protection, social norms, and personal experience with flooding have been identified by other studies as important factors of influence on flood insurance demand and risk perceptions [64–66]. We think these variables are less relevant for the Netherlands where overall trust is high, and there is hardly any experience with flooding nor with purchasing flood insurance, so we do not include these variables in our analysis.[7]

[5] We left the bounds unspecified because individuals may anchor on the bounds of the random selling price [98].

[6] See the Appendix for experiment instructions in English. A full overview of the experiment sample screens are available in the Online Supplement.

[7] < 5% of individuals sampled had experienced flood related evacuation in the past. Only 9% sampled do not believe the Dutch river dikes are well maintained.

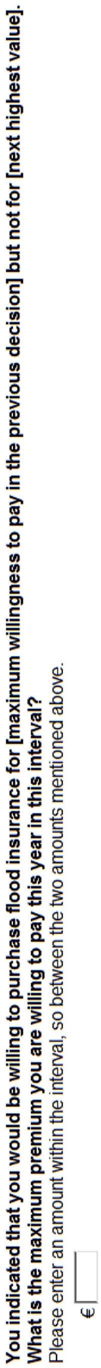

You indicated that you would be willing to purchase flood insurance for [maximum willingness to pay in the previous decision] but not for [next highest value].
What is the maximum premium you are willing to pay this year in this interval?
Please enter an amount within the interval, so between the two amounts mentioned above.
€

Fig. 2. Flood insurance decision stage 2 screenshot.

According to Ref. [44] definition of anticipated regret of insurance choices, we elicited regret by considering an individual who predicts how she/he would feel after making an ex-post incorrect flood insurance decision, as well as the disutility that this may bring about for the individual. It has been shown that anticipated regret can lead to both risk averse and risk seeking tendencies [67]. To our knowledge there is no theoretical consensus as to whether regret is related to risk preferences through probability weighting or utility curvature. Consider first an individual who may anticipate regret about not purchasing flood insurance if a flood were to occur (regret uninsured). The individual may take extra precaution by purchasing more insurance before a flood to avoid feeling regret. An experimental study by Ref. [68] found that individuals who experienced an uninsured loss as a result of hurricane damage were more likely to purchase insurance subsequently if the prior choice to be uninsured made them unhappy. These unhappy individuals may have regretted their previous decision to not purchase coverage. After omitting protest responses, 41% of respondents were inclined to believe that they would feel regret about not purchasing flood insurance if a flood were to occur. These individuals answered higher than the neutral response category regarding this type of regret, and are assigned a dummy variable called regret uninsured.

H1. Individuals with anticipated regret about not purchasing flood insurance in the event of a flood have a higher flood insurance demand.

Now consider an individual who would feel regret about paying an insurance premium if no flood were to occur (regret insurance). In anticipation of this emotion, the individual may prefer not to insure to avoid incurring ex-post potentially unnecessary out-of-pocket expenses. Individuals who anticipate this type of regret may view insurance as an investment, from which they expect a return on their policy [7]. Evidence from the U.S. suggests that certain subgroups purchase flood insurance after a catastrophic loss, but begin to feel that insurance payments have been wasted after a few years without a loss [69]. 32% of our sample answered higher than the neutral response category about feeling regret about paying an insurance premium if no flood were to occur.

H2. Individuals with anticipated regret about purchasing flood insurance in the event of no flood have a lower flood insurance demand.

We adapted our incidental immediate emotion variable according to a question in Ref. [46]. Specifically, we asked individuals to rate how their day had been going, and we assume that individuals who answered the question positively were in a good mood. The question was asked prior to flood insurance decisions to eliminate the potential impact of the insurance decisions on individuals' mood. Good mood can result in more risk seeking/less risk aversion behaviour according to studies on probability weighting (e.g., Refs. [19,46]. Fehr-Duda et al. (2011, p.15) conjectures that mood impacts risk preferences through probability weighting (not utility), because probability weights are a more malleable component of risk taking attitudes. However, note that it is theoretically unclear whether mood relates to risk preferences through utility or probability weighting. In total, 22% rated their day so far as better than usual or promising, which implies that they were in a good mood.

H3. Individuals in a better mood have a lower flood insurance demand.

Anticipatory worry was elicited using a question in Ref. [70]. A review article of flood risk perceptions shows that many studies find worry is a significant determinant of flood mitigation behaviour [45] [70]. showed that anticipatory factors, like high worry about flooding, are positively related to flood risk perceptions [53]. find that worry is a primary determinant of insurance decisions against low probability disaster type risks. Intuitively, low levels of flood insurance demand can be expected from those who have low worry about flooding.

Note that, in our experiment probabilities of flooding are provided explicitly, so individuals' perceived flood probability (which is another indicator of flood risk perception) should not play a role in the analysis. As a result of providing probabilities directly, we can examine the relationship between psychological factors like worry, on components of risk attitude like probability weighting (Section 4.2). Although we are not aware of a firm theoretical underpinning for this matter, it seems reasonable to suspect that individuals who have low worry about flooding may attach lower decision weights to flood events (worst outcomes), and thus display more probabilistic optimism/less probabilistic pessimism. In total, 50% of individuals strongly disagreed that they were worried about the danger of flooding at their current residence.

H4. Individuals with low worry about flooding have a lower flood insurance demand.

It is our assertion that an individual's belief about whether they have control over outcomes in their life is the most relevant personality trait to the question of how individuals respond to the risk of flooding. Although there has been some research on other personality traits like the big five and their relation to risky behaviour in other domains (e.g., in risky sexual behaviour [71], unsafe driving [72] and smoking [73]), locus of control appears to be the most dominant personality component in relation to mitigation and protection against catastrophic risk and risk perceptions [74–78] [79]. found that locus of control is a significant predictor of various risk perceptions related to environmental matters. In addition [47], showed that a higher percentage of internals hold flood insurance in floodplain communities in the U.S., compared to individuals who have an external locus of control. Individuals who believe that they have the capability to control unfavorable events and their outcomes may pay more attention to the potential danger of flooding, compared to those who take a fatalistic approach to flood insurance decisions. However, we have no theoretical guidance as to whether locus of control is related to flood insurance demand through probability weighting or utility curvature.

Four statements were used to measure internal locus of control types, i.e., individuals who tend to believe that they have control over events and their outcomes in life. These were the same items used by Ref. [77]; which were modified from an extended list of statements in Ref. [48]. Our internal locus of control variable was created by summing the Likert scale responses for individuals who are inclined to believe people can take measures to reduce their risks, and believe they have the power to control what happens in their lives. Then summing responses for individuals who do not find it necessary to plan ahead because outcomes tend to be based on fortune, and believe that getting what you want in life is down to luck. A dummy category was assigned to 47% of the respondents who had combined scores of 7 or higher on the former (internal statements) and 5 or less on the latter (external statements).

H5. Individuals with an internal locus of control have a higher flood insurance demand.

We conjecture that individuals prioritize their attention to matters which are worth assessing the probability of each outcome in a calculated manner, i.e., those which exceed their threshold of concern. The finding that individuals tend to purchase an inadequate amount of flood insurance on average may be consistent with them dismissing low probability risks which fall below subjective threshold levels of concern [6,80]. We suspect that threshold of concern may relate to demand for insurance through probability weighting in light of the fact that threshold of concern is about probability neglect. The threshold of concern variable was adapted from Ref. [70]; and represents individuals who think the flood probability is too low to be concerned about. 55% of respondents answered higher than the neutral response category regarding the flood probability being too low to be concerned about, and we expect that these individuals do not find it necessary to take precautionary measures like purchasing flood insurance.

H6. Individuals who feel that the flood probability is too low to be concerned about have a lower flood insurance demand under low probability flood risks.

The Appendix (Section A5) contains information about the questions and variables of interest. We generate dummy variables according to the percentage of individuals identifying with the explanatory variables of interest to use in the analysis of flood insurance demand.

3. Methods

This section provides information about the methods by which the hypotheses are tested, and methods used to conduct an exploratory analysis of the relationship between our variables of interest and the CPT preference functionals, namely probability weighting and utility curvature. A non-parametric analysis (Section 3.1) is used for hypothesis testing, which involves the least tampering with the data [81]. A parametric analysis (Section 3.2) is used to examine through which component of risk preference variables may relate to flood insurance demand, i.e., probability weighting and/or utility curvature. The parametric analysis also allows us to filter out behavioural noise, which has been shown to systematically interfere with risk preferences [82]. Note that the parametric analysis should be treated as exploratory because there is not a very strong theoretical underpinning with regards to whether the variables impact risk preferences through probability weighting and/or utility curvature. Moreover, a relationship to probability weighting and/or utility curvature does not necessarily imply a relationship to flood insurance demand. For example, a given variable may be related to probability weighting and utility curvature in such a way that results in a null effect on flood insurance demand, under a given flooding probability.

3.1. Methods of non-parametric analysis

Prior to presenting the analysis of flood insurance demand based on the hypothesis dummy variables described in Section 2.3, we will display histograms of the overall response patterns for these variables. We will then provide a non-parametric examination of the relative risk premia (RRP) across the probabilities of flooding in our experiment. RRP is the difference between the expected value of a prospect and it's certainty equivalent divided by the absolute expected value of the prospect: $RRP(X) = [EV(X) - CE(X)]/|EV(X)|$. A positive (negative) RRP indicates risk aversion (seeking), and when RRP $= 0$ preferences are risk neutral. It follows that individuals are willing to pay flood insurance amounts above (below) the actuarially fair insurance price when RRP values are positive (negative).

We calculate a series of Wilcoxon rank-sum tests across probabilities relevant to decisions with flood losses of either €60,000 or zero, to examine whether there is a relationship between RRP and our variables to interest. To avoid the multiple testing problem we apply Bonferroni adjustments to ensure that the cumulative probability of Type I error is low [83]. The Bonferroni adjusted critical values are calculated by dividing the unadjusted critical values (1%, 5% and 10%) by the number of comparisons.

3.2. Methods of parametric analysis

Under CPT, the utility function, v, and the probability weighting function, w, are subjective parameters, and in addition to loss aversion they define risk preferences.[8] w is applied to loss ranks, where a loss rank is the probability of obtaining an outcome ranked worse in a prospect. Since the prospects in our experiment contained two outcomes, x_1 and x_2 (where: $x_2 < x_1 < 0$), the CPT value of a prospect is as follows:

$$CPT(X^j) = w(p_2)v(x_2) + (1 - w(p_2))v(x_1) \tag{1}$$

For w we use the two-parameter [84] specification:

[8] The experiment involved no mixed prospects, therefore loss aversion cannot be estimated.

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}} \tag{2}$$

δ captures elevation of the probability weighting function while γ controls curvature. Elevation measures optimism/pessimism, i.e., the higher the probability weighting function, the more pessimistic/less optimistic the individual (in the loss domain). Curvature captures discriminability, which is the ability of the individual to discriminate between probabilities, i.e., the more linear the curve, the better this ability.

For utility we adopt the power specification:

$$v(x) = -(-x)^{\beta} \tag{3}$$

β indexes the concavity/convexity of the utility function. Certainty equivalents are sure amounts (maximum willingness-to-pay values) where the individual is indifferent between these amounts and the respective prospects. Predicted certainty equivalents $\hat{CE}$ are inverse utilities of the CPT prospect values:

$$\hat{CE}(X^j) = v^{-1}(CPT(X^j)) \tag{4}$$

Equation (4) can deviate from actual *CEs*, because of imprecise maximum willingness-to-pay valuations, therefore, actual *CEs* are specified as:

$$CE(X) = \hat{CE}(X) + \varepsilon \tag{5}$$

with. $\varepsilon \sim N(0, \sigma^2)$

We assume that prospects with widely-spaced outcomes will increase random errors, by incorporating a dependency between the size of the error term and the standard deviation of prospect j [85]. Following [55]; the following stochastic error specification is used:

$$\sigma = \omega|(x_1 - x_2)| \tag{6}$$

We model parameters with respect to individual characteristics, and estimate coefficients of interest by maximum likelihood estimation. Moreover, we cluster errors at the individual level. Given that behavioural noise can bias estimates of risk preferences [82], we also allow the variables of interest to depend on ω.

Upon initial inspection of the data, we found that our variables of interest are related to β and δ in opposite directions in terms of their relationship with risk preferences. This is likely due to collinearity between utility and probability weighting. Therefore, we eliminate the collinearity by only modelling either the utility or the probability weighting parameters as a function of variables of interest in the proceeding section.[9] Note, given no standard exists in the literature on choosing the utility function, the probability weighting function and the stochastic component, we chose a combination which resulted in a best fitting model according to the AIC and BIC criteria. The use of other functional forms does not influence the collinearity between β and δ.

4. Results

Section 4.1 outlines the results of the non-parametric analysis in relation to the hypothesis variables of interest. The exploratory analysis of the relationship between our variables of interest and the CPT preference functionals is given in Section 4.2.

4.1. Non-parametric analysis

Respondents answered the regret uninsured, regret insurance, worry, locus of control and threshold of concern questions based on the extent to which they agree with the associated statements on a scale ranging between: “Strongly disagree” (1) and “Strongly agree” (5). Respondents answered the good mood question based on a scale ranging between: “Badly” (1) and “Promising” (5).

Fig. 3 shows that most individuals are in the neutral category with regards to feeling regret about not purchasing flood insurance, and about feeling regret if the individual were to pay an insurance premium if no flood were to occur. Individuals are also mostly in the neutral category regarding good mood and there is less variation from this category compared to the two regret variables. Moreover, most respondents appear to have very low worry about flooding and are inclined to believe that the flood probability is too low to be concerned about, which is no surprise because individuals think highly of Dutch flood risk management in general, which may lower flood risk perceptions [86]. The histogram of the internal locus of control response pattern represents the summed Likert scale responses for individuals who are inclined to believe people can take measures to reduce their risks, and believe they have the power to control what happens in their lives, and subtracting responses for individuals who do not find it necessary to plan ahead because outcomes tend to be based on fortune, and believe that getting what you want in life is down to luck. The combined responses are predominantly positive, which indicates that respondents agreed more with the internal locus of control statements than with the external statements.

Although we dichotomize the independent variables, qualitative conclusions in the following analysis are robust to calculating Spearman's rank correlation coefficients between RRP and untransformed ordinal variables based on the Likert scale responses.

[9] The correlation between β and δ is large on aggregate ($\rho = -0.685$) [56]. described this correlation as unavoidable in structural estimations of CPT.

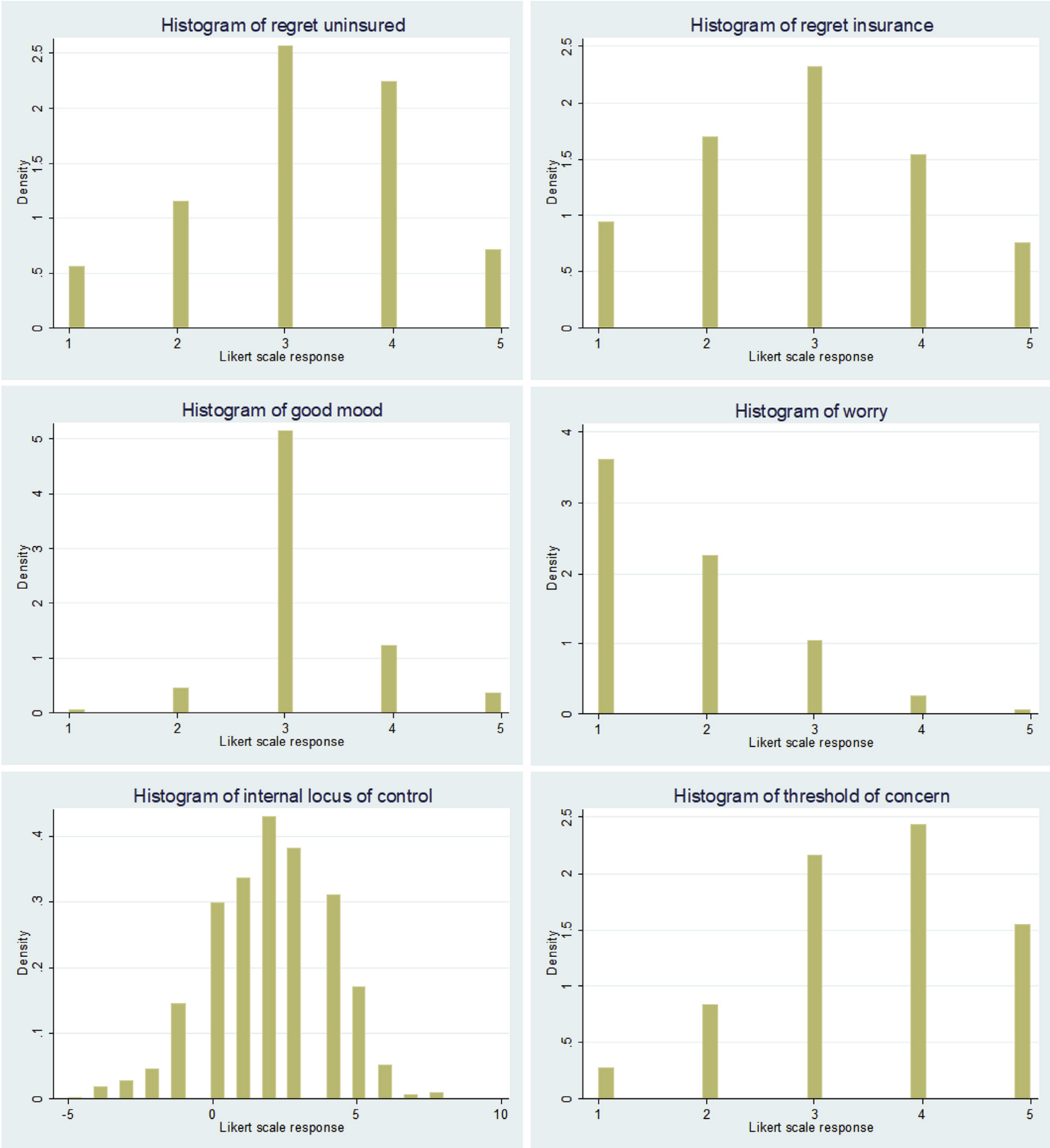


Fig. 3. Distribution of Likert scale responses for the hypothesis variables.

Table 3 shows that individuals who anticipated regret about paying for insurance in the event of no flood, those who have low worry about flooding and those who believe the flood probability is below their threshold of concern are more risk seeking/less risk averse. However, these relations are only significant at low flooding probabilities. From our point of view, it is logical that individuals would only employ emotions and decision rules related to risk perceptions and flood probabilities (like worry and threshold of concern) for the low probabilities that most of these individuals also face in practice. Previous studies have shown that low probabilities tend to induce a bimodal behaviour [87,88], with either strong probability over-weighting or probability neglect (strong probability under-weighting). The aggregated data hides that some individuals consider the risk as negligible and refuse to get insured, and other individuals feel highly worried and concerned by the risk and could purchase even too costly insurance.[10] Regarding anticipated regret about paying for insurance in the event of no flood, for larger probabilities this emotion may be less influential given that a

Table 3
Relative risk premia (RRP) difference per variable of interest.

Variable	Flood probability	1 in 10,000	1 in 1000	1 in 100	1 in 20	1 in 4	1 in 3	1 in 2	3 in 4	19 in 20
Regret uninsured	Median RRP regret uninsured = 1	9	1.5	−0.417	−0.833	−0.933	−0.949	−0.947	−0.96	−0.963
	RRP difference[a]	3.333*	0.833***	0.25***	0.05***	0.039***	0.03***	0.033***	0.028***	0.026***
Regret insurance	Median RRP regret insurance = 1	3.167	0.5	−0.667	−0.883	−0.967	−0.97	−0.967	−0.978	−0.975
	RRP difference[b]	−5.833**	−0.167	−0.067	−0.017	−0.007	0.005	0.003	0	0.008
Good mood	Median RRP good mood = 1	7.333	0.667	−0.658	−0.867	−0.965	−0.966	−0.955	−0.976	−0.968
	RRP difference[c]	0	0	−0.033	0.012	−0.005	0.009	0.015	0.002	0.014
Low worry	Median RRP low worry = 1	4	0.667	−0.667	−0.883	−0.967	−0.975	−0.967	−0.98	−0.979
	RRP difference[d]	−8.333***	−0.333*	−0.067	−0.016	−0.016	−0.005	0	−0.002	0.004
Internal locus of control	Median RRP internal locus of control = 1	7.333	0.667	−0.5	−0.833	−0.933	−0.949	−0.95	−0.967	−0.974
	RRP difference[e]	0	0	0.167**	0.067***	0.037***	0.03***	0.025**	0.017**	0.012*
Threshold of concern	Median RRP threshold of concern = 1	5	0.667	−0.667	−0.877	−0.96	−0.965	−0.967	−0.978	−0.977
	RRP difference[f]	−7.333***	−0.333	−0.083	−0.01	0.007	0.01	0.007	0	0.005

***Significant at 1%; **Significant at 5%; *Significant at 10% according to a two-sample Wilcoxon rank-sum test with Bonferroni corrections.
[a] Median RRP difference for regret uninsured = 1 vs. regret uninsured = 0.
[b] Median RRP difference for regret insurance = 1 vs. regret insurance = 0.
[c] Median RRP difference for good mood = 1 vs. good mood = 0.
[d] Median RRP difference for low worry = 1 vs. low worry = 0.
[e] Median RRP difference for internal locus of control = 1 vs. internal locus of control = 0.
[f] Median RRP difference for threshold of concern = 1 vs. threshold of concern = 0.

flood event is more likely to occur.

Note that median RRP levels for individuals who have low worry about flooding, who anticipated regret about paying for insurance in the event of no flood and who believe the flood probability is below their threshold of concern, are positive under flood probabilities 1 in 10,000 and 1 in 1000. Therefore, demand for insurance is still higher than actuarially fair insurance prices for a large proportion of individuals who identify with these variables under low probabilities of flooding.

Anticipated regret about uninsured flood loss is associated with more risk aversion/less risk seeking across the flooding probabilities. Furthermore, good mood is not significantly related to RRP. We can conclude that anticipated and anticipatory emotions have a more meaningful relation to risk preferences than incidental good mood.

Regarding personality traits, internal locus of control is related to more risk aversion/less risk seeking for higher flooding probabilities (> 1 in 1000).

Lastly, we tested for the effect of the hypothetical incentives in our experiment separate to the results reported in Table 3, which are related to our hypothesis variables. Individuals are more risk seeking/less risk averse under hypothetical incentives, but the relation is only significant when the flooding probabilities are 1 in 1000 and 1 in 100 (p-values < 0.1 according to a two-sample Wilcoxon rank-sum test with Bonferroni corrections). This finding lends support to a hypothetical bias for these low probabilities in our dataset.

4.2. Parametric analysis

Table 4 displays the maximum likelihood estimation results, where probability weighting parameters are modelled as a function of the variables of interest.[11] Table 4 shows that regret about uninsured flood losses and internal locus of control is associated with more over-weighting/less under-weighting of flood probabilities, because both variables have a positive relation to parameter δ after

[10] Upon closer inspection of the data, we find that of the 984 respondents under investigation, 20.5%, 7.6% and 4.6% are willing to pay zero for flood insurance under probabilities 1 in 10,000, 1 in 1000 and 1 in 100 respectively, which may imply that they neglected these flood risks. Of those willing to pay zero, the majority have low worry about flooding or believe the flood probability is below their threshold of concern. That is, 64.9%, 66.7% and 68.9% of those willing to pay zero have low worry about flooding under probabilities 1 in 10,000, 1 in 1000 and 1 in 100, and 66.8%, 66.7% and 68.9% believe the flood probability is below their threshold of concern, respectively.

[11] Relative to previous studies, the values of δ and γ are considerably lower, and probable flood events are heavily under-weighted. However, these values are not completely unrealistic given our flooding context. For example, a real-time survey of hurricane risk perceptions found that despite the limitless information available about the severity of flood risks posed by Hurricane Isaac and Sandy, residents underestimated their highly likely flooding risks considerably, even those located in waterfront properties [99]. Moreover, it has been shown that individuals tend to weight decisions based on the frequency at which they occur outside experiments differently. For example [100], who found that probability weighting for insurance decisions involving low-frequency events like flooding display more probabilistic optimism/less probabilistic pessimism, compared to high-frequency events like laptop theft and home burglary. The authors conclude that the probability weighting function is impacted by the accessibility of events in memory, suggesting that individual experiences leak into risky decisions despite specified probability and loss information.

Table 4
Maximum likelihood estimation results (probability weighting parameters are a function of variables of interest).

	Model I: including variables of interest				Model II: including variables of interest and socio-economic controls			
	β	δ	γ	ω	β	δ	γ	ω
Regret uninsured		0.022** (0.01)	0.048** (0.022)	0.007 (0.015)		0.02** (0.01)	0.038 (0.024)	0.005 (0.015)
Regret insurance		0.012 (0.012)	0.004 (0.026)	0.025 (0.018)		0.011 (0.011)	0.015 (0.027)	0.016 (0.017)
Good mood		0.013 (0.014)	0.001 (0.034)	0.027 (0.022)		0.011 (0.014)	−0.023 (0.039)	0.026 (0.021)
Low worry		0.009 (0.01)	−0.029 (0.026)	0.026* (0.016)		0.009 (0.01)	−0.032 (0.026)	0.031** (0.015)
Internal locus of control		0.023** (0.01)	0.048** (0.024)	0.011 (0.015)		0.023** (0.011)	0.028 (0.026)	0.017 (0.016)
Threshold of concern		0.006 (0.01)	0.053** (0.024)	−0.009 (0.015)		0.004 (0.01)	0.057** (0.025)	−0.011 (0.017)
Hypothetical		−0.004 (0.009)	.05** (0.025)	−0.014 (0.015)		0.000 (0.01)	0.056* (0.029)	−0.009 (0.015)
Constant	1.142*** (0.031)	0.042*** (0.01)	0.179*** (0.029)	0.148*** (0.017)	1.142*** (0.032)	0.035** (0.015)	0.119** (0.05)	0.156*** (0.024)
LL	−141,298.58				−136,969.6			
N	984				955			

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Model standard errors are in parentheses. Model II includes control variables for the δ, γ and ω parameters. Control variables are as follows: male is a dummy variable which equals 1 for males and 0 for females; higher education equals 1 if an individual possesses either a Bachelor's degree, higher professional education diploma (HBO), Master's degree or PhD, and 0 otherwise; low income equals 1 for individuals with household monthly income lower than the median income category, and 0 otherwise and high risk equals 1 for individuals who live in areas with flood risks of 1 in 1250 or higher, and 0 otherwise.
Observations are lower in model II due to individuals listing their education as "Other" and providing invalid postcode addresses.

Table 5
Maximum likelihood estimation results (utility parameter is a function of variables of interest).

	Model I: including variables of interest				Model II: including variables of interest and socio-economic controls			
	β	δ	γ	ω	β	δ	γ	ω
Regret uninsured	0.135** (0.058)			0.007 (0.015)	0.123** (0.061)			0.005 (0.015)
Regret insurance	0.077 (0.064)			0.026 (0.018)	0.074 (0.065)			0.017 (0.017)
Good mood	0.051 (0.074)			0.027 (0.022)	0.022 (0.077)			0.026 (0.022)
Low worry	0.048 (0.058)			0.026 (0.016)	0.056 (0.06)			0.03** (0.015)
Internal locus of control	0.151*** (0.058)			0.011 (0.015)	0.145** (0.062)			0.017 (0.015)
Threshold of concern	0.048 (0.059)			−0.009 (0.015)	0.043 (0.062)			−0.011 (0.017)
Hypothetical	−0.012 (0.056)			−0.013 (0.015)	0.018 (0.061)			−0.008 (0.015)
Constant	0.939*** (0.059)	0.072*** (0.007)	0.271*** (0.011)	0.148*** (0.017)	0.87*** (0.097)	0.073*** (0.007)	0.284*** (0.012)	0.157*** (0.024)
LL	−141,315.92				−137,008.35			
N	984				955			

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Model standard errors are in parentheses. Model II includes control variables for the β and ω parameters. Control variables are as follows: male is a dummy variable which equals 1 for males and 0 for females; higher education equals 1 if an individual possesses either a Bachelor's degree, higher professional education diploma (HBO), Master's degree or PhD, and 0 otherwise; low income equals 1 for individuals with household monthly income lower than the median income category, and 0 otherwise and high risk equals 1 for individuals who live in areas with flood risks of 1 in 1250 or higher, and 0 otherwise.
Observations are lower in model II due to individuals listing their education as "Other" and providing invalid postcode addresses.

controlling for socio-economic variables (p-values < 0.05). This implies that bad outcomes (large floods) are assigned larger decision weights by individuals who anticipate regret about uninsured flood losses and internal locus of control types. We also find that if we drop the variables for the probability weighting parameters and allow a relation between the variables and utility, regret uninsured and internal locus of control show up as significant and related to more risk aversion/less risk seeking (Table 5). Therefore, we cannot distinguish whether these variables are related to flood insurance demand through probability weighting or outcome valuation. Regardless, the effects are consistent with the non-parametric results, and are not due to behavioural noise.

There is no significant relation to probability weighting or utility parameters for those who would regret paying for insurance premium payments in the event of no flood, nor for individuals who were in a good mood (p-values > 0.1). The non-parametric estimates in Section 4.1 showed that the latter variables either have no correlation with risk preferences (good mood), or only have a relatively minor relation with preferences when flood probabilities are very low.

In Table 4, threshold of concern has a positive relation to γ after controlling for socio-economic factors (p-value < 0.05). We conjecture that this is driven by the relatively large negative relation between threshold of concern and RRP when the flood probability is very low, i.e., more under-weighting/less over-weighting of very low probabilities. Therefore, large flood events are given lower decision weights for individuals who employ the threshold level of concern decision rule. The threshold of concern variable is not significantly related to utility curvature, so the effect on insurance demand appears to go through probability weighting.

Individuals who have low worry about flooding have more noisy responses because the variable is positively related to parameter ω (p-value < 0.05). This implies that the significant result found in Section 4.1 may be due to behavioural noise.

Hypothetical incentives also have a marginally significant positive relation with γ after controlling for socio-economic factors (p-value < 0.1). However, this marginally significant relation is not robust to alternative specifications of the probability weighting function, namely, neo-additive weighting.

5. Discussion

This section is organized as follows: Section 5.1 discusses the results in relation to our hypotheses, and Section 5.2 outlines several recommendations for policy which are based on these results.

5.1. Discussion of main results

We find that internal locus of control and anticipated uninsured flood loss regret are related to higher flood insurance demand, in support of **H1** and **H5**. The non-parametric results showed that internal locus of control leads to more risk aversion/less risk seeking for higher flooding probabilities ($>$ 1 in 1000). This may imply that internal types better prepare for higher probability flood risks, consistent with research conducted by Ref. [77]; who find that locus of control predicts hurricane preparation in communities under the immediate threat of a hurricane. In general, individuals with an internal locus of control are more likely to protect themselves against impending hazard events [76,78], e.g., flooding caused by increased water levels. The fact that locus of control does not correlate with RRP at very low probabilities may suggest that internals do not deem it necessary to exercise control over potential flood events when probabilities are sufficiently low.

Of the variables related to RRP when flood probabilities are low, like low worry about flooding, regret about paying for flood insurance if no flood were to occur, threshold of concern and hypothetical incentives, only threshold of concern is related to more probability under-weighting/less probability over-weighting for low flood probabilities according to the structural estimation. Some insurance demand studies have implemented high-impact losses by randomly selecting one or a few respondents to receive experimental payments (e.g., Refs. [51–54]. Our finding of more risk seeking/less risk aversion for low flood probabilities under hypothetical incentives (indicative of hypothetical bias), suggests that real incentives implemented according to this random selection may matter for eliciting risk preferences under low probability risks. Note however, that the result regarding hypothetical incentives being related to more probability under-weighting/less probability over-weighting under low flood probabilities, is not robust to alternative specifications of the probability weighting function. The threshold of concern result is consistent with **H6**. In particular, the finding confirms suggestions made by Ref. [80]; that individuals who utilize a threshold model may have lower demand for loss mitigation measures, because they view the probabilities of risks which fall below threshold levels as having a zero chance of occurrence.

With regards to **H2** and **H4**, the variables regret insurance and low worry have a significant relationship with flood insurance demand only for low flooding probabilities. In contrast to our single measure of subjective flood risk perception according to levels of stated worry about flooding [27], utilized several variables in their study of flood insurance demand in the Netherlands, such as perceptions about climate change induced flood risk, perceived risk of experiencing flood damages, as well as expected flood damage amounts and expected return period. They found a positive significant influence of risk perception on flood insurance demand [59]. also showed that flood insurance demand under several hypothetical climate change scenarios is significantly related to a higher perception of future flood risk for a sample of Dutch house-dwellers. The significant result in our study found in Section 4.1 with regards to low worry relating to increased levels of risk seeking/lower levels of risk aversion at low probabilities of flooding, may have been due to behavioural noise. One might suspect that low worry about flooding may be related to random decision making in our experiment, because low worry individuals may have taken the flood insurance decisions less seriously on average.

We also find that good mood has no relationship with risk preferences, so **H3** can be rejected. This is in contrast to Ref. [19]; who found that a music-induced positive emotional state is related to more risk seeking/less risk aversion behaviour due to differences in probability weighting. Moreover [46], showed that good mood is related to more risk seeking/less risk aversion due to lower probability weights in insurance decisions involving the risk of portable computer repair costs [89]. showed in an incentivized lab experiment that positive incidental emotion, elicited by playing subjects a joy-inducing movie clip, increases individual proneness to the gambler's fallacy in demand for bicycle loss insurance. That is, a loss in a prior round coupled with positive incidental emotion has a negative impact on insurance demand. This result suggests that the impact of positive incidental emotion on risk seeking behaviour may be more apparent immediately after a loss. Our study differs from these examinations in several respects. Our experiment has more contextual richness than the first study, where individuals chose between pairs of neutrally framed prospects to elicit probability weighting. In addition, the maximum loss in the latter two studies is considerably lower than the high-impact flood losses of our study. Lastly, we do not examine the impact of loss experience and it's interaction with good mood on insurance demand, in contrast to the third study. Nevertheless, from our perspective mood should not be related to long term decisions such as flood insurance purchase. However, we cannot rule out that the stated mood measure used in our study is neither specific or intense enough to induce changes in risk preferences with regards to flood risk. One might conclude that induced mood has a greater correlation with risk preferences than when it is stated. However, the significant [46] result comes from a stated mood study. Moreover [90], find that while sad movie-induced mood has an effect (toward less risk seeking) on behaviour, happy movie-induced mood does not, compared to a neutral mood baseline. Overall, risk specific emotions like anticipated regret have a more meaningful relationship with flood risk attitudes and insurance choices than emotion unrelated to flood risk in our experiment.

5.2. Policy recommendations

Our results have practical implications for policymakers who aim to increase flood insurance demand and protective efforts. External locus of control types, who deem that potential flood events and their consequences are out of their control, may benefit from education policies which emphasize the importance of undertaking preparations to mitigate potentially catastrophic damages [75]. In general, asserting the view that individuals have the propensity to control the extent of potential damages from flooding is likely to benefit future preparation efforts.

Individuals who adopt the threshold level of concern decision rule are less likely to neglect flood risk if perceived probabilities exceed their threshold levels. This can be achieved through bundling flood insurance with several other risks into one insurance policy, to create a combined probability of any event occurring which overcomes threshold levels [6]. Another solution is to reframe probability information over longer time periods, e.g., an equivalent way of framing a 1 in 100 year annual flood probability is that within 40 years, there is a 1 in 3 chance of a flood occurring [91]. It has been shown that risk perceptions and intentions to undertake damage mitigation measures are higher when probabilities are reframed in this way [92,93]. This policy measure falls under the "nudges" category of policy tools, because it does not alter material incentives or limit freedom of choice [94]. This nudge could also be justified from an ethical point of view, because we know that a significant proportion of homeowners in high risk areas may feel regret about not purchasing flood insurance if a flood were to occur. However, note that the ethical dimension of nudging has been debated in the literature regarding its effect on consumer autonomy and welfare [95].

Another policy related to risk framing is to communicate risk so that individuals are given a worst-case scenario [69]. Highlighting potential uninsured flood losses to homeowners in hazard prone areas may incentivize individuals to purchase insurance, because the expected regret they might feel upon experiencing an uninsured flood may become more salient.

6. Conclusion

An economic experiment was conducted with 1041 homeowners in the Netherlands. We elicited flood insurance demand under the low probabilities of flooding which homeowners face presently, as well as higher probabilities which are more imminent dangers of flooding due to extremely high water levels at a certain point in time. We focus on insurance specific risk to examine psychological mechanisms related to flood insurance demand. A better understanding of flood risk preferences is important for risk management and policymaking.

We find that individuals who anticipate regret about uninsured flood losses, as well as internal locus of control personality types have higher flood insurance demand. Furthermore, individuals who follow the threshold level of concern decision rule have lower flood insurance demand under low probabilities of flooding. Our exploratory analysis suggests that this effect on insurance demand goes through more probability under-weighting/less probability over-weighting.

Climate change is projected to intensify flood risk in many regions around the world due to sea-level rise and increased levels of precipitation. Because many homeowners underestimate probable flooding risks and underweight these risks like our study shows, there is a role for policy makers to continually manage water levels and to maintain flood barriers to mitigate the potential increase in the frequency and severity of flooding in the future as a result of climate change. Despite possibilities to improve public flood protection, a residual flood risk will remain since complete protection is often infeasible or not cost-effective. This implies there is a need for individuals in flood-prone areas to adequately prepare for flooding, including purchasing insurance for residual flood risk. However, in practice we observe that many people do not purchase flood insurance, and regret this decision after a flood event has occurred, while a sub-group of people are well prepared and do insure. Our study delivers insights into reasons that explain this behaviour, on the basis of which recommendations can be given for policies that aim to improve flood preparedness.

We suggest several policy recommendations to overcome psychological factors related to more risk seeking/less risk aversion to improve flood preparations, the effectiveness of which can be examined by further research. These include policies that promote better risk communication to enhance insurance decisions for individuals adopting the threshold of concern decision rule, and education and information provision to change the behaviour of external locus of control types. Moreover, bundling low probability risks with more immediate risks may achieve an overall covered risk which is less likely to be judged as falling below threshold levels of concern. These measures could aid the development of the flood insurance market in the Netherlands.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wre.2019.100144.

Appendix

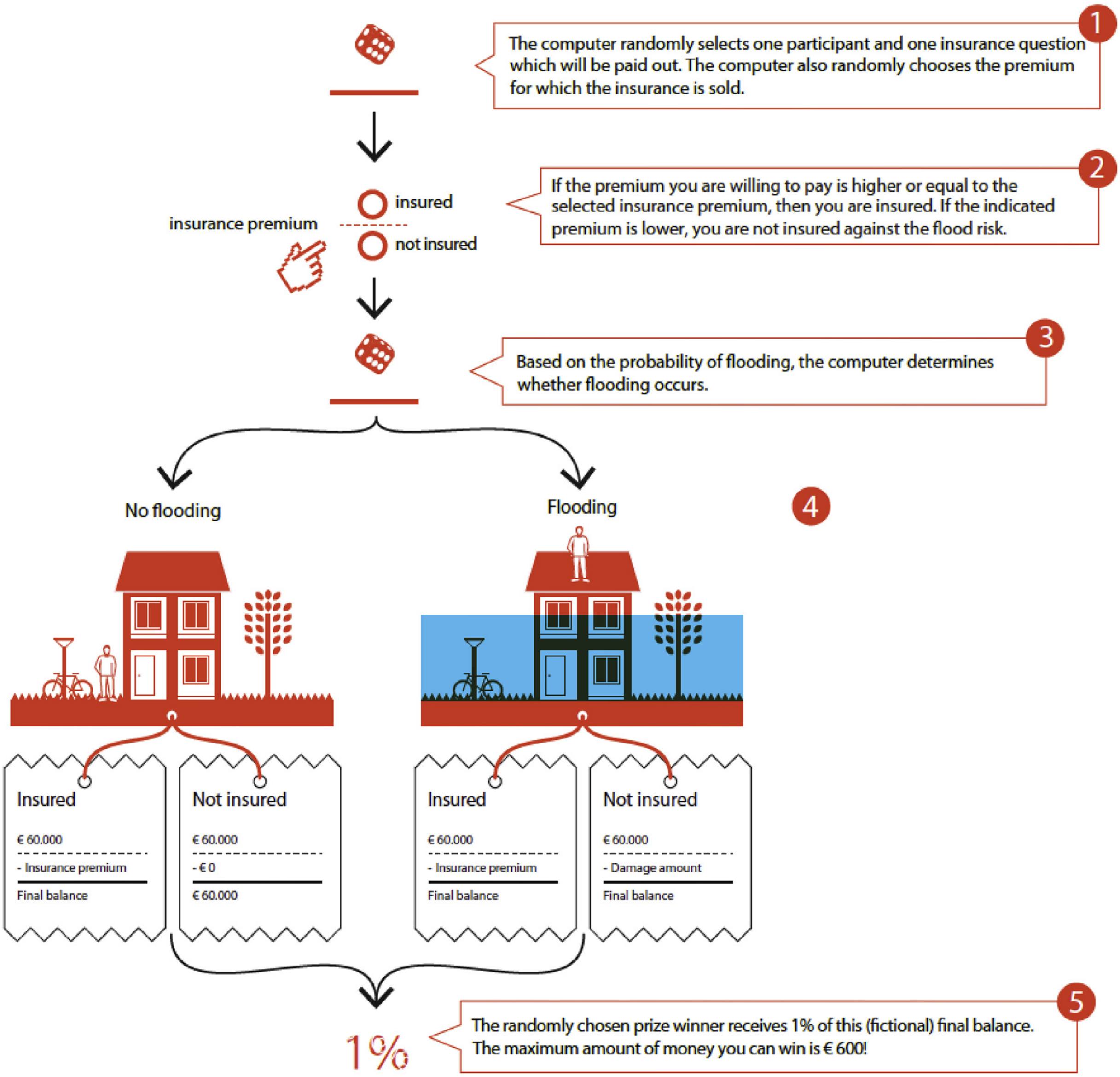

Fig. A1. Payment illustration

(Incentivized flood insurance experiment instructions are translated from Dutch.)

A1. First screen

Welcome to this questionnaire. This is an investigation that is part of a research project undertaken by the Institute for Environmental Issues (IVM), Vrije Universiteit (VU) Amsterdam and funded by the Netherlands Organization for Scientific Research (NWO).

The questionnaire is about your views about flood safety and flood insurance.

A2. Flood insurance instructions

Here is a brief explanation of the next questions. Read this carefully.

Your current insurance policy for your house and contents does not cover damage caused by flooding. Imagine you recently purchased a property worth €240,000 in an area that can flood and that it is possible to buy flood insurance.

You will get 14 questions about how much you are willing to pay for flood insurance for this property. With each question: The government will not reimburse your flood damage if you are not insured. Every question is about another year with a different risk due to different water levels. Each year you have €60,000 in your bank account from which insurance premiums or flood damage can be paid.

There are no correct or incorrect answers. We are only interested in your opinion!

A3. Payment

(The hypothetical condition is identical to the incentivized version with the following instructions omitted.)

We randomly choose one respondent to be paid.

The picture below explains a lottery that will be used to determine whether you will be paid based on your answers in the insurance questions.

[see Figure A1 for the payment illustration].

It is therefore in your best interest to answer your real willingness to pay. For example, if you state a willingness to pay higher than your real willingness, you may pay too much, while if you state a willingness to pay lower than your real willingness, you may end up without insurance and regret not stating a higher willingness.

Again, the prize winner of this research is randomly chosen by the computer.

Each participant has an equal chance of winning!

A4. Flood insurance decisions

[see Figs. 1 and 2].

(Subsequent flood insurance decisions were presented analogously.)

A5. Survey questions

(Respondents answered the following based on the extent to which they agree with the following statements on a scale ranging between: “Strongly disagree” (1) and “Strongly agree” (5).)

I would feel regret about not purchasing flood insurance if a flood occurs.

I would feel regret about paying an insurance premium if no flood occurs.

I am worried about the danger of flooding at my current residence.

It is not always wise for me to plan too far ahead because many things turn out to be a matter of good or bad fortune.

When I get what I want, it is usually because I'm lucky.

I believe that there are a number of measures that people can take to reduce their risk.

I can pretty much determine what will happen in my life.

The probability of flooding is too low to be concerned about.

(Respondents answered the following based on a scale ranging between: “Badly” (1), “Worse than usual” (2), “As usual” (3), “Better than usual” (4) and “Promising” (5).)

How has your day been going?

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