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# Risk reduction in compulsory disaster insurance: Experimental evidence on moral hazard and financial incentives

Jantsje M. Mol[*,a], W. J. Wouter Botzen[a,b,c], Julia E. Blasch[a]

[a] Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, The Netherlands
[b] Utrecht University School of Economics (USE), Utrecht University, Utrecht, The Netherlands
[c] Risk Management and Decision Processes Center, The Wharton School, University of Pennsylvania, United States

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ABSTRACT

In a world in which economic losses due to natural disasters are set to increase, it is essential to study risk reduction strategies, including individual homeowner investments in damage-reducing (mitigation) measures. In this lab experiment (N = 357), we investigated the effects of different financial incentives, probability levels, and deductibles on self-insurance investments in a natural disaster insurance market with compulsory coverage. In particular, we examined how these investments are jointly influenced by financial incentives, such as insurance, premium discounts, and mitigation loans. We also studied the influence of behavioral characteristics, including individual time and risk preferences. We found that investments increase when the expected value of the damage increases (i.e., higher deductibles, higher probabilities). Moral hazard is found in the high-probability (15%) scenarios, but not in the low-probability (3%) scenarios. This suggests that moral hazard is less of an issue in an insurance market where probabilities are low. Our results demonstrate that a premium discount can increase investment in damage-reduction, as can a policyholder's risk aversion, perceived efficacy of protective measures, and worry about flooding.

## 1. Introduction

Economic losses due to low-probability/high-impact natural disaster events, such as floods, have increased in the past 25 years and this trend is likely to continue (IPCC, 2012; Munich RE, 2018). Insurance arrangements can be useful tools for limiting the costs of natural disasters by spreading risk intertemporally and geographically over a large group of policyholders[1] and for providing financial compensation after a disaster to facilitate recovery. Despite growing interest in insurance as a tool in disaster risk management, the design of such insurance arrangements is heavily debated among governments, which tend to focus on affordability and coverage, and the insurance industry, which tends to focus on risk-based pricing and risk reduction (Hudson, Botzen, Feyen, & Aerts, 2016).

Different options exist for policyholders to reduce risk, including self-insurance (reducing the damage in case of a loss) and self-protection (reducing the probability of a loss occurring). The interplay of insurance, self-insurance, and self-protection has been extensively studied, starting with an influential theoretical paper by Ehrlich and Becker (1972). Their model shows that market insurance and self-insurance are substitutes, whereas self-protection can be complementary to market insurance. Over the years, many experiments tested the normative predictions of insurance demand (see, e.g., Jaspersen, 2016, for a comprehensive review). While most of these papers investigate empirical regularities related to insurance demand, few focus on the interaction with risk reduction activities. This paper relates to the empirical literature on self-insurance and self-protection, with a focus on the relevant dimensions of heterogeneity of self-insurance under compulsory insurance coverage for low-probability/high-impact risk. From an expected utility theory perspective, self-insurance investments should increase when the probability of a loss increases and when the insurance coverage decreases through a higher deductible. Investments in self-insurance should decrease in the presence of insurance due to moral hazard (Winter, 2013). Insurance arrangements could be further combined with explicit financial incentives to stimulate policyholders to install damage-reduction measures, such as premium discounts that reflect reduced risk. Our study aims to answer the following research questions: to what extent are investments in self-insurance under compulsory insurance coverage for low-probability/high-impact risk determined by loss probabilities, deductibles,

* Corresponding author.
*E-mail address:* j.m.mol@vu.nl (J.M. Mol).

[1] For example the Caribbean Catastrophe Risk Insurance Facility: http://www.ccrif.org.

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and a moral hazard effect? Are financial incentives from insurance effective in increasing such investments?

### 1.1. Loss probabilities

Several previous studies have examined the value of self-insurance and self-protection under different probability levels, using an experimental methodology. In his seminal paper, Shogren (1990) studied individual responses to risk by self-insurance and self-protection, with experimental auctions under different probabilities (1%, 10%, 20%, and 40%). The study found higher investments in both risk reduction methods under increasing probabilities. Di Mauro and Anna (1996) examined the valuation of self-insurance and self-protection while varying the probability levels (3%, 20%, 50%, and 80%). They found higher bids on self-insurance and self-protection for increasing probabilities. Shafran (2011) examined preferences for self-protection against low and high probabilities of loss (1%, 2%, 20%, and 40%). In line with normative predictions from prospect theory, the study found that subjects were more likely to protect against risks with high probability than those with low probability and the same expected loss. Note that they examined self-protection rather than self-insurance, which is a key difference between this and our own study. More recently, Ozdemir (2017) compared the valuation of self-insurance and self-protection under risky and ambiguous prospects with different probabilities of loss (3%, 50%, and 80%) and found that the willingness to pay for self-insurance increases with probability, but only weakly.

### 1.2. Moral hazard

A potential difficulty in the promotion of damage-reduction measures is information asymmetry between the insurer and the policyholder regarding implemented measures. This asymmetry can lead to moral hazard, whereby insured individuals take fewer preventive measures, as these do not lower their premiums as long as the insurer cannot observe them (Arrow, 1963; Stiglitz, 1974; Arnott & Stiglitz, 1988). Many studies have empirically investigated moral hazard in insurance markets (see Cohen and Siegelman, 2010; Rowell and Connelly, 2012, for an overview), finding that it varies across markets, depending on the type of insurance product, amongst other factors. In this regard, studying the effect of insurance coverage on self-insurance in isolation from other factors enables getting insights into the moral hazard effect under different probabilities. Some researchers have examined moral hazard using an experimental approach (see Table A.1). The contexts vary, including the principal-agent paradigm (work effort), field experiments on default in micro finance, and studies related to insurance. The closest to our experiment are Berger and Hershey (1994) and Di Mauro (2002), as they examine insurance contexts. These experiments show that moral hazard is less likely to occur under deterministic losses and low probability of compensation (amongst other circumstances).

### 1.3. Deductibles

To overcome the moral hazard problem, insurance companies have traditionally adopted deductibles to decrease the coverage of their clients (Winter, 2013). The deductible is the amount of damage that must be paid by the policyholder before the insurer will cover any expenses, which provides a financial incentive to reduce risk for the policyholder. In other words, the deductible reduces a policyholder‘s level of insurance coverage. Some studies used an experimental methodology to investigate insurance behavior under different levels of deductibles or insurance coverage. However, to the best of our knowledge, there is no previous research that examines the effect of different deductible levels on investment in risk reduction. Papon (2008) conducted an experiment on insurance demand with different levels of deductibles (full coverage, 10%, 30%, 50%, and no insurance) under low-probability risks and found that participants prefer extreme cases of coverage: no insurance or full insurance. Krieger and Felder (2013) conducted an experiment in the health insurance domain, where participants could select different levels of deductibles (full coverage, 20%, 30%, 40%, and 50%) under different types of information provision. The results indicate the presence of a status-quo bias in health insurance policies: respondents chose their insurance policies based on the default offer. In a related laboratory experiment, Corcos, Pannequin, and Montmarquette (2017) examined the demand for insurance coverage by presenting subjects with 20 equally-spaced deductible options, reaching from no insurance to full coverage. The results confirmed the bimodal pattern in flood insurance demand, with clear preferences for both extreme cases.

### 1.4. Financial incentives

In addition to deductibles, other financial incentives can be provided to stimulate damage-reduction investment by homeowners, such as premium discounts that reflect reduced damage due to policyholder's investments in self-insurance (Kleindorfer, Kunreuther, & Ou-Yang, 2012; Poussin, Botzen, & Aerts, 2014). Policymakers are increasingly using financial incentives to facilitate behavioral change in different domains of society, including health and financial decisions. However, recent research has shown that these incentives must be carefully designed to be effective (Patel, Asch, Troxel, Fletcher, Osman-Koss, Brady, Wesby, Hilbert, Zhu, Wang, & Volpp, 2016; Hooker, Wooldridge, Ross, & Masters, 2018). Financial incentives have been used for decades in the insurance industry, but studies evaluating the effectiveness of these are relatively recent (Stevenson, Harris, Mortimer, Wijnands, Tapp, Peppard, & Buckis, 2018). This paper contributes to the literature by evaluating the effectiveness of a premium discount and a mitigation loan on self-insurance in the context of disaster risk insurance. A premium discount serves as a financial reward for reducing damage, which is already common practice in health insurance (Tambor, Pavlova, Golinowska, Arsenijevic, & Groot, 2016). Alternatively, low-interest mitigation loans may be provided by the government or other financial institutions to encourage investment in damage-reduction measures that have high upfront costs, such as flood-proofing a house (Michel-Kerjan & Kunreuther, 2011). Loans spread the investment costs over time. This can encourage individuals with high discount rates (i.e., those who place more emphasis on immediate risk mitigation costs than on future risk mitigation benefits) to invest in damage reduction measures. We are not aware of any previous experimental work that directly tests the influence of these insurance incentives (premium discount and mitigation loan) on self-insurance investment.

This paper advances the experimental literature on self-insurance by systematically studying the effects of different probability levels, deductibles, and other financial incentives on self-insurance investments. Moreover, to our knowledge, moral hazard has not been studied experimentally in relation to a variety of probability levels and deductibles. The current study aims to fill this gap by operationalizing investment in damage-reduction in a controlled lab experiment under different financial incentive treatments, starting from a baseline treatment without insurance and mitigation incentives. The results are likely to be useful for insurance companies and policymakers who aim to increase both insurance coverage and policyholder damage-reduction activities. Note that the dominant natural risk reduction strategy for individuals is self-insurance: One cannot prevent a flood or earthquake, but simple measures such as floodproofing may significantly decrease damage. Both theory and experiments have shown that policyholders respond differently to self-insurance than to self-protection (Ehrlich & Becker, 1972; Shogren, 1990). While most empirical papers concern self-protection, we cannot simply generalize these results to self-insurance. Rather, the drivers of self-insurance should be systematically examined; and this is an important contribution of the current paper.

The remainder of this article is organized as follows: Section 2 describes the experimental design; Section 3 derives hypotheses for each

of the treatments, based on simulations of a theoretical model; Section 4 presents results; Section 5 discusses policy implications; and Section 6 concludes.

## 2. Experimental design

We examined investment levels in damage-reduction under different financial incentives for mitigation of disaster risk. Participants were presented with six independent scenarios of an investment game under flood risk for multiple rounds. The experiment was framed in the context of insurance, thus all treatments (except "No Insurance") included a deductible.

The experiment consisted of several individual decision-making tasks, computerized in oTree (Chen, Schonger, & Wickens, 2016). Earnings were in Experimental Currency Units (ECU) and converted back to euros at the end of the game. In the first stage, the initial endowment was earned and invested in a virtual house. As in Laury, McInnes, and Todd Swarthout (2009), participants were given a real effort task to earn this endowment, to overcome the "house money effect" (Thaler & Johnson, 1990). Participants were thus shown the prospect of losing rather than winning money (see Harrison & Rutström, 2008). One result of an earnings task in which initial earnings are determined by effort could be variability among subjects, with high performing subjects earning more than low performing subjects, leading to an unwanted stake effect (Dannenberg, Riechmann, Sturm, & Vogt, 2012). Therefore, a new real effort task was developed in oTree,[2] in which participants were asked to collect ECU by clicking on a grid of 100 boxes which either contained money or did not. The money was randomly distributed by the software to 60 of the 100 boxes. When 30 boxes with money had been collected, the boxes were deactivated, such that all subjects finished with the same budget. To enhance a game-like situation, a timer was placed on the *Collect money* page, although there was no consequence of collecting quickly or slowly. (Screenshots of the new real effort task can be found on page 2 of the Supplementary Material.) After earning their starting capital, participants were asked to buy a virtual house (worth 240,000 ECU) with which to play the investment game. The remainder of the starting capital (75,000 ECU) was stored as "savings" and could be used to pay for investments, premiums, and damages. We explained to subjects that the house was prone to flood risk.

### 2.1. Investment game

A scenario began with the introduction of the parameters: Flood probability, maximum damage, and deductible level. This lasted for 12 rounds. The sequence of pages in each round was *Invest, Pay premium*, then *Flood risk result*. The *Invest* page offered five discrete investment levels with accompanying benefits, as shown in Fig. 1. Investments were effective for damage-reduction in all rounds of a scenario, beginning with the investment round. On the *Pay premium* page, subjects paid a fair premium (participants were price-takers). After each payment, the savings balance was adjusted accordingly. The *Flood risk result* page showed 100 houses, with the house of the participant indicated by a dotted square. The software selected the flooded house(s) at random, according to flood probability. The flooded house(s) was indicated in blue (see Fig. 2). If a participant's house were flooded, the deductible (or damage, in the No Insurance treatment) was paid from the savings balance. After the *Flood risk result*, an income of 4000 ECU was added to the savings balance in each round. In each subsequent round, participants could either invest more or stay with the current investment (reducing the investment was not possible). Participants in the "Loan" treatment were offered a 1% interest loan to spread the investment costs over 10 rounds. When those participants chose a positive investment level, a *Pay loan cost* page was added between *Invest* and *Pay premium*. In the No Insurance treatment, the *Pay premium* page was skipped. The full experimental instructions can be found in the Supplementary Material.

The delivery of the instructions was followed by five rounds in a test scenario to ensure participants were familiar with the game. The instructions were available as a pop-up screen throughout the experiment. The test scenario was followed by comprehension questions. These questions were conditional on treatment and are listed in Appendix E. The answers could be retrieved from the (pop-up) instructions. The software kept track of the number of times a participant (re)opened the instructions, as well as the number of failed attempts to answer the comprehension questions. These were used as experimental control variables in the regression analysis. After answering the comprehension questions correctly, subjects began with the first scenario of the investment game.

### 2.2. Scenarios

Subjects played 6 scenarios of 12 rounds each, with different flood probabilities and deductibles per scenario. An overview of the scenarios is given in Table 1. Their order was randomly shuffled by the software and was saved to control for order effects. Participants were paid the final savings balance[3] of one randomly chosen scenario, at a conversion rate of 20,000 ECU = € 1 (between € 0 and € 7 on top of the participation fee), and the independence of the scenarios was made salient by a pop-up screen at the start of each scenario. This screen also indicated the change since the previous scenario in flood probability, deductible, and premium. When a new scenario began, the savings balance was restored to the starting value of 75,000 ECU.

In addition to these payments, one participant was randomly selected from the full sample when all sessions had ended. This participant was rewarded with a large payment: his/her results in one random scenario or the additional time preferences task were paid at a conversion rate of 200 ECU = € 1. The fact that each subject had a chance to earn up to € 700 based on the results in the investment game was stated on all payment pages, thus highlighting the high stakes of the experiment. Fig. 3 gives a schematic overview of the experiment.

### 2.3. Treatments

Participants were randomly distributed over five treatments: No Insurance ($n = 60$), Baseline Insurance ($n = 120$), Premium Discount ($n = 59$), Loan ($n = 60$) and Loan + Discount ($n = 58$). The relation between treatments and our hypotheses is explained in Section 3.2 and in more detail in Appendix D. Baseline Insurance included only a deductible and served therefore as the baseline mandatory insurance treatment. As we expected the highest variability in this treatment, we doubled the number of subjects allocated to it.[4] In the Premium Discount treatment, a premium discount was offered to participants if they invested in damage-reducing measures, proportional to the estimated damage-reduction. To overcome the effects of time-discounting, the Loan treatment offered the participants a loan to spread the costs of investment over multiple rounds. The final treatment, Loan + Discount, was a combination of the previous two, including both the premium discount and the mitigation loan. The advantage of this combination is that it makes the cost-effectiveness of the measures very salient when the annual premium discounts exceed the annual loan cost.

[2] The task was based on the JavaScript code of the Bomb Risk Elicitation Task (Holzmeister & Pfurtscheller, 2016) with help of Mathijs Luger, a programmer of Vrije Universiteit Amsterdam.

[3] Savings balance = starting value (75,000 ECU) + income - premiums - deductibles - damages - investments.

[4] As we introduced a novel design, we had no priors regarding effect sizes to perform a power analysis.

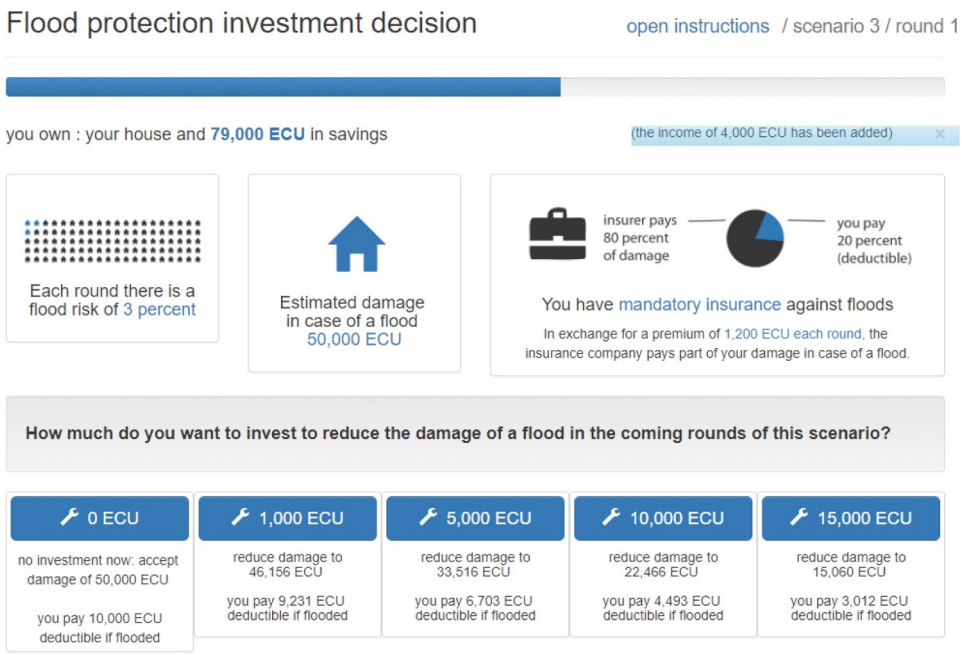


**Fig. 1.** Investment decision screen in "Baseline Insurance" treatment.

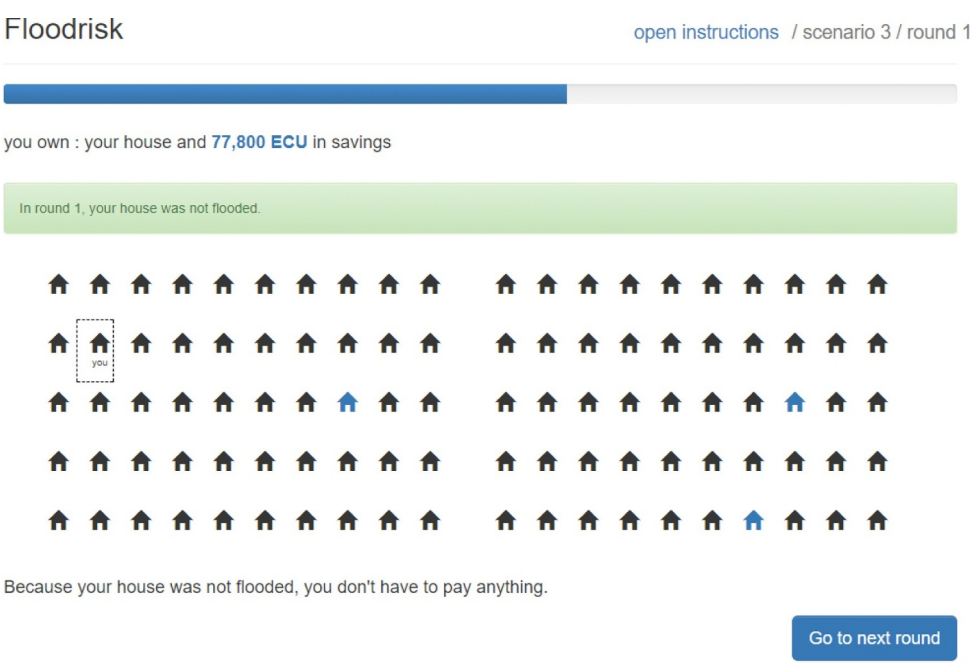


**Fig. 2.** Flood risk result under low probability - three houses are blue, indicating flooded, and participant is not flooded). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### 2.4. Extra tasks

Following the experiment, there were a set of questions and decision-tasks to gather data on risk preferences, time preferences, and other behavioral characteristics that could be related to the investment decisions. Risk preferences were measured using two price lists and the Bomb Risk Elicitation Task (BRET) (Crosetto & Filippin, 2013). Based on a recent review on risk-elicitation tasks (Csermely & Rabas, 2016), we used the new price list proposed by Drichoutis and Lusk (2016) and did not include the original (Holt & Laury, 2002). In this new iteration, probabilities are held constant at 0.50 and the payoff amounts are varied. This method seems to perform well in forecast accuracy and is relatively simple. The same price list was adapted from Drichoutis and Lusk (2016) and framed in the loss domain. In this task, subjects were first endowed with the maximum possible loss (€ 4.70) and the outcomes of the lotteries were negative. In both price lists, subjects were prevented by the oTree software from switching more than once between options (Holzmeister, 2017): All rows were shown on the screen simultaneously (see screenshots in Supplementary Material). Finally, a *static* version of the BRET by Holzmeister and Pfurtscheller (2016) was played once. This contained 100 boxes, each worth € 0.05, and one bomb. Subjects were asked to choose a total number of boxes, which were then picked at random and opened by the software. The total value of the opened boxes was earned by the subject, unless the bomb was among them, which would lead to a payoff of zero. To prevent income effects, the software selected at random one of the tasks for the

**Table 1**
Overview of scenarios by treatment, deductible (xL, L, H) and probability (L, H).

| Treatment | Deductible | Probability | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0.01 | 0.03 | 0.05 | 0.10 | 0.15 | 0.20 |
| No Insurance | 1.00 | 1% | L- | 5% | 10% | H- | 20% |
| Baseline Insurance | 0.05 | *n.a.* | LxL | *n.a.* | *n.a.* | HxL | *n.a.* |
| | 0.15 | *n.a.* | LL | *n.a.* | *n.a.* | HL | *n.a.* |
| | 0.20 | *n.a.* | LH | *n.a.* | *n.a.* | HH | *n.a.* |
| Premium Discount | 0.05 | *n.a.* | LxL | *n.a.* | *n.a.* | HxL | *n.a.* |
| | 0.15 | *n.a.* | LL | *n.a.* | *n.a.* | HL | *n.a.* |
| | 0.20 | *n.a.* | LH | *n.a.* | *n.a.* | HH | *n.a.* |
| Loan | 0.05 | *n.a.* | LxL | *n.a.* | *n.a.* | HxL | *n.a.* |
| | 0.15 | *n.a.* | LL | *n.a.* | *n.a.* | HL | *n.a.* |
| | 0.20 | *n.a.* | LH | *n.a.* | *n.a.* | HH | *n.a.* |
| Loan + Discount | 0.05 | *n.a.* | LxL | *n.a.* | *n.a.* | HxL | *n.a.* |
| | 0.15 | *n.a.* | LL | *n.a.* | *n.a.* | HL | *n.a.* |
| | 0.20 | *n.a.* | LH | *n.a.* | *n.a.* | HH | *n.a.* |

*Notes:* Initial wealth = 75,000; Maximum damage = 50,000; Interest rate Loan treatments = 1%; Nr of installments in Loan treatments = 10; Premium = (1 - Deductible) × Probability × Damage. *n.a.* = not applicable.

was given on the next page. At the end of the experiment, subjects were presented with risk preferences questions and some additional questions (e.g., beliefs regarding flood risk). The coding of the questions can be found in Appendix B.

### 2.5. Procedure

To test the instructions for the newly developed investment game, a pilot experiment was carried out with Master's students in October 2017. Subjects were sent a link through which they could play the game online on their own laptop or desktop computer. The pilot experiment was made available on the server for one week. All participants were paid according to their performance in the game by bank transfer, one week after the pilot. To keep incentives equal for the pilot and the experiment, all pilot students were eligible for the large payment. The payment structure was explained verbally in one of the lectures and again in the invitation e-mail. In total, 20 students took part in the pilot experiment. They earned an average of approximately € 12.00 in 34 minutes. We were mostly interested in testing the procedure and the

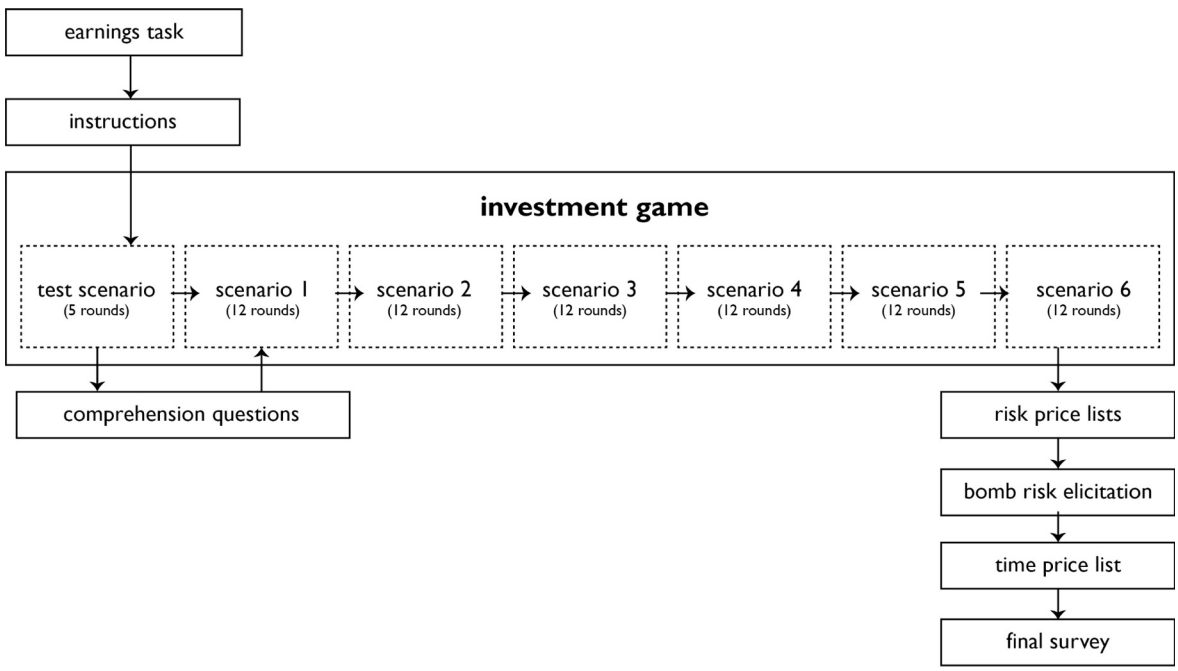


**Fig. 3.** Schematic overview of the experiment.

payment at the end of the three risk-elicitation tasks.[5] The results of the selected task were shown on the screen and the earnings saved for payment. For the time preferences, we used the price list of the Preference Module by Falk, Becker, Dohmen, Huffman, Uwe, and Sunde (2016), where subjects had to choose 25 times between an immediate payment of € 100 and a delayed payment in 12 months. The delayed payment ranged from € 100 to € 185. Again, consistency was enforced by the software. After the time preferences, one task was selected for the large payment: one of the six scenarios or the result of the time preferences task. Note that the time preferences task was thus only incentivized by the large payment; both 'immediate' and delayed time preferences payments would be paid by bank transfer, which resulted in a front-end delay with constant transaction costs. A summary of the payments (participation fee, investment game, and risk-elicitation task) average time required to finish the game. The pilot students finished faster than expected, and many invested in all scenarios. To increase heterogeneity in investment decisions across subjects, we added two scenarios to the game with an extra low deductible and two more risk levels in the No Insurance treatment. To test the length of the final procedure, a second pilot was conducted with five PhD students in our institute. No major changes were made after the second pilot.

The experiment was conducted in the CREED lab of the University of Amsterdam in November 2017. A total of 361 participants earned an average of € 12.95 in 29 minutes. We conducted 11 sessions in 4 days. Note that subjects were randomly assigned to a treatment by the software; hence different treatments were played during one experimental session. Three subjects participated twice due to a minor error with the subject database. The results of their second experiment were removed from the analysis. One result was incomplete, as this subject did not finish the final survey, and the result was thus removed. This left 357 observations for analysis. All earnings - except the large payment, which included the time preferences payment - were paid out privately,

[5] Subjects were informed about this procedure before the start of the first risk-elicitation task, which was introduced together with the others as 'additional tasks'.

in cash, immediately after the experiment. The large payment was arranged via bank transfer, after all sessions had ended.[6]

## 3. Theory and hypotheses

Based on the previous literature referred to in Section 1, we developed several hypotheses, which we then tested in the lab experiment. The parameters of the experiment were based on simulations of a theoretical model, as described in Appendix C.

### 3.1. Simulations

We used a comparative statics approach to predict best responses to the simplest hypothesis (a comparison between Baseline Insurance and No Insurance), reported in Appendix C. However, no clear-cut analytical solution was found for the other hypotheses. Therefore, we predicted the best response of risk-averse (versus neutral, seeking) and low (versus high) time-discounting individuals investing in self-insurance under each treatment based on simulations of the theory. We used these simulations to set our experimental parameters, such that all hypotheses could be tested with the lab experiment. The results of these simulations, which are based on Eq. C.2, are reported in Appendix D. The final set of parameters includes initial wealth $W = 75{,}000$, maximum loss $V = 50{,}000$, effectiveness of self-insurance $\beta = 0.00008$, number of installments in Loan treatment = 10 and interest rate = 1%. The following section provides the hypotheses and the intuition behind them.

### 3.2. Hypotheses

From the comparative statics in Appendix C, we know that investments under insurance coverage (Baseline Insurance) should be lower than without coverage (No Insurance). In general, Winter (2013) states that even though moral hazard is considered as a major issue in insurance from a theoretical perspective, empirical results are mixed. An overview of empirical studies on moral hazard has been carried out by Cohen and Siegelman (2010). The authors conclude that the existence of moral hazard is largely dependent on the type of insurance market. In survey studies, moral hazard has been found to play only a minor role in voluntary flood insurance markets (Hudson, Botzen, Czajkowski, & Kreibich, 2017; Thieken, Petrow, Kreibich, & Merz, 2006). Therefore, the first hypothesis concerns the role of moral hazard in the flood risk insurance context. In simulations of the theory (Appendix D), damage-reduction investments in the Baseline Insurance treatment are lower than in the No Insurance treatment. Positive investments in the Baseline Insurance treatment may be optimal in high-probability scenarios, depending on the deductible level and attitude to risk.

**Hypothesis 1.** Damage-reduction investments in the Baseline Insurance treatment are lower than in the No Insurance treatment, but greater than zero.

In line with risk-based insurance premiums, researchers (Kunreuther, 1996; Surminski, Aerts, Botzen, Hudson, Mysiak, & Pérez-Blanco, 2015) and policymakers (European Commission, 2013) have suggested that a premium discount may motivate policyholders to take mitigation measures. So far, there is little empirical evidence of the effectiveness of premium discounts, except for the findings of Botzen, Aerts, and van den Bergh (2009), which concern the willingness of a large sample of Dutch homeowners in floodplains to pay for low-cost flood-mitigation measures. The researchers found that the main incentive for investment was the premium discount on the flood insurance policy that was offered in the survey. The following hypothesis therefore concerns the Premium Discount treatment. The simulations in Appendix D show that damage-reduction investments should be higher in the Premium Discount treatment than in the Baseline Insurance treatment, under all scenarios and risk attitudes.

**Hypothesis 2a.** Damage-reduction investments are higher in the Premium Discount treatment than in the Baseline Insurance treatment.

A second financial incentive to promote policyholder damage-reduction measures is a mitigation loan or a payment in installments (Michel-Kerjan, 2010), aimed at individuals who heavily discount the future. This treatment could overcome both high time-discounting and a moral hazard effect. The Loan + Discount treatment could be powerful, assuming that a considerable share of individuals is risk-averse and present-oriented. Therefore, we expect that the combination of incentives will lead to the largest damage-reduction investment. The simulations in Appendix D indicate that Loan + Discount gives the highest optimal investments for all treatments in the low-probability scenarios.

**Hypothesis 2b.** Damage-reduction investments are largest in the Loan + Discount treatment.

Policyholder damage-reduction measures may be cost-effective under expected utility theory (Kreibich, Bubeck, van Vliet, & De Moel, 2015), but myopic individuals with high discount rates weigh the present costs much more heavily than the projected future benefits. Damage-reduction investments are lower in the Baseline Insurance and Premium Discount treatments under high time-discounting, according to our simulations. A mitigation loan may overcome this discounting effect by spreading the costs over multiple periods. The simulations indeed show that in the Loan and Loan + Discount treatments, time-discounting has no effect on damage-reduction investment.

**Hypothesis 3a.** Damage-reduction investments are lower among participants with high time discount rates. This effect is strongest in the Baseline Insurance and Premium Discount treatments, and it disappears in the Loan and Loan + Discount treatments.

Hudson et al. (2017) argue that in natural disaster markets, decisions are mainly driven by risk attitudes, where highly risk-averse individuals take multiple precautionary measures, including flood insurance and flood damage-reduction measures. In this scenario, advantageous selection may prevail over the moral hazard effect, which may be explained by a misunderstanding of risk (Kunreuther & Pauly, 2004). However, Hudson et al. (2017) did not examine the behavioral mechanisms to back up their claim. The current experiment aims to fill that gap. The simulations show that risk-seeking individuals will not invest in the Baseline Insurance and Loan treatments, while investing 1000 or 5000 could be optimal for risk-neutral individuals and 10,000 for risk-averse individuals.

**Hypothesis 3b.** Risk-averse individuals will invest more in damage-reduction in the Baseline Insurance treatment and the Loan treatment than risk-neutral individuals will, while risk-seeking individuals will invest less.

## 4. Results

This section reports our results, beginning with the moral hazard effect (Hypothesis 1) and the effect of financial incentives related to insurance (loan and premium discount, Hypotheses 2a and 2b) with non-parametric tests and a multivariate regression analysis. Subsequently, we examine the effect of time and risk preferences on investment behavior (Hypotheses 3a and 3b). Finally, we present some additional analyses, including a trend analysis and the effects of flood beliefs on investment behavior. We conclude with an overview of the

[6] Large earnings ranged from € 86.70 to € 615. The randomly selected participant earned € 196.49 from one of the scenarios. The payment was thus made immediately and not delayed by 12 months, which could have happened if the time preferences payment had been selected.

**Table 2**
Descriptive statistics per treatment group.

| | No Insurance | Insurance Baseline | Discount | Loan | Loan + Discount | p-value |
|---|---|---|---|---|---|---|
| Age in years | 21.05 | 21.89 | 21.39 | 21.17 | 21.48 | 0.593 |
| | (2.22) | (4.82) | (2.33) | (3.24) | (3.60) | |
| Gender (1 = female) | 0.58 | 0.52 | 0.49 | 0.50 | 0.67 | 0.264 |
| | (0.50) | (0.50) | (0.50) | (0.50) | (0.48) | |
| Income (1 = above € 5000) | 0.05 | 0.03 | 0.09 | 0.07 | 0.02 | 0.364 |
| | (0.22) | (0.18) | (0.29) | (0.25) | (0.13) | |
| Risk averse | 5.65 | 5.83 | 5.79 | 5.82 | 5.81 | 0.932 |
| | (1.30) | (1.14) | (1.34) | (1.36) | (1.39) | |
| Present biased | 13.49 | 14.02 | 12.39 | 13.05 | 12.70 | 0.726 |
| | (7.80) | (8.17) | (8.19) | (8.05) | (8.62) | |
| Observations | 59 | 121 | 57 | 60 | 60 | |

*Notes:* Table displays means, SD in parentheses. Final column presents the *p*-value for an *F*-test of the null hypothesis of equal means across the treatment groups.

predicted margins of our key findings, comparing investments in self-insurance under different loss probabilities, deductibles, and financial incentives.

Table 2 displays descriptive statistics of the demographic variables that should not be influenced by our experimental treatments. Demographic variables did not significantly vary between treatment groups.[7] We further analyzed the balance of the flood perception variables efficacy, worry, and regret across treatments, which were measured in a post-experimental survey and could be affected by different versions of the investment game.[8] Precise coding of the variables can be found in Appendix B.

### 4.1. Testing the moral hazard effect

To test Hypothesis 1, we compared the investment levels in the Baseline Insurance treatment with those in the No Insurance treatment. We began with a non-parametric analysis of the most independent unit of observation: The first round. A one-sided *t*-test revealed that the average investment in the first round of Baseline Insurance was significantly higher than 0, both in the high-probability scenario ($M_{BaselineHL} = 4049.59$, $t = 9.20$, $df = 120$, $p < 0.0000$) and in the low-probability scenario ($M_{BaselineLL} = 2404.96$, $t = 6.22$, $df = 120$, $p < 0.0000$). Fig. 4 shows the average investments in the first round in Baseline Insurance (gray boxes) and No Insurance (black boxes), split by probability and deductible levels (shade of gray). Note that the No Insurance treatment is equivalent to a 100% deductible.

Table 3 shows the average investment in the first round, by treatment.[9] Significant differences between investments in Baseline Insurance and No Insurance are indicated by asterisks in the third column of the table (non-parametric Mann–Whitney–Wilcoxon (MWW) tests). The results show significant differences for the high-probability scenarios, indicating a moral hazard effect: subjects invest less in damage-reduction when insurance is available and probabilities are high. However, we do not observe such a strong effect in the low-probability scenarios. Only in the scenario with the smallest deductible (5%) do subjects invest slightly less than in a scenario without insurance ($p < 0.1$).

To test Hypothesis 1 over all 12 rounds of the investment game, we ran panel regressions with scenario dummies and controls. We opted for a random effects ML specification[10] to control for subject and scenario effects. All explanatory variables were checked for high correlations to rule out issues of multicollinearity. As all correlation coefficients were smaller than 0.5, multicollinearity is not regarded as problematic (Field, 2009). The dependent variable is the log-transformed[11] damage-reducing investment. Table 4 restricts the sample to the Baseline Insurance and No Insurance treatments. The results show the same pattern as in the non-parametric tests. In the high-probability scenarios (15%), we find significantly less investment in damage-reduction when insurance is available under all deductible levels. In the low-probability scenarios, we only find lower investments when the deductible is particularly small (5%). The regression results confirm that there is no moral hazard effect in the low-probability scenarios (3%), under low (15%) or high (20%) deductible levels. The negative and significant estimates for order of scenario indicate that damage-reducing investment declines with experience. Note that the order of scenarios was determined at random by the software.

Overall, we find mixed support for Hypothesis 1. There is no significant difference between investments in the No Insurance and Baseline Insurance treatments in the low-probability scenario, which suggests that there is no moral hazard in an insurance market where probabilities are low and expected damages are high, while moral hazard might occur with increasing probabilities of damage. The latter finding is in line with previous literature on moral hazard in different insurance markets (Cohen & Siegelman, 2010). Under low probabilities and high expected damages, a substantial share of the "cautious" types might decide to insure and invest in damage-reducing investments. Note, however, that the probability information in this experiment was objective information.

### 4.2. Testing financial incentives to increase self-insurance

Next, we investigated the effect of financial incentives related to insurance on investments in damage-reduction. Hypothesis 2a concerns the effect of the Premium Discount treatment. Table 3 shows non-parametrically for round 1 that subjects invest significantly more in the Premium Discount treatment than in the Baseline Insurance treatment, regardless of risk and deductible levels. Table 5 presents the results of a

[7] Note, however, that the benefit of balancing checks after experimental randomization is debatable (see e.g. Mutz & Pemantle, 2015 or Deaton & Cartwright, 2018 for recent discussions).

[8] Significant differences were found for efficacy of protection ($p = .008$) and regret about investment ($p = .000$), but not for worry and regret about no investment. Participants in the Discount treatments reported higher efficacy values, which may be caused by a positive experience of mitigation measures due to the financial benefit of the premium discount. Furthermore, participants reported lower regret values in case of investment without a flood event in the game. This finding is consistent with the design of the Discount treatment, where participants received benefits (namely, premium discounts) of their self-insurance investments regardless of flood events.

[9] Note that both Table 3 and Fig. 4 illustrate investments in the first round in ECU. However, Table 3 presents means, while Fig. 4 presents medians.

[10] To control for unobservable subject-specific and scenario-specific effects, we created subject-scenario dummies and used these to cluster standard errors. The random effects ML estimates are not conditional on subject and time effects to account for clustered standard errors per subject and scenario (see e.g. Bell & Jones, 2015).

[11] We used the transformation $transformed = \log(investment + 1)$ to deal with 0 investments.

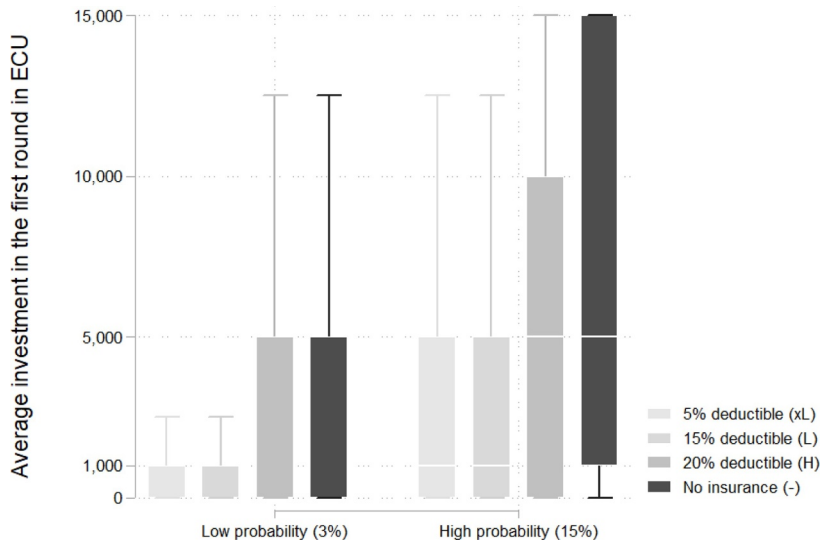


**Fig. 4.** Boxplots of investments in the first round, by probability and deductible. Boxplot whiskers indicate the inter-quartile range, middle lines represent medians.

**Table 3**
Average investment in the first round in ECU.

| | No Insurance | Baseline Insurance | Premium Discount | Loan | Loan + Discount |
|---|---|---|---|---|---|
| scenario H- | 7,288.14 | | | | |
| | (5717.64) | | | | |
| scenario HH | | 5,421.49** | 9,233.33*** | 3,816.67 | 8,614.04*** |
| | | (5,431.01) | (5,732.35) | (3716.62) | (5,512.18) |
| scenario HL | | 4,049.59*** | 8,416.67*** | 3,050.00 | 7,807.02*** |
| | | (4,843.98) | (5,681.64) | (4,188.06) | (5,717.89) |
| scenario HxL | | 3,471.07*** | 8,966.67*** | 3,500.00 | 7,771.93*** |
| | | (5,010.11) | (5,971.59) | (5,000.00) | (5,840.19) |
| scenario L- | 2,711.86 | | | | |
| | (4,102.36) | | | | |
| scenario LH | | 2,727.27 | 3,850.00** | 1,883.33 | 3,719.30 |
| | | (4,222.95) | (4,398.86) | (3,796.04) | (4,806.08) |
| scenario LL | | 2,404.96 | 3,283.33* | 1,750.00 | 3,421.05 |
| | | (4,253.58) | (4,584.76) | (4,015.33) | (5,119.81) |
| scenario LxL | | 1,793.39* | 3,550.00*** | 1,633.33 | 2,087.72 |
| | | (3,976.84) | (4,560.05) | (3,723.34) | (3,434.49) |
| Observations | 59 | 121 | 60 | 60 | 57 |

*Notes:* Table reports means, st.dev in parentheses. Asterisks in the Baseline Insurance column indicate significant differences with the No Insurance treatment. Asterisks in last three columns indicate significant differences with the Baseline Insurance treatment (MMW tests, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$).

random-effects panel regression ML estimates, which takes all rounds into account, as well as treatment dummies, scenario dummies, demographics, and various controls. We chose a panel specification to account for the correlation of decisions by the same subject and clustered standard errors by id (subject) and scenario. All models control for (1) attempts to answer understanding questions,[12] (2) perceived difficulty, (3) flood risk perception, (4) one over round to control for experience, and (5) order of scenario × probability interaction; but coefficients have been suppressed for brevity. The positive coefficients of the Premium Discount treatment confirm the results of the non-parametric analysis: a premium discount leads to larger investment. This effect is large and statistically significant under all possible controls. We can therefore confirm Hypothesis 2a: A premium discount leads to larger damage-reduction investment, compared to a baseline insurance situation.

The Loan treatment, however, does not encourage subjects to invest more in damage-reduction. Neither the non-parametric analysis in Table 3, nor the multivariate regression analysis in Table 5 reveal a significant effect of the Loan treatment, compared to the Baseline Insurance treatment. We expected a positive investment effect for the Loan + Discount treatment (Hypothesis 2b). In that case, the economic return on the loan was salient on the decision screen, because cost effective investments show lower annual costs than benefits in terms of the premium discount. Average investment in the first round in the Loan + Discount treatment, as displayed in Table 3 is lower than in the Premium Discount treatment in almost all scenarios. These results are confirmed by the negative insignificant estimates of the Loan × Discount dummy in Table 5 after controlling for Premium Discount only. Hypothesis 2b thus finds no support in the data.

Our findings could be explained by the dislike for the mandatory 1% interest in the Loan treatment, or a general dislike of lending among the students in our sample. Alternatively, one could argue that the operationalization of a Loan treatment in the lab lacks external validity,[13] as

[12] One subject attempted the comprehension questions more than 10 times. For robustness, we re-ran all analyses excluding this subject. The results do not change qualitatively.

[13] Note that lab experiments are in general low in external validity, although we did all we could to increase external validity: an engaging task explained with parameters based on real data, an incentive compatible payment scheme and a high stakes random lottery incentive mechanism to mimic the large consequences of flood risk investment decisions.

**Table 4**
Random effects ML panel regression estimates of investments.

| | (1) | (2) |
|---|---|---|
| | Probability L: 3% | Probability H: 15% |
| *Deductible (ref. No Insurance)* | | |
| H: 20% | −0.171 | −1.089* |
| | (0.561) | (0.562) |
| L: 15% | −0.501 | −1.894*** |
| | (0.561) | (0.562) |
| xL: 5% | −1.611*** | −3.182*** |
| | (0.561) | (0.563) |
| Order of scenario | −0.562*** | −0.227** |
| | (0.103) | (0.100) |
| Constant | 3.083* | 4.681*** |
| | (1.780) | (1.778) |
| $\sigma_u$ | 3.332*** | 3.342*** |
| | (0.121) | (0.122) |
| $\sigma_e$ | 0.989*** | 0.946*** |
| | (0.011) | (0.010) |
| Observations | 4596 | 4596 |
| Nr of subjects | 163 | 163 |
| AIC | 14,867 | 14,488 |
| Log likelihood | −7,415 | −7,225 |

*Notes:* Standard errors clustered by id and scenario in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Controls: age, gender, high income, understanding, perceived difficulty, flood risk perception, risk aversion, time preferences, worry, perceived efficacy, regret, 1/round. Dependent variable log-transformed.

the investment costs are spread over 12 rounds, ranging from seconds to minutes in the lab, rather than years, as in the real world. However, incorporating true intertemporal payoffs would require a complicated experimental design, in which subjects were to return to the lab to pay back their loans. We considered this impossible to enforce. Further research on loans in the context of disaster risk reduction should therefore focus on field rather than lab experiments.

### 4.3. The effect of time and risk preferences

To examine our last two hypotheses, we use the multivariate regression analysis reported in Table 5. We find no effect of time-discounting on investments,[14] suggesting no support for Hypothesis 3a.

The risk-aversion variable is a linear combination of our four risk-elicitation methods,[15] as in Menkhoff and Sakha (2017). We find that risk-averse subjects invest more in damage-reducing investments, providing evidence for Hypothesis 3b. Table F.1 provides additional robustness checks for each of the four risk-elicitation methods. The direction of the risk aversion effect is equal for all elicitation methods and the estimates of other variables do not change qualitatively.

### 4.4. Additional results

In addition to the evaluation of our hypotheses, some other interesting patterns emerge from our data. Model 2 in Table 5 includes three control variables that varied between rounds: participant flooded in the previous round, direct neighbors (see Fig. 5) flooded in the previous round, and decision time in seconds at the Invest screen. The positive and significant estimate for decision time shows that investments are greater when subjects spend more time on the Invest page. This effect may be explained by the decisions in the first round requiring some deliberation, while subjects learn to move quickly to the next page without extra investments in later rounds. The neighbor variable was constructed to control for erroneous impressions of spatial correlations between floods in the game. Both participant- and neighbor-flooded variables are not significant. Note that the dependent variable here is log-transformed investment, which may not differ substantially between rounds. In Appendix F, we specifically analyze 'extra investments' and find that subjects invest extra in damage-reduction after experiencing floods themselves, but not when a neighbor has been flooded in the game.

Model 3 includes demographic variables. All else being equal, we find that investments decrease slightly with age, that women invest significantly more than men, and that subjects with a high income in real life invest less in damage-reduction in the game. In Model 4, we further include variables concerning flood beliefs. We observe significant and positive coefficients of believed efficacy of protective measures and worry about flooding. A significant negative estimate is seen for regret of investment. Note that this question was asked after the experiment had ended, thus the causal direction is likely to be reversed: subjects who invested significantly less indicated in the post-experimental survey that they felt regret about investing when no flood occurred.

Fig. 6 shows the average damage-reducing investments per round and scenario of all subjects in the Baseline Insurance and No Insurance treatments. It is no surprise that investments do not decrease, as this was not an option for subjects during a scenario. Note that investments were effective for all subsequent rounds: Investing in the first round leads to the highest expected benefits over all rounds. Still, average investments increase through the rounds, with the largest increase in the high-probability treatments of the No Insurance treatment. This can be explained by a small share of individuals who initially invest little and realize during the game that they want more protection, following the experience of a flood (see Appendix F). In our initial design, the No Insurance treatment contained only two scenarios (H- 15% probability and L- 3% probability), where all other treatments tested six scenarios. To keep the workload for all participants approximately equal, we added four scenarios to the No Insurance treatment to study the effect of expected value of flood losses on investments with a more refined pattern of probabilities. Fig. 6 also shows that subjects did invest more when the expected value of a loss increased (i.e., higher deductible and/or higher probability). These extra probability scenarios in the No Insurance treatment are not included in any of the other analyses.

### 4.5. Predicted margins

Finally, Fig. 7 summarizes our key findings with regards to the effects of probabilities, deductibles and financial incentives for self-insurance investments. It shows the adjusted predicted margins at the 95% confidence level of a log-transformed OLS regression of interactions between probabilities, deductibles, and treatments in the first round. For readability, the null-effect of the Loan treatment is not displayed. The graph further facilitates comparison of effect sizes. For example, adding a premium discount in the low-probability scenarios leads to a similar increase in self-insurance investments as that seen when increasing the probability of loss from 1% to 5%.

#### 4.5.1. Loss probabilities

The black diamond markers in Fig. 7 show that respondents invested more in self-insurance when they were confronted with a higher probability of loss, confirming the results of Fig. 6. However, the increase in investment is not proportional to the increase in loss probabilities, which is in line with experimental work on the relationship between probabilities and self-protection investments (Shafran, 2011; Ozdemir, 2017).

#### 4.5.2. Moral hazard

The graph further illustrates the mixed findings around the moral hazard problem. In the high-probability scenarios, we find evidence for

[14] We have included an interaction term of time-discounting × Loan, but the results were not statistically significant.

[15] See Section 2.4 for a description of these tasks.

**Table 5**
Random-effects ML panel regression estimates on log-transformed damage-reducing investments.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Treatments | Previous rounds | Demographics | Flood beliefs |
| *Treatment (ref. Baseline Insurance)* | | | | |
| Discount | 2.372*** | 2.370*** | 2.200*** | 1.916*** |
| | (0.230) | (0.230) | (0.228) | (0.248) |
| Loan | −0.169 | −0.169 | −0.172 | 0.099 |
| | (0.231) | (0.231) | (0.227) | (0.234) |
| Loan × Discount | −0.455 | −0.457 | −0.241 | −0.285 |
| | (0.356) | (0.356) | (0.351) | (0.367) |
| *Probability (ref. L: 3%)* | | | | |
| H: 15% | 1.301*** | 1.301*** | 1.374*** | 1.649*** |
| | (0.386) | (0.386) | (0.379) | (0.390) |
| *Deductible (ref. xL: 5%)* | | | | |
| L: 15% | 0.597*** | 0.596*** | 0.597*** | 0.708*** |
| | (0.207) | (0.207) | (0.203) | (0.209) |
| H: 20% | 1.163*** | 1.162*** | 1.163*** | 1.223*** |
| | (0.207) | (0.207) | (0.203) | (0.209) |
| Order of scenario | −0.556*** | −0.554*** | −0.543*** | −0.493*** |
| | (0.071) | (0.071) | (0.069) | (0.071) |
| Participant flooded | | −0.018 | −0.018 | −0.024 |
| | | (0.026) | (0.026) | (0.027) |
| Neighbor flooded | | −0.012 | −0.012 | 0.001 |
| | | (0.026) | (0.026) | (0.027) |
| Decision time round | | 0.005*** | 0.005*** | 0.004*** |
| | | (0.001) | (0.001) | (0.001) |
| Age in years | | | −0.086*** | −0.064*** |
| | | | (0.022) | (0.023) |
| Gender (1 = female) | | | 0.867*** | 0.618*** |
| | | | (0.171) | (0.181) |
| Income (1 = above € 5,000) | | | −0.989** | −1.141*** |
| | | | (0.396) | (0.407) |
| Risk averse | | | 0.221*** | 0.262*** |
| | | | (0.067) | (0.069) |
| Present biased | | | 0.008 | 0.001 |
| | | | (0.010) | (0.011) |
| Efficacy protection | | | | 0.275*** |
| | | | | (0.044) |
| Worried about flood | | | | 0.389*** |
| | | | | (0.092) |
| Regret no investment / flood | | | | 0.108 |
| | | | | (0.088) |
| Regret investment / no flood | | | | −0.267*** |
| | | | | (0.079) |
| Constant | 4.810*** | 4.808*** | 4.891*** | 1.928** |
| | (0.423) | (0.423) | (0.761) | (0.932) |
| $\sigma_u$ | 3.554*** | 3.554*** | 3.490*** | 3.416*** |
| | (0.060) | (0.060) | (0.059) | (0.060) |
| $\sigma_e$ | 0.983*** | 0.983*** | 0.983*** | 0.972*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Observations | 21,456 | 21,456 | 21,456 | 19,440 |
| Nr of subjects | 298 | 298 | 298 | 270 |
| AIC | 69,251 | 69,227 | 69,172 | 62,245 |
| Log likelihood | −34,610 | −34,594 | −34,562 | −31,094 |

*Notes:* Standard errors clustered by id and scenario in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Controls: Understanding questions, perceived difficulty, flood risk perception, 1/round, scenario-order × probability. Model 4 excludes the 28 subjects of session 1 because of incomplete efficacy responses. For robustness, we ran Models 1, 2 and 3 without these subjects; the results do not change.

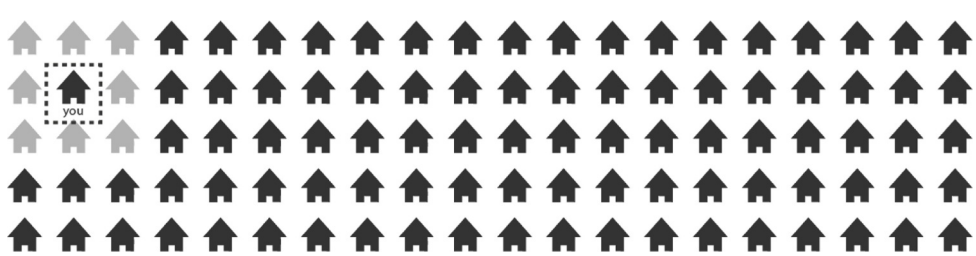


**Fig. 5.** Grey color indicates direct neighbors for construction of neighbors variable.

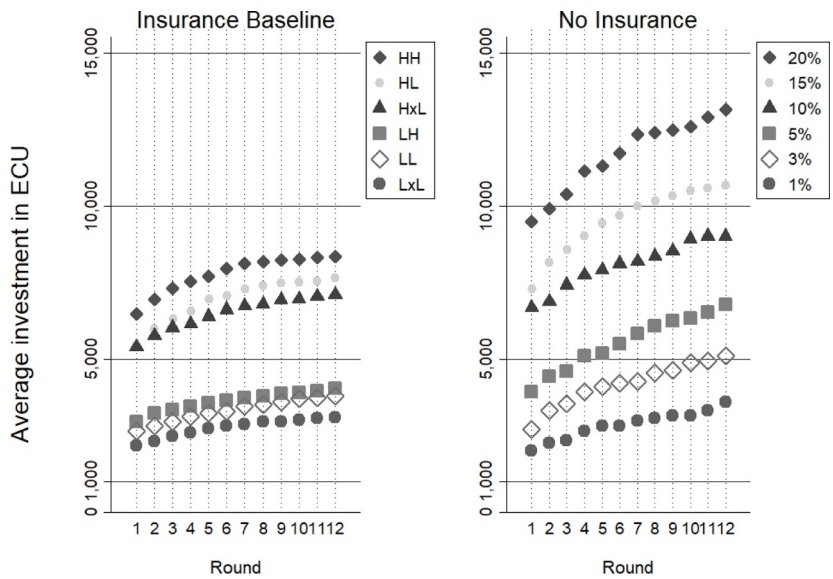


**Fig. 6.** Average investment in damage-reducing measures by scenario.

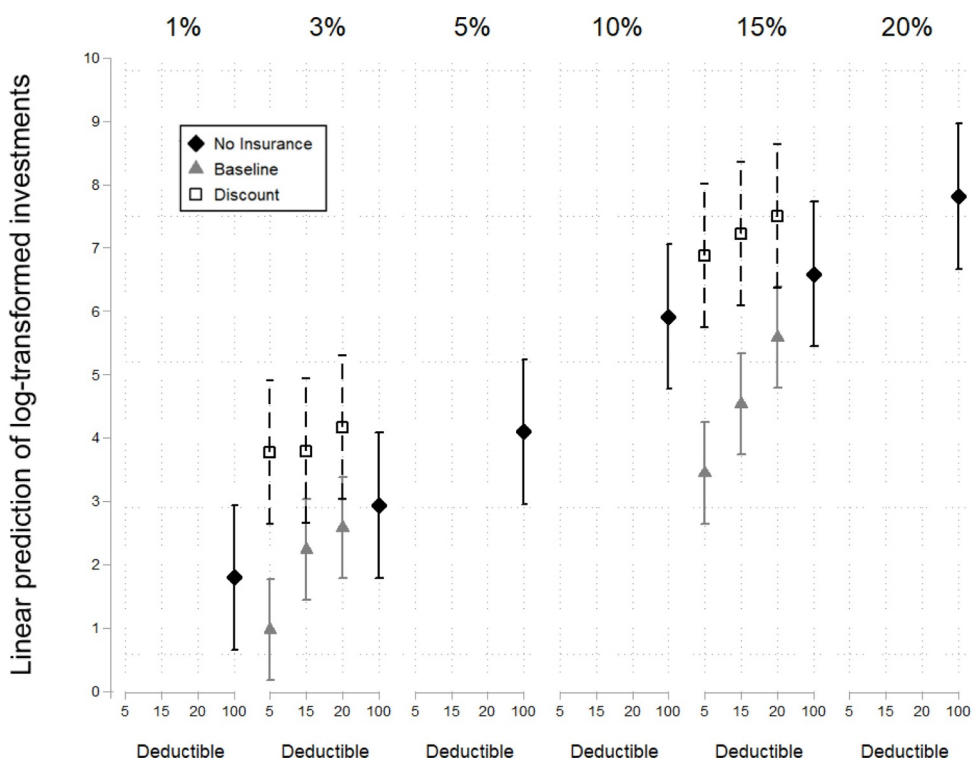


**Fig. 7.** Adjusted predictions of log-transformed investments in the first round by treatment, deductible, and probability of loss. Error bars indicate 95% confidence intervals. We used the *marginsplot* command in Stata to create this figure.

moral hazard: self-insurance investments are significantly lower in the Baseline treatment (indicated with gray triangles) than the No Insurance treatment (indicated with black diamonds). The only significant difference in the low-probability scenarios, however, is under the lowest deductible. In other words, a large deductible (at least 15%) may alleviate the moral hazard problem in a low-probability/high-impact context. This finding validates the empirical conjecture that moral hazard is absent in low-probability/high-impact insurance markets (Thieken et al., 2006; Hudson et al., 2017).

### 4.5.3. Deductibles

The effect of deductibles is represented in Fig. 7 on the x-axis of each subplot. The figure shows that, in line with theoretical predictions, increasing the deductible leads to slightly higher investments in self-

insurance. We thus find support for the substitution hypothesis of Carson, Mccullough, and Pooser (2013), which theorizes that insurance and mitigation may be substitute goods. The deductible effect is smallest in the low-probability (3%) scenarios, which confirms previous survey research in natural disaster insurance markets (Hudson et al., 2017).

#### 4.5.4. Financial incentives

Fig. 7 shows that a premium discount (indicated with white squares) can significantly increase investment in self-insurance, although the effect is largest under high probability of loss and low levels of deductibles. Note that the premium discount is based on the expected value of damage-reduction, leading to a larger premium discount in absolute terms in the high-probability scenarios. The finding that a premium discount can be effective in increasing self-insurance investments even under low probabilities of loss, confirms previous empirical studies (Botzen et al., 2009; Hudson et al., 2016).

## 5. Implications for disaster risk management

Both the effects of climate change and ongoing socio-economic development in floodplains are contributing to the projected increase in flood damage (Jongman, Hochrainer-Stigler, Feyen, Aerts, Mechler, Botzen, Bouwer, Pflug, Rojas, & Ward, 2014). Floods are one of the costliest extreme weather events worldwide, with more than 26 billion US dollars in losses in 2017 (Munich RE, 2018). Flood risk insurance is often mandatory or at least heavily regulated when provided by private insurers. The implementation of mandatory insurance in our experiment closely resembles the characteristics of many natural disaster insurance markets (Paudel, Botzen, & Aerts, 2012), for which it is impossible to distill moral hazard by survey and market data because a control group without insurance coverage does not exist in practice. Our experiment investigated the effect of deductibles, financial incentives, and time and risk preferences on private investments for reducing disaster risk damage. These investments can be taken by individual homeowners and are cost-effective in reducing flood risk (Poussin, Wouter Botzen, & Aerts, 2015; Kreibich, Christenberger, & Schwarze, 2011). While the estimated prevented damage can be substantial (Kreibich et al., 2015), only a small proportion of homeowners has currently taken these measures.

Our results reveal why current voluntary take-up rates of damage mitigation measures are low and how they might be improved. For example, policyholders should be well-informed about cost-effective ways of reducing damage. Furthermore, appeals to negative feelings about flooding (in terms of worry) may stimulate investment in flood damage mitigation measures. Although deductibles have a significant impact on damage-reduction, the size of this effect is not very large, which draws into question the effectiveness of high deductibles for stimulating policyholder flood risk reduction activities. Moreover, our finding that moral hazard effects are minor when probabilities of damage are low suggests that there is less need for high deductibles to limit such an effect. Premium discounts are likely to be a more effective way of stimulating policyholders to reduce flood risk.

In the face of increasing disaster risk, such as climate change, it is important to understand individual preparedness and risk-reduction activities. In our No Insurance treatment, we systematically varied the yearly probability of loss in six scenarios, from 1% to 20%. The results show that damage-reducing investment increases with loss probability, but less than proportionately. Hence, there is a need to improve individual preparedness in the face of increasing disaster risk. Experiencing a flood in the game triggers extra investment in flood damage mitigation measures. It is more beneficial for people to take such measures before a flood, rather than after, which highlights the need to explore the effectiveness of incentives that motivate people to reduce risk ex ante flood events. Future work could examine the behavior of homeowners in floodplains, who might respond differently due to their greater experience with insurance and possibly flooding than the current student sample.

## 6. Conclusion

With economic losses due to natural disasters expected to increase, it is important to study risk reduction strategies, including individual investments of homeowners in damage-reducing (mitigation) measures. Different options exist for policyholders to reduce risk, including self-insurance and self-protection. While there is an extensive literature on the empirical regularities related to insurance demand and self-protection, research on the drivers of self-insurance is limited. This study contributes to the discussion by investigating the relevant dimensions of heterogeneity of self-insurance under compulsory insurance coverage for low-probability/high-impact risk. These characteristics include probability levels, deductibles, and other financial incentives, which cannot be varied systematically in actual insurance markets. A new investment game was developed to study the causal relationship between financial incentives related to insurance and self-insurance investments, taking into account behavioral characteristics of individuals in an insurance market with mandatory coverage.

We found that subjects invested more when the expected value of a loss increased (higher deductible and/or higher probability of loss), although this increase in investment was not proportional to the increase in risk. Furthermore, we identified that the investments in the No Insurance treatment were significantly higher than in the Baseline Insurance treatment for the high-probability (15%) scenarios, but not significantly different in most low-probability (3%) scenarios. Mean investments in Baseline Insurance were greater than zero, confirming our conjecture that moral hazard is less of a problem in an insurance market where probabilities of damage are low and expected damages are high. Regarding financial incentives for damage-reduction, our results indicate that a premium discount can increase investment in damage-reduction, while the availability of a mitigation loan does not increase investments. Behavioral characteristics that have a positive effect on these investments are risk aversion, perceived efficacy of protective measures, and anticipated regret.

While the current research focuses on mandatory insurance, information asymmetries such as moral hazard may also emerge in insurance markets where policyholders are able to select the level of coverage. Future work could examine the interplay between financial incentives and behavioral characteristics in these voluntary insurance schemes. Another important topic for further research is uncertainty about the future. For simplicity, our participants played a fixed number of rounds in the game. An interesting possibility would be to add a random stopping rule to the game to mimic the indefinite time horizon of real-world policyholders.

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## Appendix A. Literature

**Table A1**
Overview of experimental literature on moral hazard.

| Publication | Journal | Type | Treatments | Context | N |
|---|---|---|---|---|---|
| Berger and Hershey (1994) | Journal of Risk and Uncertainty | laboratory | stochastic/deterministic loss | Insurance | 101 |
| Di Mauro (2002) | Journal of Socio-Economics | laboratory | coverage | Insurance | 60 |
| McKee, Berrens, Jones, Helton, and Talberth (2004) | Society & Natural Resources | laboratory | size of loss | Insurance | 60 |
| McKee, Santore, and Shelton (2007) | The Journal of Legal Studies | laboratory | contingency fees | Legal services | 22 |
| Deck and Reyes (2008) | The Southern Economic Journal | laboratory | second investor | Work effort | 48 |
| Du, Shelley, and Zhao (2008) | Working paper (SSRN) | laboratory | group identity, disclosure | Group dynamics | 90 |
| Burger and Kolstad (2009) | Working paper (SSRN) | laboratory | coalitions | Group dynamics | 80 |
| Gong, Baron, and Kunreuther (2009) | Journal of Risk and Uncertainty | laboratory | group / individual | Public goods | 202 |
| Karlan, Zinman, Carter, Chiappori, Djebbari, Duflo, Finkelstein, Gale, Kling, Klonner, Lehnert, Lizzeri, Morduch, Pande, and Robe (2009) | Econometrica | field | contract rates | Micro finance | 5028 |
| Banerjee, Chakravarty, and Mohanty (2011) | Journal of Quantitative Economics | laboratory | cut-off investment | Public goods | 100 |
| Hoppe and Kusterer (2011) | European Economic Review | laboratory | group size, conflict | Work effort | 474 |
| Cason, Gangadharan, and Maitra (2012) | Journal of Economic Behavior and Organization | laboratory | group/individual | Micro finance | 348 |
| Hasson, Löfgren, and Visser (2012) | South African Journal of Economics | laboratory | stochastic/deterministic loss | Climate change | 144 |
| Nieken and Schmitz (2012) | Games and Economic Behavior | laboratory | wage schemes | Work effort | 358 |
| Füllbrunn and Neugebauer (2013) | Economic Inquiry | laboratory | transparency | Public goods | 112 |
| Biener, Eling, Landmann, and Pradhan (2014) | Working paper | laboratory | coverage, group/individual | Micro finance | 992 |
| Bixter and Luhmann (2014) | Journal of Economic Psychology | laboratory | face-to-face contact | Group dynamics | 40 |
| Dhillon, Peeters, and Yuksel (2014) | Working paper | laboratory | social networks | Work effort | 136 |
| Gong, Heal, Krantz, Kunreuther, and Weber (2014) | Journal of Behavioral Decision Making | laboratory | group/individual | Public goods | 294 |
| Czura (2015) | Journal of Development Economics | field | monitoring, punishment | Microfinance | 105 |
| Hopfensitz, Mantilla, and Miquel-Florensa (2016) | Working paper | lab-in-the-field | deterministic/stochastic loss | Public goods | 110 |
| Huck, Lünser, Spitzer, and Tyran (2016) | Journal of Economic Behavior and Organization | laboratory | competition | Health | 336 |
| Janssens and Kramer (2016) | Journal of Economic Behavior and Organization | field | group/individual, communication | Micro finance | 355 |
| Neuß, Peter, and Knoller (2016) | Working paper | laboratory | volunteer/insurer | Public goods | 162 |
| Biener, Eling, Landmann, and Pradhan (2018) | European Economic Review | field | group / individual | Insurance | 1692 |
| Giraudet, Houde, and Maher (2018) | Journal of the Association of Environmental and Resource Economists | field | insurance, quality standards | Energy | 2936 |
| Gelade and Guirkinger (2018) | Journal of Economic Behavior and Organization | field | internal/external monitoring | Micro finance | 890 |
| Hoppe and Schmitz (2018) | Games and Economic Behavior | laboratory | observability | Work effort | 754 |
| Rud, Rabanal, and Horowitz (2018) | Journal of Financial Intermediation | laboratory | competition | Work effort | 79 |
| Macera (2018) | Journal of Economic Behavior and Organization | laboratory | practice | Work effort | 300 |

*Notes*: Laboratory = laboratory experiment, field = field experiment.

## Appendix B. Variable coding

**Table B1**
Summary overview of the variables used in the statistical analysis.

| Age | Continuous variable, age in years |
|---|---|
| Gender | Dummy variable, 1 = participant is female |
| High income | Dummy variable, 1 = monthly household after-tax income is within the highest category > € 5000 |
| Worried about flood | Categorical variable (range 1–5), worried about danger of flooding at current residence, 1 = strongly disagree, 5 = strongly agree |
| Regret no investment | Categorical variable (range 1–5), I felt regret about not investing in protection when a flood occurred in the game, 1 = strongly disagree, 5 = strongly agree |
| Regret investment | Categorical variable (range 1–5), when in a certain year in the game no flood occurred, I felt regret about paying for protection, 1 = strongly disagree, 5 = strongly agree |
| Risk averse | Risk aversion index: weighted average of four risk elicitation methods, 1 = very risk seeking, 10 = very risk averse |
| Present biased | Switching row in time list[a] (range 1–26), 1 = no time discounting, 26 = high time discounting |
| Efficacy protection | Categorical variable (range 0–10), How effective do you consider investing in flood protection measures that limit flood damage[b], 0 = very ineffective, 10 = very effective |
| Participant flooded | Dummy variable, 1 = participant flooded in previous round |
| Neighbor flooded | Dummy variable, 1 = one or more neighbors[c] flooded in previous round |

[a] Time list parameters from Falk et al. (2016).
[b] This question was taken from Poussin et al. (2014).
[c] see Fig. 5.

## Appendix C. Comparative statics

The following section briefly describes the model, which extends the expected utility framework on optimal loss mitigation of Kelly and Kleffner (2003) to a multiple-years framework. Note that mitigation refers to investments that reduce the size of a potential loss but not the probability, which is known as self-insurance in the original model by Ehrlich and Becker (1972).

First, consider the one-year framework. Consider an individual with initial wealth $W$ who faces a loss $V$ with probability $p$ and no loss with probability $1-p$. The individual has the possibility to reduce the size of the loss by implementing mitigation expenditures r. The effectiveness of mitigation is captured in the mitigation function $L(r)$ that denotes the maximum possible loss if r is spent on mitigation. If a consumer does not spend anything on mitigation, the size of the loss will be $V$. Increasing mitigation expenditures leads to a decrease of maximum possible loss such that $L(0) = V$ and $L'(r) < 0$. Finally, assume that $L''(r) \leq 0$, meaning that the marginal effectiveness of mitigation decreases with an increase in mitigation expenditures. Insurance coverage is mandatory to protect against the possible loss, with a coverage of $\alpha \in [0, 1]$. In other words, the insurance contains a deductible of $1-\alpha$ per dollar of coverage. The term $\alpha L(r)$ denotes the compensation in case of a loss. The insurer sets the premium $\alpha\pi$, where $\pi = pL(0)$. The insurer does not observe r and, hence, does not give premium discounts for risk reduction. The individual will choose a level of $r$ to maximize expected utility $EU$:

$$\max EU_r = (1-p)U[W - \alpha\pi - r] + pU[W - \alpha\pi - (1-\alpha)L(r) - r] \tag{C.1}$$

Now consider the multi-year framework. The model is constructed such that the policyholder considers a damage reduction investment in the present based on of the net present value of utility in both the present year (in which he/she considers an investment in mitigation) and in the years to come. For simplicity, we assume that the policyholder can invest only once, namely in the first year. A parallel with reality may be that you cannot elevate your house twice. Thus, the costs of mitigation r are paid in the first year $t = 1$ only, while the benefits (a decrease in $L$) extend in the future up to and including the last year $T$. Future years are discounted with a discount factor $\delta$ (see Frederick, Loewenstein, & O'Donoghue, 2002). The individual will choose a level of $r$ to maximize expected utility $EU$:

$$\begin{aligned}\max_r EU &= (1-p)U[W_1 - \alpha\pi - r] + pU[W_1 - \alpha\pi - (1-\alpha)L(r) - r] \\ &+ \sum_{t=2}^{T} \frac{1}{(1+\delta)^{t-1}}\Big((1-p)U[W_t - \alpha\pi] + pU[W_t - \alpha\pi - (1-\alpha)L(r)]\Big)\end{aligned} \tag{C.2}$$

We aimed to derive theoretical predictions based on comparative statics for each of our treatments. We start with the simplest case: the effect of insurance coverage, by comparing the Insurance Baseline and the No Insurance treatments (Hypothesis 1).

### *C1. Insurance Baseline versus No Insurance*

Coverage $\alpha$ determines the difference between the Insurance Baseline and the No Insurance treatments. We determine the optimal investment in mitigation $r$ in relation to $\alpha$. Taking the derivative of Eq. C.2 with respect to $r$ leads to the first order condition:

$$\begin{aligned}F &= -(1-p)U'[W_1 - \alpha\pi - r] - p((1-\alpha)L'(r) + 1)U'[W_1 - \alpha\pi - (1-\alpha)L(r) - r)] \\ &- p((1-\alpha)L'(r)) \sum_{t=2}^{T} \frac{1}{(1+\delta)^{t-1}}\Big(U'[W_t - \alpha\pi - (1-\alpha)L(r)]\Big) = 0\end{aligned} \tag{C.3}$$

Using the implicit function theorem:

$$\frac{\partial r}{\partial \alpha} = -\frac{F'_\alpha}{F'_r}$$

Fulfilled second order condition implies:

$$F'_r < 0$$

Abbreviating $W_1 - \alpha\pi - r$ as $nL_1$, $W_1 - \alpha\pi - (1-\alpha)L(r) - r$ as $L_1$ and $W_t - \alpha\pi - (1-\alpha)L(r)$ as $L_t$:

$$F'_\alpha = (1-p)\pi U''(nL_1) - p((1-\alpha)L'(r)+1)(L(r)-\pi)U''(L_1) + L'(r)pU'(L_1) + L'(r)p\sum_{t=2}^{T}\frac{1}{(1+\delta)^{t-1}}U'(L_t) - p((1-\alpha)L'(r))\sum_{t=2}^{T}\frac{1}{(1+\delta)^{t-1}}(L(r)-\pi)U''(L_t) \tag{C.4}$$

If we assume $1 < |(1-\alpha)L'(r)|$ and a concave utility function, $F'_\alpha$ is negative. Then:

$$\frac{\partial r}{\partial \alpha} < 0 \tag{C.5}$$

Under more insurance coverage, optimal investment in $r$ decreases, which is part of Hypothesis 1.

### C2. Loan treatment

We have found a comparative statics prediction for the simplest treatment, under the assumption that $1 < |(1-\alpha)L'(r)|$. This holds for the parameters used in our experiment, but it is not necessarily always the case. Furthermore, analytical solutions for the other hypotheses cannot be obtained. For example, consider the Loan treatment (Hypothesis 3a). Individuals pay part $q \in [0, 1]$ of investment $r$ for $1/q$ periods until the loan has been repaid, maximizing utility:

$$\max_r EU = (1-p)U[W_1 - \alpha\pi - qr] + pU[W_1 - \alpha\pi - (1-\alpha)L(r) - qr] + \sum_{t=2}^{T}\frac{1}{(1+\delta)^{t-1}}\left((1-p)U[W_t - \alpha\pi - qr] + pU[W_t - \alpha\pi - (1-\alpha)L(r) - qr]\right) \tag{C.6}$$

Taking the derivative of Eq. C.6 with respect to $r$ leads to the first order condition:

$$F = -q(1-p)U'[W_1 - \alpha\pi - qr] - p((1-\alpha)L'(r)+q)U'[W_1 - \alpha\pi - (1-\alpha)L(r) - qr)] - p((1-\alpha)L'(r)+q)\sum_{t=2}^{T}\frac{1}{(1+\delta)^{t-1}}\left(U'[W_t - \alpha\pi - (1-\alpha)L(r) - qr]\right) = 0 \tag{C.7}$$

Abbreviate $W_1 - \alpha\pi - qr$ as $X_1$, $W_1 - \alpha\pi - (1-\alpha)L(r) - qr$ as $X_2$ and $W_t - \alpha\pi - (1-\alpha)L(r) - qr$ as $X_3$:

$$F'_q = -(1-p)U'[X_1] + rq(1-p)U''[X_1] - pU'[X_2] + pr((1-\alpha)L'(r)+q)U''[X_2] - p\sum_{t=2}^{T}\frac{1}{(1+\delta)^{t-1}}U'[X_3] + pr((1-\alpha)L'(r)+q)\sum_{t=2}^{T}\frac{1}{(1+\delta)^{t-1}}U''[X_3] \tag{C.8}$$

It is not straightforward to determine the sign of $F'_q$ without restricting some of the parameters. Similar problems occur with Hypothesis 2a, 2b and 3b. Therefore, we decided to use numerical simulations to generate predictions about our hypotheses (see Appendix D).

## Appendix D. Parameter calculations

To determine the parameters of our investment game, we calculated the net present value (NPV) based on Expected Utility (Eq. C.2) for different combinations of parameters. Some parameters were chosen based on estimations from reality, such as the maximum damage (50,000 ECU) and the interest rate (1%). For the effectiveness of damage reducing investments, we used the loss function $L(r) = Ve^{-\beta r}$ proposed by Kelly and Kleffner (2003), where $V$ denotes the maximum loss and the effectiveness of mitigation is captured by parameter $\beta$. We aimed to base our loss function on damage reduction estimates from real data: Federal Emergency Management Agency (FEMA) cost estimates and damage reduction estimates for a typical single family dwelling of flood mitigation measures. Fig. D.1 plots these estimates[16] against the loss function with different values of $\beta$, with V = 200,000, the average value of this type of building. The mitigation function $L(r) = Ve^{-\beta r}$ with $0.00001 \leq \beta \leq 0.00008$ seems to fit the data well.

We varied the parameters (savings account, income per round, probabilities, deductibles, $\beta$, number of installments) to find a reasonable combination[17] which allowed us to test all our hypotheses. Table D.1 shows the results of these simulations with our final set of parameters. The table displays the NPV of Expected Utility of investments in damage mitigation over 10 rounds[18], discounted by $\delta = 0.01$ for different degrees of risk aversion $\theta$ and normalized over the minimal and maximal possible expected values in the game. We used a power utility function of the form $u(x) = x^\theta$. The results are shown in comparison to zero investment. Therefore, all positive numbers are displayed in bold, as they indicate a net gain from investing a positive amount. For each combination of treatment and scenario, the largest positive number gives the optimal investment (underlined) for an individual. If no number is underlined the optimal investment is zero. Table D.2 shows the results for high discounting, $\delta = 0.1$.

The following section repeats the hypotheses and explains briefly how each hypothesis can be tested based on the predictions in Table D.1 and Table D.2.

*Hypothesis 1. Damage reduction investments in the Insurance Baseline treatment are lower than in the No Insurance treatment, but greater than zero.* The

[16] Table 2.10, Table 2.13 and Table 2.18 from Aerts, Botzen, de Moel, and Bowman (2013) to be precise.

[17] For example: $0.00001 \leq \beta \leq 0.00008$, positive income.

[18] Note that the actual design uses a fixed number of 12 rounds, but participants are only informed that each scenario takes at least 10 rounds. The results of the simulations for 12 rounds (not shown here in detail) are very similar to the tables reported here and the corresponding hypotheses are identical.

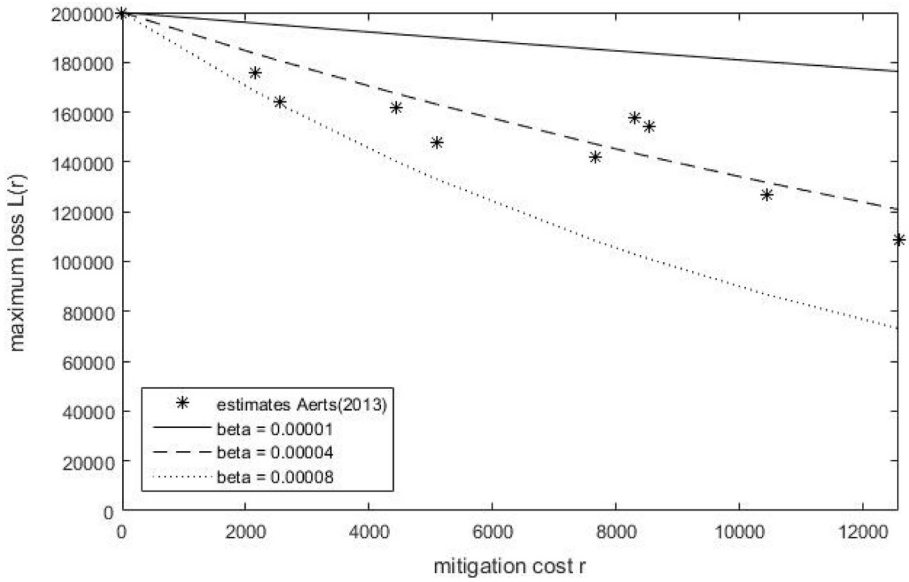


**Fig. D1.** Parameter estimation of the mitigation function.

**Table D1**
Normalized NPV of investment by scenario and treatment at $\delta = 0.01$.

| Risk averse ($\theta = 0.3$) | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Insurance Baseline | | | | Premium Discount | | | | Loan | | | | Loan + Discount | | | |
| | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 |
| H - | **0.025** | **0.103** | **0.163** | **0.195** | | | | | | | | | | | | |
| HH | **0.003** | **0.005** | −0.016 | −0.055 | **0.059** | **0.239** | **0.374** | **0.440** | **0.003** | **0.004** | −0.015 | −0.048 | **0.058** | **0.239** | **0.375** | **0.446** |
| HL | −0.001 | −0.013 | −0.046 | −0.092 | **0.057** | **0.231** | **0.361** | **0.425** | −0.001 | −0.013 | −0.042 | −0.082 | **0.057** | **0.232** | **0.365** | **0.434** |
| HxL | −0.008 | −0.046 | −0.099 | −0.159 | **0.054** | **0.219** | **0.342** | **0.401** | −0.008 | −0.043 | −0.091 | −0.143 | **0.054** | **0.221** | **0.349** | **0.416** |
| L - | **0.001** | −0.001 | −0.012 | −0.028 | | | | | | | | | | | | |
| LH | −0.008 | −0.045 | −0.097 | −0.154 | **0.001** | −0.003 | −0.026 | −0.063 | −0.008 | −0.043 | −0.089 | −0.139 | **0.002** | **0.000** | −0.018 | −0.049 |
| LL | −0.009 | −0.048 | −0.102 | −0.160 | **0.001** | −0.003 | −0.026 | −0.064 | −0.009 | −0.046 | −0.094 | −0.145 | **0.002** | −0.001 | −0.019 | −0.049 |
| LxL | −0.010 | −0.054 | −0.111 | −0.172 | **0.001** | −0.004 | −0.028 | −0.066 | −0.010 | −0.051 | −0.103 | −0.156 | **0.002** | −0.001 | −0.019 | −0.049 |
| (b) Risk neutral ($\theta = 1$) | | | | | | | | | | | | | | | | |
| | Insurance Baseline | | | | Premium Discount | | | | Loan | | | | Loan + Discount | | | |
| | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 |
| H - | **0.025** | **0.103** | **0.163** | **0.195** | | | | | | | | | | | | |
| HH | **0.001** | −0.003 | −0.024 | −0.057 | **0.052** | **0.216** | **0.341** | **0.406** | **0.002** | −0.001 | −0.020 | −0.052 | **0.053** | **0.218** | **0.345** | **0.412** |
| HL | −0.002 | −0.017 | −0.047 | −0.086 | **0.052** | **0.216** | **0.341** | **0.406** | −0.002 | −0.015 | −0.043 | −0.081 | **0.053** | **0.218** | **0.345** | **0.412** |
| HxL | −0.008 | −0.044 | −0.093 | −0.144 | **0.052** | **0.216** | **0.341** | **0.406** | −0.008 | −0.042 | −0.089 | −0.139 | **0.053** | **0.218** | **0.345** | **0.412** |
| L - | **0.001** | −0.001 | −0.012 | −0.028 | | | | | | | | | | | | |
| LH | −0.009 | −0.047 | −0.097 | −0.150 | **0.001** | −0.003 | −0.024 | −0.057 | −0.009 | −0.045 | −0.093 | −0.144 | **0.002** | −0.001 | −0.020 | −0.052 |
| LL | −0.010 | −0.050 | −0.102 | −0.156 | **0.001** | −0.003 | −0.024 | −0.057 | −0.009 | −0.048 | −0.098 | −0.150 | **0.002** | −0.001 | −0.020 | −0.052 |
| LxL | −0.011 | −0.055 | −0.111 | −0.168 | **0.001** | −0.003 | −0.024 | −0.057 | −0.011 | −0.053 | −0.107 | −0.162 | **0.002** | −0.001 | −0.020 | −0.052 |
| Risk seeking ($\theta = 3$) | | | | | | | | | | | | | | | | |
| | Insurance Baseline | | | | Premium Discount | | | | Loan | | | | Loan + Discount | | | |
| | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 |
| H - | **0.025** | **0.103** | **0.163** | **0.195** | | | | | | | | | | | | |
| HH | −0.002 | −0.014 | −0.029 | −0.046 | **0.029** | **0.123** | **0.202** | **0.249** | −0.001 | −0.008 | −0.022 | −0.042 | **0.030** | **0.129** | **0.209** | **0.253** |
| HL | −0.003 | −0.018 | −0.037 | −0.055 | **0.031** | **0.134** | **0.220** | **0.272** | −0.002 | −0.013 | −0.033 | −0.057 | **0.033** | **0.138** | **0.224** | **0.270** |
| HxL | −0.006 | −0.030 | −0.058 | −0.083 | **0.036** | **0.155** | **0.255** | **0.316** | −0.006 | −0.030 | −0.062 | −0.096 | **0.037** | **0.156** | **0.251** | **0.303** |
| L - | **0.001** | −0.001 | −0.012 | −0.028 | | | | | | | | | | | | |
| LH | −0.008 | −0.039 | −0.075 | −0.107 | **0.000** | −0.003 | −0.015 | −0.031 | −0.008 | −0.039 | −0.079 | −0.121 | **0.001** | −0.003 | −0.020 | −0.046 |
| LL | −0.008 | −0.041 | −0.077 | −0.110 | **0.001** | −0.002 | −0.013 | −0.029 | −0.008 | −0.041 | −0.083 | −0.125 | **0.001** | −0.002 | −0.019 | −0.045 |
| LxL | −0.009 | −0.044 | −0.084 | −0.118 | **0.001** | **0.000** | −0.011 | −0.026 | −0.009 | −0.045 | −0.090 | −0.136 | **0.001** | −0.001 | −0.017 | −0.044 |

NPV is higher for all investments in No Insurance (denoted as H − and L − in Table D.1) compared to investments in Insurance Baseline. In the high probability scenarios, positive investments may be optimal with insurance, depending on the deductible level and attitude to risk. For example, for a risk averse individual in scenario HH (Table D.1a) the optimal investment in Insurance Baseline is 5000 ECU, which leads to a positive NPV of 0.005 compared to no investment. This allows for evaluation of Hypothesis 1.

*Hypothesis 2a. Damage reduction investments are higher in the Premium Discount treatment than in the Insurance Baseline treatment.* Comparing the

**Table D2**
Normalized NPV of investment by scenario and treatment at $\delta = 0.1$.

(a) Risk averse ($\theta = 0.3$)

| | Insurance Baseline | | | | Premium Discount | | | | Loan | | | | Loan + Discount | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 |
| H - | **0.016** | **0.065** | **0.099** | **0.113** | | | | | | | | | | | | |
| HH | −0.001 | −0.015 | −0.048 | −0.095 | **0.037** | **0.150** | **0.226** | **0.253** | **0.002** | **0.003** | −0.011 | −0.034 | **0.041** | **0.167** | **0.262** | **0.312** |
| HL | −0.004 | −0.027 | −0.069 | −0.121 | **0.036** | **0.145** | **0.218** | **0.244** | −0.001 | −0.009 | −0.030 | −0.057 | **0.040** | **0.162** | **0.256** | **0.304** |
| HxL | −0.009 | −0.050 | −0.106 | −0.168 | **0.034** | **0.137** | **0.206** | **0.230** | −0.006 | −0.030 | −0.064 | −0.101 | **0.038** | **0.156** | **0.246** | **0.293** |
| L - | −0.001 | −0.009 | −0.024 | −0.044 | | | | | | | | | | | | |
| LH | −0.009 | −0.048 | −0.102 | −0.161 | −0.002 | −0.018 | −0.052 | −0.097 | −0.006 | −0.030 | −0.063 | −0.098 | **0.001** | **0.000** | −0.013 | −0.034 |
| LL | −0.010 | −0.051 | −0.106 | −0.166 | −0.002 | −0.019 | −0.052 | −0.097 | −0.006 | −0.032 | −0.066 | −0.102 | **0.001** | **0.000** | −0.013 | −0.035 |
| LxL | −0.011 | −0.055 | −0.113 | −0.174 | −0.002 | −0.019 | −0.053 | −0.098 | −0.007 | −0.036 | −0.073 | −0.110 | **0.001** | −0.001 | −0.014 | −0.035 |

(b) Risk neutral ($\theta = 1$)

| | Insurance Baseline | | | | Premium Discount | | | | Loan | | | | Loan + Discount | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 |
| H - | **0.016** | **0.065** | **0.099** | **0.113** | | | | | | | | | | | | |
| HH | −0.003 | −0.019 | −0.051 | −0.092 | **0.033** | **0.135** | **0.207** | **0.236** | **0.001** | −0.001 | −0.014 | −0.036 | **0.037** | **0.154** | **0.244** | **0.291** |
| HL | −0.005 | −0.029 | −0.067 | −0.112 | **0.033** | **0.135** | **0.207** | **0.236** | −0.001 | −0.010 | −0.031 | −0.057 | **0.037** | **0.154** | **0.244** | **0.291** |
| HxL | −0.009 | −0.048 | −0.099 | −0.153 | **0.033** | **0.135** | **0.207** | **0.236** | −0.006 | −0.030 | −0.063 | −0.098 | **0.037** | **0.154** | **0.244** | **0.291** |
| L - | −0.001 | −0.009 | −0.024 | −0.044 | | | | | | | | | | | | |
| LH | −0.010 | −0.050 | −0.103 | −0.157 | −0.003 | −0.019 | −0.051 | −0.092 | −0.006 | −0.032 | −0.066 | −0.102 | **0.001** | −0.001 | −0.014 | −0.036 |
| LL | −0.010 | −0.052 | −0.106 | −0.161 | −0.003 | −0.019 | −0.051 | −0.092 | −0.007 | −0.034 | −0.069 | −0.106 | **0.001** | −0.001 | −0.014 | −0.036 |
| LxL | −0.011 | −0.056 | −0.112 | −0.169 | −0.003 | −0.019 | −0.051 | −0.092 | −0.007 | −0.038 | −0.076 | −0.114 | **0.001** | −0.001 | −0.014 | −0.036 |

(c) Risk seeking ($\theta = 3$)

| | Insurance Baseline | | | | Premium Discount | | | | Loan | | | | Loan + Discount | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 | 1000 | 5,000 | 10,000 | 15,000 |
| H - | **0.016** | **0.065** | **0.099** | **0.113** | | | | | | | | | | | | |
| HH | -0.004 | −0.021 | −0.042 | −0.062 | **0.019** | **0.078** | **0.125** | **0.149** | **0.001** | −0.005 | −0.016 | −0.031 | **0.022** | **0.094** | **0.152** | **0.184** |
| HL | −0.005 | −0.024 | −0.047 | −0.069 | **0.020** | **0.085** | **0.136** | **0.163** | −0.002 | −0.010 | −0.024 | −0.041 | **0.024** | **0.100** | **0.162** | **0.195** |
| HxL | −0.007 | −0.033 | −0.063 | −0.089 | **0.023** | **0.098** | **0.158** | **0.190** | −0.004 | −0.021 | −0.044 | −0.068 | **0.026** | **0.111** | **0.179** | **0.215** |
| L - | −0.001 | −0.009 | −0.024 | −0.044 | | | | | | | | | | | | |
| LH | −0.009 | −0.042 | −0.079 | −0.111 | −0.003 | −0.016 | −0.037 | −0.059 | −0.005 | −0.028 | −0.056 | −0.086 | **0.001** | −0.002 | −0.014 | −0.032 |
| LL | −0.009 | −0.043 | −0.080 | −0.114 | −0.002 | −0.015 | −0.035 | −0.057 | −0.006 | −0.029 | −0.059 | −0.089 | **0.001** | −0.001 | −0.013 | −0.032 |
| LxL | −0.009 | −0.045 | −0.085 | −0.119 | −0.002 | −0.014 | −0.034 | −0.055 | −0.006 | −0.032 | −0.064 | −0.096 | **0.001** | −0.001 | −0.012 | −0.031 |

Premium Discount column with the Insurance Baseline column gives higher NPV values in each of the rows and sub − tables in Table D.1. Therefore, this hypothesis can be tested under all scenarios and risk attitudes.

*Hypothesis 2b. Damage reduction investments are highest in the Loan + Discount treatment* Under low time discounting (Table D.1), investments in the Premium Discount treatment were already optimal, such that they stay optimal in Loan + Discount treatment. Under high time discounting (Table D.2), Loan + Discount gives the highest optimal investments of all treatments in the low probability scenarios.

*Hypothesis 3a. Damage reduction investments are lower for participants with high time discount rates. This effect is strongest in the Insurance Baseline and Premium Discount treatments, but disappears in the Loan and Loan + Discount treatments.* In the Insurance Baseline and Premium Discount treatments, increasing the time discount rate from low time discounting ($\delta = 0.01$ in Table D.1) to high time discounting ($\delta = 0.1$ in Table D.2) decreases the optimal investment level. No change is observed in the Loan and Loan + Discount treatments.

*Hypothesis 3b. Risk-averse individuals will invest more in damage reduction in the Insurance Baseline treatment and the Loan treatment than risk-neutral individuals, where risk-seeking individuals will invest less.* In the Insurance Baseline and the Loan treatment, risk-neutral ($\theta = 1$, Table D.1a) individuals will invest (scenario HH and HL). A risk-averse individual ($\theta = 0.3$, Table D.1 b) will also get a positive NPV for investing 5,000. Risk-seeking individuals ($\theta = 3$, Table D.1 c) will not invest in any of these scenarios.

## Appendix E. Comprehension questions

Correct answers are marked in **bold**.

### *E1. Questions asked in all treatments*

- What was the flood risk in the test scenario?
  a) 1% b) 3% c) 5% d) 10% e) 15% f) 20%
  The answer depends on the risk in the test scenario (randomly determined).
- If you are flooded in year 1, what is the flood risk in year 2?
  (a) Less than in year 1

**Table F1**
Random-effects ML panel regressions for log-transformed investments.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Qualitative | List gain | List loss | BRET | Combined |
| *Treatment (ref. Baseline Insurance)* | | | | | |
| Premium Discount | 1.886*** | 1.927*** | 1.909*** | 1.892*** | 1.916*** |
| | (0.249) | (0.249) | (0.249) | (0.249) | (0.248) |
| Loan | 0.137 | 0.139 | 0.115 | 0.048 | 0.099 |
| | (0.235) | (0.235) | (0.236) | (0.235) | (0.234) |
| Loan × Discount | −0.217 | −0.302 | −0.243 | −0.228 | −0.285 |
| | (0.368) | (0.369) | (0.369) | (0.367) | (0.367) |
| *Probability (ref. L: 3%)* | | | | | |
| H: 15% | 1.656*** | 1.639*** | 1.623*** | 1.640*** | 1.649*** |
| | (0.391) | (0.392) | (0.392) | (0.390) | (0.390) |
| *Deductible (ref. xL: 5%)* | | | | | |
| L: 15% | 0.708*** | 0.708*** | 0.708*** | 0.708*** | 0.708*** |
| | (0.209) | (0.209) | (0.210) | (0.209) | (0.209) |
| H: 20% | 1.223*** | 1.223*** | 1.223*** | 1.223*** | 1.223*** |
| | (0.209) | (0.209) | (0.210) | (0.209) | (0.209) |
| Order of scenario | −0.492*** | −0.494*** | −0.497*** | −0.494*** | −0.493*** |
| | (0.071) | (0.071) | (0.071) | (0.071) | (0.071) |
| Participant flooded | −0.024 | −0.024 | −0.024 | −0.024 | −0.024 |
| | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) |
| Neighbor flooded | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) |
| Decision time round | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Risk averse self reported | 0.145*** | | | | |
| | (0.046) | | | | |
| Risk averse in gain domain | | 0.062** | | | |
| | | (0.030) | | | |
| Risk averse in loss domain | | | −0.007 | | |
| | | | (0.036) | | |
| Risk averse in BRET on 1–10 scale | | | | 0.153*** | |
| | | | | (0.042) | |
| Risk averse | | | | | 0.262*** |
| | | | | | (0.069) |
| Constant | 2.785*** | 3.084*** | 3.541*** | 2.856*** | 1.928** |
| | (0.867) | (0.P61) | (0.894) | (0.855) | (0.932) |
| $\sigma_u$ | 3.421*** | 3.426*** | 3.431*** | 3.417*** | 3.416*** |
| | (0.060) | (0.061) | (0.061) | (0.060) | (0.060) |
| $\sigma_e$ | 0.972*** | 0.972*** | 0.972*** | 0.972*** | 0.972*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Observations | 19,440 | 19,440 | 19,440 | 19,440 | 19,440 |
| Nr of subjects | 270 | 270 | 270 | 270 | 270 |
| AIC | 62,249 | 62,255 | 62,259 | 62,246 | 62,245 |
| Log likelihood | −31,097 | −31,099 | −31,101 | −31,095 | −31,094 |

*Notes:* Standard errors clustered by id and scenario in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Controls: Understanding questions, perceived difficulty, flood risk perception, scenario-order × probability, high income, gender, age, efficacy, worry, regret and 1/round.

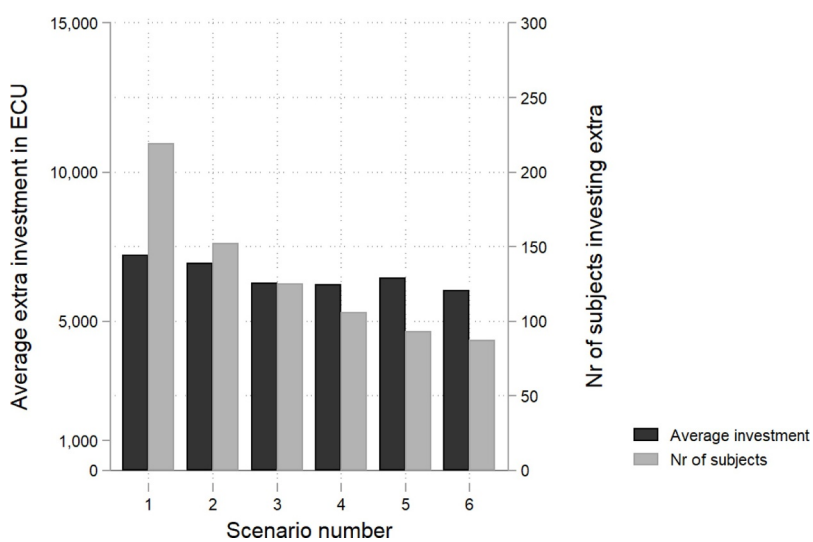


**Fig. F1.** Extra investments after first round.

(b) **Flood risk does not change**
(c) More than in year 1

- How long are protective investments effective?
  (a) From the moment you implement to the end of the experiment
  (b) **From the moment you implement to the end of the scenario**
  (c) From the start of the scenario to the end of the scenario

*Extra question in the No Insurance treatment*

- What happens if you are flooded and you did not take protective investments?
  (a) **I have to pay the full damage: 50.000 ECU**
  (b) I have to pay a small fee
  (c) I will cry

*E2. Extra question in all Insurance treatments*

- What was your deductible (eigen risico) in the test scenario?
  a) 5 percent b) 15 percent c) 20 percent d) 50 percent
  The answer depends on the deductible in the test scenario (randomly determined).

*Extra question in the Loan and Loan + Discount treatments*

- Should you always repay your loan?
  (a) No, I can refuse to pay the loan cost
  (b) No, if the loan is not fully repaid in the last year, I am lucky
  (c) Yes, I will pay the loan cost in the first 5 years
  (d) **Yes, if the loan is not fully repaid in the last year, I will pay the remainder**

*Extra question in the Premium Discount and Loan + Discount treatments*

- What is the benefit of a protective investment?
  (a) A reduced damage in case of a flood
  (b) A lower premium
  (c) **Both reduced damage and a lower premium**
  (d) None of the above

## Appendix F. Additional analyses

*Risk aversion index*

Our risk aversion index was a linear combination of the four risk aversion measures, following Menkhoff and Sakha (2017). Table F.1 shows the results of our random-effects ML panel regressions for each of the four measures separately, in comparison to the combined measure (Model 5). All risk aversion measures except the price list in the loss domain have positive and significant estimates.

*Extra investors* As investments in damage reduction lasted for all rounds of the game, it was optimal to invest in the first round. However, a substantial number of subjects increased their existing investment after the first round, or started investing after the first round. The number of these 'extra investors' and the average extra investment, pooled by the appearance of each scenario, are plotted in Fig. F.1. The number of subjects that invests extra drops by half from the first to the last scenario. Even though all subjects started with 5 rounds of the test scenario, a substantial number of subjects invests extra in the experimental scenarios. Interestingly, extra investments are rather stable over the scenarios at about 7000 ECU.

To analyze the extra investors in more detail, we ran our random-effects ML panel regressions with log-transformed extra investments as the dependent variable. This variable was constructed to capture a change in investment from the previous round, starting from round 2. For example, if a subject invests 1000 ECU in round 1, nothing more in round 2 and increases to 5000 ECU in round 3, the extra investment variable takes the values 0, 0, 4000. Table F.2 shows that extra investments increase after a flood in the game that hit the subject's house, but not after hitting the neighbors. The non-significant estimates of probability and deductibles suggest that extra investments do not differ per scenario. In contrast to the analysis of investments in all rounds, we find no effect of risk aversion and efficacy of protection on extra investments; these seem to be primary motivators to invest at the start of the game. Extra investors seem to be primarily motivated by firsthand experience of flood in the game and anticipated regret.

**Table F2**
Random-effects ML panel regressions for extra investments.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Treatments | Previous rounds | Demographics |
| *Treatment (ref. Baseline Insurance)* | | | |
| Premium Discount | 0.132*** | 0.118*** | 0.145*** |
| | (0.028) | (0.028) | (0.030) |
| Loan | 0.016 | 0.012 | 0.003 |
| | (0.028) | (0.028) | (0.028) |
| Loan × Discount | −0.184*** | −0.166*** | −0.149*** |
| | (0.044) | (0.044) | (0.044) |
| *Probability (ref. L: 3%)* | | | |
| H: 15% | −0.032 | −0.026 | 0.043 |
| | (0.048) | (0.047) | (0.047) |
| *Deductible (ref. xL: 5%)* | | | |
| L: 15% | 0.039 | 0.039 | 0.038 |
| | (0.025) | (0.025) | (0.025) |
| H: 20% | 0.021 | 0.021 | 0.028 |
| | (0.025) | (0.025) | (0.025) |
| Order of scenario | −0.051*** | −0.050*** | −0.043*** |
| | (0.009) | (0.009) | (0.009) |
| Participant flooded | 0.197*** | 0.198*** | 0.197*** |
| | (0.034) | (0.034) | (0.035) |
| Neighbor flooded | 0.016 | 0.016 | 0.022 |
| | (0.034) | (0.034) | (0.035) |
| Decision time round | 0.009*** | 0.009*** | 0.008*** |
| | (0.001) | (0.001) | (0.001) |
| Age in years | | −0.011*** | −0.003 |
| | | (0.003) | (0.003) |
| Gender (1 = female) | | 0.070*** | 0.050** |
| | | (0.021) | (0.022) |
| Income (1 = above € 5,000) | | −0.025 | −0.017 |
| | | (0.049) | (0.049) |
| Risk averse | | 0.007 | 0.005 |
| | | (0.008) | (0.008) |
| Present biased | | 0.001 | 0.001 |
| | | (0.001) | (0.001) |
| Efficacy protection | | | 0.008 |
| | | | (0.005) |
| Worried about flood | | | 0.012 |
| | | | (0.011) |
| Regret no investment / flood | | | 0.046*** |
| | | | (0.011) |
| Regret investment / no flood | | | 0.043*** |
| | | | (0.010) |
| Constant | 0.261*** | 0.419*** | −0.115 |
| | (0.053) | (0.095) | (0.112) |
| $\sigma_u$ | 0.223*** | 0.216*** | 0.183*** |
| | (0.015) | (0.015) | (0.017) |
| $\sigma_e$ | 1.312*** | 1.312*** | 1.278*** |
| | (0.007) | (0.007) | (0.007) |
| Observations | 21,456 | 21,456 | 19,440 |
| Nr of subjects | 298 | 298 | 270 |
| AIC | 73,104 | 73,085 | 65,112 |
| Log likelihood | −36,533 | −36,518 | −32,528 |

*Notes:* Standard errors clustered by id and scenario in parentheses (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$). Controls: Understanding questions, perceived difficulty, flood risk perception, order × probability and 1/round.

## Supplementary material: experimental instructions

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.socec.2019.101500 .

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