Personalized information and willingness to pay for non-financial risk prevention : an experiment

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Abstract

When receiving personalized rather than population-based information, agents improve their knowledge about their probability of experiencing adverse events (e.g. health shocks). Being revealed as high or low risk, they may revise their willingness to pay (WTP) for prevention programs. If the WTP changes of the high- and low-risk individuals go in opposite directions, the overall impact on the WTP for prevention depends on whether the relationship between WTP and the initial probability of damage is convex or concave. We address this question in a laboratory experiment. Participants received an endowment and were exposed to a non-financial damage - consisting in electrical shocks - with a certain probability. We elicit subjects' WTP for self-protection and self-insurance, *i.e.* actions reducing respectively the probability and the number of shocks, using the Becker-DeGroot-Marschak mechanism. Our results suggest that WTP for self-protection is insensitive to the baseline probability to undergo pain, but reveal that WTP for self-insurance increases at a decreasing rate with this probability. This implies that the diffusion of personalized information should reduce the demand for self-insurance programs.

Keywords: willingness to pay; experiment; prevention; personalized information

JEL classification: C91; D81; I13; I12

1. Introduction

Personalized information, defined as risk-related information tailored to subgroups of individuals, is increasingly available and is modifying the strategies used to cope with risks. For instance, crime and pollution statistics are now available at a finer geographical scale (i.e. by areas of the city), allowing people to make better informed choices about where to live and/or about the actions to perform in order to reduce the related risks. Likewise, choices of hospitals, schools, hotels, restaurants, etc. are now facilitated by the information provided on specialized websites. This evolution is accelerated by technological changes in several domains: connected objects redirect car drivers towards less congested roads or available parking spaces, smart grids re-allocate energy consumption across time periods, weather forecasts tailored to specific locations allow better informed production decisions in sectors such as agriculture, construction, etc.

The development of genetic testing offers another good illustration of this trend and of a specific issue it raises. Individuals' knowledge about their health characteristics is constantly improving through predisposition tests that provide personalized information about their baseline probability of disease (i.e. their probability of disease before any prevention action). This information, once available, influences the amount of money individuals are willing to forgo in order to improve the distribution of health risks they are exposed to. However, while genetic tests inform some agents that their probability of experiencing a disease is higher than average, other agents receive the opposite information. According to the newly available information, both groups of agents are expected to revise their willingness to pay (WTP) for prevention in opposite directions, but not necessarily by the same magnitude. As a consequence, personalized information on the probability of disease has an uncertain effect on the total WTP. The objective of our paper is to address this question through a lab experiment designed to determine whether the total WTP for prevention based on average information (i.e. in the absence of personalized information) is higher or lower than the total WTP for prevention based on personalized information.

The literature dedicated to the WTP for reductions in the risk of mortality or in the risk of disease has been initiated by Drèze (1962). Since then, various contributions in risk theory have analyzed the effects of individuals' characteristics such as wealth (Pratt and Zeckhauser, 1996), risk aversion (Dachraoui et al., 2004) or overall health status (Bleichrodt et al., 2003) on this WTP. The effect of the baseline probability of death on the value of marginal changes in this probability has been examined by Jones-Lee (1974). This work assumes that successive changes in the baseline probability of death result from actions undertaken by individuals. If one is interested in the effect of the information provided by predisposition tests on the WTP for disease prevention, one must instead consider that changes in baseline probabilities of diseases are exogenous since they result from previously unknown genetic information. This is the assumption made by Crainich and Eeckhoudt (2017) who examine the effect of personalized health information on two types of preventive actions, those reducing the probability of disease and those reducing the severity of disease (respectively, self-protection and self-insurance in the terminology coined by Ehrlich and Becker (1972)). The main question they address is that of the effect of the genetic information on the total WTP for self-protection and for self-insurance[1]. They show that personalized health information about the probability of disease always increases the total WTP for self-protection while it increases the total WTP for self-insurance if the marginal utility of wealth rises with health[2].

[1] In their analysis, Crainich and Eeckhoudt (2017) assume that individuals have complete information and that their WTP are based on objective baseline probabilities of diseases. This is not necessarily the case in practice, as shown by Carman and Kooreman (2014) who establish the connection between objective risks, perceived risks, and the propensity to undertake disease prevention actions.

[2] More generally, WTP for changes in the distribution of non-financial risks are closely related to the structure of utility functions (see for instance Viscusi, 2019).

In our paper, we expose the main results of a laboratory experiment conducted to provide an answer to the question analyzed from a theoretical perspective by Crainich and Eeckhoudt (2017). Attempting to capture trade-offs between wealth and health (or, more broadly, quality of life) in a laboratory experiment is challenging because it requires the transposition of a health-related consequence. As a result, most papers analyzing such trade-offs use hypothetical outcomes (see for instance Whynes et al., 2003; Potoglou and Kanaroglou, 2007; Levy and Nir, 2012; Tengstam, 2014; Gyrd-Hansen, 2017; Attema et al., 2019), which potentially limits the extension of their findings to real-life choices. In order not to expose subjects to hypothetical decisions, some experiments propose choices supposed to affect subjects' quality of life, but whose effective consequences are only purely financial (see for instance Krieger and Mayrohfer, 2012).

The originality of our experiment is to keep the advantage of a controlled environment while capturing incentivized behaviors towards non-financial risks. To set up a trade-off between discomfort and money, we provided a financial endowment to subjects and then exposed them to a risk of undergoing a painful stimulus. Participants then had the opportunity to use their endowment to purchase risk reductions on a fictive market. Inflicting pain to subjects is rather rare in economics (see Berns et al., 2008) but quite common in psychology, either through the application of heat (Ariely, 1998), the submersion of hands in cold water (Jameson et al., 2011; Kahneman et al., 1993; Pesheva et al., 2011) or the administration of aversive sounds (Schreiber and Kahneman, 2000). Because of its wider use in the literature, we chose another instrument for inflicting pain: transcutaneous electric shocks (see among others Berns et al., 2008; Claes et al., 2016; Crockett et al., 2014; Vlaev et al., 2009, 2014). Our use of this method was also motivated by the fact that it has already been exploited to evaluate the WTP for pain relief (Vlaev et al., 2009). Our approach is similar except that pain is administered on a probabilistic basis in our experiment whereas it is certain in that of Vlaev et al. (2009). More precisely, we elicit through the Becker-DeGroot-Marschak (BDM) auction-based mechanism the WTP for self-protection actions (lowering the probability to receive a given number of electric shocks) and self-insurance tools (lowering the number of electric shocks but letting the probability to receive these shocks unchanged) for three baseline probabilities: 30%, 50% and 70%. The provision of high and low probabilities (70% and 30%) specifically aims to mimic the effects of personalized information in our experimental setting, while the provision of a probability of 50% is designed to mimic the absence of personalized information[3]. We then compare the results obtained for the two types of risks in both situations. This enables us to determine whether the WTP for prevention actions: 1) increases or decreases with the baseline probability; 2) changes at an increasing, constant or decreasing rate with the baseline probability. If the WTP function is found to be convex (resp. concave) in that probability, it implies that the perceived benefit from prevention programs would be increased (resp. reduced) following the generalized availability of personalized information.

The paper is organized as follows. Section 2 presents the experimental setting. Section 3 describes the pool of participants. Section 4 reports the empirical strategy and the results. Section 5 discusses these results. Section 6 concludes.

2. Experimental design

2.1. General statements

The experiment received the approval from the ethical committee of the University of Lille, France (ref. 2017-3-S52) and took place at the Strasbourg Experimental Economics Laboratory (LEES) from May 15 to 18, 2018. Seven 4-hour sessions were organized. In each session, 20 subjects were summoned at

[3] Note, however, that our experiment does not implement a transition from a situation without personalized information to a situation with personalized information as it could happen in real life, as the three baseline probabilities of harm were presented to each subject.

intervals of 10 minutes. Upon arrival, each participant received a flat €5 show-up fee and was informed that s/he would receive - on a probabilistic basis - money and aversive stimuli taking the form of cutaneous electrical shocks. Before starting the experiment, the subjects had to check whether they fulfill any of the exclusion criteria[4] and provided full written informed consent to participate. They were also informed that they could end their participation at any time.

The stimulus consisted in monophasic electric pulses, delivered by a Digitimer DS-7A stimulator combined with a DG-2A module, using a bar electrode attached on the top of the subjects' wrist with a Velcro strap. These devices are approved by the European Commission and the Food and Drug Administration for scientific studies on healthy subjects. In accordance with the existing literature using this apparatus in a similar context (*e.g.* Vlaev et al., 2014), the pulses were administered at a frequency of 10Hz for a duration of one second.

The experiment consisted of 5 phases: 1) a thresholding phase; 2) a learning phase without real consequences; 3) 12 experimental tasks; 4) response to an auxiliary questionnaire; 5) implementation of one task randomly drawn from the 12 tasks completed in phase 3. Three rooms were used in this experiment. One was used to welcome participants, obtain their signed consent forms and complete phases 2, 3 and 4 in individual boxes using a computerized interface (EconPlay). The technological apparatus used during phases 1 and 5 was located in a second room. The lottery draw from phase 5 was organized in a third adjacent room.

2.2. Thresholding procedure

The thresholding procedure, designed to individually determine the stimulus while controlling for the heterogeneity of pain resistance among subjects, is derived from studies in health psychology using similar apparatus (*e.g.* Claes et al., 2016; Meulders et al., 2011; Peeters and Vlaeyen, 2011; Seymour et al. 2004; Vlaev et al., 2014). Two series of 1-sec pulses were administered to the subjects, starting from an initial level of 1mA and followed by shocks with 1mA step increases in amplitude. After each 1-sec train of pulses received, the subjects had to rate the level of pain they just experienced on a Likert scale ranging from 0 (no pain at all) to 10 (intolerable pain) using an e-tablet. Each series of shocks ended when the subjects rated the pain as intolerable and asked to stop further increases. The reference aversive stimulus (constituting a personalized "pain dose" thereafter) took the form of a 1-sec train of shocks rated 8/10 during the second series of pulses. This rating of 8/10 is generally selected in the experiments from the aforementioned literature. It is defined as a very aversive stimulus that requires effort to endure but remains tolerable and safe.

During this phase, we excluded subjects: 1) who showed important signs of anxiety; 2) who rated as intolerable a shock of 10mA or less (this level was too low to be considered as reliable). We informed subjects that they could receive up to 20 pain doses during the experiment. They then received a sample of 5 doses to figure out the effect of 20 doses. After completion of the thresholding phase, the subjects returned to their box to complete phases 2-4 on a computer.

2.3. Practice phase

The learning phase consisted of three tasks. It aimed to familiarize the subjects with the main experimental tasks and with the second-price auction mechanism (Becker, DeGroot and Marschak, 1964) used to elicit WTP. The subjects were informed that the monetary and physical consequences of these tasks were fictitious. For each task, each subject received a virtual sum of €30 and had to indicate the maximum amount s/he accepted to forgo (*i.e.* her/his WTP) using a list of amounts ranging from 0 to 30€ with 1€ increments. In the first task, the subjects had to give their WTP to avoid – for sure – 20 pain doses. In the second and third tasks, an urn containing 5 white balls and 5 red balls

[4] Being minor, not understanding French well, suffering from mental disorders, being pregnant, having a neurological, pulmonary or cardiovascular disease, experiencing pain in the dominant arm or hand, being sensitive to stressful situations, consuming antidepressants or anxiolytics, and being equipped with a medical device.

(denoted WB/RB thereafter) were presented to the subjects. They were informed that drawing a RB from the urn would imply receiving 20 pain doses. In task 2, they had to give their WTP for replacing one RB by one WB. In task 3, subjects had to give their WTP for lowering from 20 to 16 the number of pain doses received in the event a RB is drawn. For each task, a market price was randomly drawn from a discrete uniform distribution between €1 and €30. If the subject's WTP was greater than (or equal to) the selected price, the latter was deduced from the €30 fictitious endowment and the improvement was effective. Otherwise, the improvement was not purchased and the subject retained the virtual €30. Before bidding, the subjects were informed about the purchase conditions and were explained that the dominant strategy was to bid their real WTP.

2.4. Main experimental tasks

In the experimental phase, the subjects provided their WTP for 12 tasks consisting of every combination between: 1) three urns differing in the baseline probability to experience the aversive event, namely 3/10 (low probability), 5/10 (average probability) and 7/10 (high probability); 2) the prevention scheme available:

- replace one RB by one WB (low-efficacy self-protection action);
- replace two RB by two WB (high-efficacy self-protection action);
- reduce the number of pain doses from 20 to 16 (low-efficacy self- insurance action);
- reduce the number of pain doses from 20 to 12 (high-efficacy self- insurance action).

Subjects were endowed with a budget of €30 for each task. The 12 tasks were displayed on the subjects' screen simultaneously, in a random order. Participants could record their offers without any time limit, in the order they preferred, and had the opportunity to revise each WTP until they confirmed all of them. They were informed that the consequences of one randomly drawn task would be applied in phase 5.

2.5. End of experiment

After validating their 12 bids, the subjects were asked in phase 4 to fill out a computer administered questionnaire (see section 3). During the final phase, the subjects first rolled a 12-sided dice to select one of the 12 tasks under the supervision of a researcher (who had access to the subjects' previous decisions). Then, they drew the market price associated with the selected task by picking one token from an urn containing chips numbered 1 to 30. If this price was lower than the subjects' WTP, it was deducted from their endowments. Finally, they drew a ball from an urn. If the participant drew a WB, s/he received her/his payment and could leave; otherwise, s/he had to receive the pain doses before payment.

3. Description of participants

3.1. Recruitment and participation

Among 148 recruited subjects, 22 did not show up or canceled their participation and 20 were excluded as they did not meet inclusion criteria, either before or during the thresholding procedure[5]. None of the remaining 106 participants left the experiment once it started; all of them provided 12 WTPs.

The experiment lasted about 1 hour per participant. The mean intensity of the pain dose (rating of 8/10) was 15.7 mA (min: 7mA; max: 30mA). Earnings were on average quite high (€34.1, including the €5 show-up fee), with a minimum of €6 and 89.6% of €35. About half of the participants had to receive the aversive stimulus at the end of the experiment.

[5] We did not collect sociodemographic data on these 42 subjects, but they were drawn from the same pool of participants.

3.2. Sample characteristics

During phase 4 of the experiment, the subjects filled out a questionnaire. They provided information about themselves (age, gender, occupation, revenue). They also had to rate on 0-10 Likert scales their attitude toward risk, their degree of fear regarding the stimulus and the extent to which the following components were important when stating their WTPs: getting to the end of the experiment, avoiding electrical shocks, maximizing the monetary gain and leaving quickly. These six variables were then dichotomized with respect to sample's medians. Summary statistics for these variables are provided in Table 1.

Insert Table 1 here

Most of the subjects were students in their twenties. Half of them were female. About one third of them had less than €500 each month for all their current expenses (rent, transportation, food). They assessed themselves as mildly adventurous. They were very determined to complete the experiment and they sought to maximize their gains. They were mildly aiming at avoiding shocks or fearful of them. Leaving quickly was not at all important. Nine out of ten were convinced that their choices would involve real consequences and eight out of ten indicated that they revealed their true WTPs.

4. Results

4.1. Polarized bidding strategies

Insert Figure 1 here

When setting up the experimental procedure, we were worried that a large share of the participants would bid null WTP in the 12 experimental tasks to secure their endowment. There were two reasons for this concern. First, it was in the subjects' best interest to overrate pain during the thresholding phase, even though they were not aware of how we would use their ratings[6]. Second, as in many experiments from social sciences, our volunteer subjects are mostly students (thus, not among the better-off). Some may thus want to keep their endowment at the cost of undergoing acute but rather short-lasting pain. To some extent, the first argument would put more doubt on the results of the experiment (ineffective thresholding procedure) than the latter (exogenous selection problem). As illustrated by Figure 1, the zero-bidding strategy was only adopted by 14 out of 106 participants, whereas 46 bid only positive WTPs. The left panel of Table A1 in the appendix shows that the 14 individuals always bidding zero were on average exposed to a stimulus of higher amplitude compared to other subjects (16.93mA vs. 15.47mA), which rules out the first concern. The feedbacks provided by the subjects favor the second argument. Compared to participants stating at least one positive WTP, non-purchasers were less fearful of the shocks and less eager to avoid them (51% of purchasers rated 5/10 or more the importance of these aspects compared to 14% of non-purchasers). Non-purchasers also gave more importance to completing the experiment and less importance to leave quickly, which could suggest they aimed to secure their endowment. By contrast, the 46 subjects who always bid positive WTPs expressed more importance to avoid electrical shocks and gave less importance to the completion of the experiment (right panel of Table A1).

4.2. Summary statistics of WTP

The WTPs of the 106 participants for the 6 self-protection (resp. self-insurance) tasks were on average €3.93 (resp. €4.16), with a variance of 19.67 (resp. 26.28). Figure 2 shows that both distributions are

[6] In order to prevent this, we did not collect the WTPs of subjects whose intolerable pain was announced to be lower than 10mA (see section 2.2)

skewed to the right. Around 50% of offers were €3 or lower for self-protection tasks (€2 for self-insurance), including 28% and 32.7% of zero bids for self-protection and self-insurance respectively, and very few of them exceeded €20. In both distributions, anchoring can be noticed at the values of €5, €10 and €15.

Insert Figure 2 and Table 2 here

The objective of the research is to evaluate: 1) whether WTP for prevention increases or decreases with the baseline probability to receive 20 pain doses; 2) whether WTP for prevention changes at a constant, decreasing or increasing rate with the baseline probability to receive 20 pain doses. The upper panel of Table 2 reports the average WTP for each baseline probability of experiencing pain and each prevention action, as well as the variation of these WTPs with respect to baseline probabilities. It suggests that WTP for self-insurance significantly increases with the baseline probability of experiencing pain, whereas the WTP for self-protection is rather insensitive to changes in the baseline probability. For example, the average WTP for reducing pain doses by 4 increases by €1.01 (95%CI [0.26;1.76]) when the baseline probabilities increases from 30% to 50%, and by €1.22 (95%CI [0.70;1.73]) when it changes from 50% to 70%. Similar figures are found for 8 pain doses reductions. When the higher levels of effectiveness for the prevention actions are considered, the lower panel of Table 2 shows that access to personalized information lowers the average WTP for self-protection by €0.38 (95%CI [-0.84;+0.08]; left-sided p-value=5.2%) and by €0.42 for self-insurance (95%CI [-0.93;+0.10] ; left-sided p-value=5.6%). Access to information has no effect on the WTP for the low-efficacy versions of the actions (columns 2 and 4).

Figure 3 plots the demands for self-insurance and self-protection given the three baseline probabilities (high, low and average) of experiencing the pain. Each curve depicts the share of participants (y-axis) with WTP higher or equal to a given amount (x-axis). The demand curves are steeper when the prevention schemes are more effective (right vs. left panels of Figure 3). The demand for self-protection is rather insensitive to the initial probability, as the demand curves are nearly confounded and intersect several times (see lower panel). By contrast, the upper panel of Figure 3 shows that demand for self-insurance increases with the baseline probability of experiencing pain (the demand curves shift upward when switching from the low to the average baseline probability and from the average to the high baseline probability). This panel also suggests that the WTP for self-insurance increases at a decreasing rate with the baseline probability of experiencing pain, as the vertical distances between the demand curves corresponding to the average and high baseline probabilities are larger than the distances between the curves corresponding to the low and average baseline probabilities.

Insert Figure 3 here

4.3. Econometric strategy

Separated analyses were conducted for self-protection ($k = 1$) and self-insurance ($k = 2$). The WTP for prevention depends on both the action's features and participants' characteristics (see below).

We -naïvely- regress by ordinary least squares (OLS) the WTP of participant $j = (1,2, \dots 106)$ for the variant $i = (1, \dots 6)$ of prevention activity k:

$$WTP_{ij}^{\{k\}} = \alpha^{\{k\}} + \beta_1{}^{\{k\}} low\_r_{ij} + \beta_2{}^{\{k\}} high\_r_{ij} + \delta^{\{k\}} high\_e_{ij} + \gamma^{\{k\}} X_j + \varepsilon_{ij}^{\{k\}}$$

where low_r_{ij} (resp. $high\_r_{ij}$) takes the value 1 if the baseline probability is 0.3 (resp. 0.7), $high\_e_{ij}$ indicates whether or not the prevention action is proposed in its more effective version (*i.e.* replacement of 2 instead of 1 RB or reduction by 8 instead of 4 doses), X_j refers to a set of individual-

level determinants of WTP which are unrelated to the experiment (age, gender, occupation and risk attitude score >6), and where the $\varepsilon_{ij}^{\{k\}}$ are zero-mean normally distributed error terms.

Whether WTP is an increasing or decreasing function of the baseline probability depends on the signs of the estimated coefficients $\widehat{\beta_1}^{\{k\}}$ and $\widehat{\beta_2}^{\{k\}}$: if $\widehat{\beta_1}^{\{k\}} < 0$ (resp. $\widehat{\beta_1}^{\{k\}} > 0$) and $\widehat{\beta_2}^{\{k\}} > 0$ (resp. $\widehat{\beta_2}^{\{k\}} < 0$), the function is increasing (resp. decreasing). The relative magnitude of ${\beta_1}^{\{k\}}$ and ${\beta_2}^{\{k\}}$ indicates whether WTP is convex or concave with respect to the baseline probability. We thus compute $\Delta^{\{k\}} = \widehat{\beta_1}^{\{k\}} + \widehat{\beta_2}^{\{k\}}$ and test whether $\Delta^{\{k\}}$ significantly differs from 0. If so, the sign of $\Delta^{\{k\}}$ indicates that the relationship is convex (if $\Delta^{\{k\}} > 0$) or concave (if $\Delta^{\{k\}} < 0$).

Due to the bidding mechanism, WTP is not normally distributed (bids are non-negative integers and their distribution is skewed to the right). Regressing this outcome (or alternatively a log or power transformation) by OLS would yield inconsistent estimates since the normality assumption is violated (see for example Cameron and Trivedi, 1998). We thus opted for count models, modelling the number of euros spent out of the initial endowment. Two issues are raised with such models: over-dispersion and zero-inflation.

If the distribution of WTPs is over-dispersed, the standard errors of the parameters are likely to be underestimated with a Poisson regression, so the negative binomial (hereafter NB) becomes preferable (Cameron and Trivedi, 1998). Two arguments support the use of a NB model for our data. First, sample variances exceed by far sample means (see section 4.1). Second, we obtain a better fit of the observed WTP distributions using a NB distribution (see Figure 2)[7]. The NB model can be written as a Poisson model with random expectation (Poisson-gamma mixture). Omitting individual, game and prevention type indicators, the probability mass function (pmf) is:

$$p_s = \mathbb{P}(WTP = s | \Theta = \theta) = \frac{e^{-\theta\lambda}(\theta\lambda)^s}{s!} \; ; \; s = \{0,1,2,\dots,30\}$$

where $\Theta \sim \Gamma(a, 1/a)$ is Gamma distributed, with $\mathbb{E}(\Theta) = 1$ and $\mathrm{Var}(\Theta) = \frac{1}{a}$,

$\lambda = \exp(\alpha + \beta_1 low\_r + \beta_2 high\_r + \delta high\_e + X'\gamma)$ is the fixed component of the expectation, and θ its random component. Since $\mathrm{Var}(WTP) = \lambda\left(1 + \frac{\lambda}{a}\right)$, the NB regression reduces to the Poisson model if $\mathrm{Var}(\Theta) = \frac{1}{a} \sim 0$. Given that the Poisson regression is nested within the NB, we compare the two models using a likelihood ratio test.

The second issue arises when the high occurrence of zeros in the sample violates the assumptions of the above distributions (see Hilbe, 2014). The observed shares of null WTP are higher than those expected for NB-distributed data (28% (observed) vs. 24.1% (expected) for self-protection, 32.7% vs. 29.2% for self-insurance; see Figure 2). We account for that excess mass at zero by the use of zero-inflated (ZI) count models, which were introduced by Lambert (1992). Two types of zero bids are distinguished: those resulting from the same decision process as the non-zero bids (count equation), reflecting the true WTP of bidders, and structural zeros, occurring with a probability π (logit equation). Excess zeros can be interpreted as arising from subjects securing their 30€ endowment at the cost of receiving the electric shocks: their stated WTP is always zero, although their –unobserved– real WTP is positive. The pmf of ZI models is:

$$\mathbb{P}(WTP = s) = \begin{cases} \pi + (1-\pi)p_0, & s = 0 \\ (1-\pi)p_s, & s \geq 1 \end{cases}$$

The control variables used in the count equation (modelling the p_s) are the same as in the OLS and NB regressions (age, gender, occupation and risk attitude). To model the excess zeros, the logistic part

[7] Expected probability mass functions were computed from empty regression models.

also includes variables describing the strategies adopted by the subjects (scores[8] indicating whether they feared shocks and whether they were eager to get to the end of the experiment, to avoid electrical shocks, to maximize their monetary gain and to leave quickly; see discussion of Table A1 in section 3.3). As count models and ZI models are not nested, we compare them using Vuong's test (Vuong, 1989).

The coefficients from the non-linear models (logit and count models) are exponentiated, so that the effects of explanatory variables are interpreted as odd or rate-ratios (RR). For instance, for a one-unit increase in an explanatory variable, the expected WTP is multiplied by a factor of RR = *exp*(coef.). Cluster-robust standard errors are used in all specifications (where participants are defined as clusters). Analyses were carried out with Stata 14.

4.4. Main results

Table 3 reports the multivariate regression results for self-protection and Table 4 those for self-insurance. The NB models are found to outperform Poisson models for self-insurance and self-protection (the variances of the expectation's random components are significantly non-null, in line with the likelihood ratio tests). The ZINB dominates the NB according to the Vuong's test. Introducing a distinct process for structural zeros has two advantages over the standard NB, as highlighted by Table A2 in appendix. It enables to capture more heterogeneity from the sample distribution: WTP predicted with ZINB range from 0.52 to 7.53 for self-protection (vs. [1.02; 6.66] for NB), and from 0.11 to 9.81 for self-insurance (vs. [0.55; 9.01]). The average probabilities of bidding null amounts predicted by the ZINB increase compared to the NB model, and become closer to the observed proportions of zero bids (predicted: 28.45% and 32.91% for self-protection and self-insurance respectively; observed: resp. 27.99% and 32.70%). Results from the ZINB are therefore more robust than those obtained with the NB (and, of course OLS which predicts negative WTP for some observations).

Insert Tables 3 and 4 here

Turning to our coefficients of interest, we can first notice that, for both types of prevention and with all models, WTPs are higher for more effective prevention actions: subjects were significantly willing to pay more to reduce by 20% (instead of 10%) the probability of pain and to reduce by 8 doses (instead of 4) the pain administered on a probabilistic basis (p-values<1%).

Our results suggest that subjects' bids for self-protection actions are not sensitive to the baseline probability of experiencing pain (Table 3). Indeed, participants did not significantly increase their WTP to replace one or two RB as the proportion of RB in the urn raised. Being exposed to an initial probability of 30% (as opposed to a 50% probability) lowered the amount proposed by subjects by a non-significant extent in all our specifications. Similarly, we find no significant difference in the WTP for self-protection between 70% and 50% baseline probabilities.

The WTP for self-insurance is more responsive to the probability of experiencing pain: estimates of $\beta_1^{\{2\}}$ and $\beta_2^{\{2\}}$ are respectively negative and positive, and significantly different from 0 (p<1%) in all our specifications. For instance, in the ZINB regression, the expected WTP decreases by a factor of 0.66 when the baseline probability decreases from 50% to 30% and increases by a factor of 1.24 when the baseline probability raises from 50% to 70%. These results support the assumption that the WTP for self-insurance is an increasing function of the baseline probability of experiencing adverse events.

To assess whether one of the above gaps in WTP for self-insurance significantly outweighs that of opposite sign, we compute the sums of these differences $\Delta^{\{2\}}$. Regardless of the specification, they are found to be negative. When the effect of initial probabilities is estimated by OLS (column 1 from Table 4), $\Delta^{\{2\}}$ does not significantly differ from 0. In the NB and ZINB specifications (columns 2 and 3 of Table 4), $\Delta^{\{2\}}$ is negative and a left-sided test rejects the null hypothesis at 5.1% (for NB) and 3.9% (for ZINB). According to the NB and ZINB models, the expected WTP with personalized information is

[8] Dichotomized scores for the results presented in the main text. Scores as continuous in appendices A3 and A4.

reduced by a factor of 0.82 compared to WTP in the absence of information. Our results thus rather support that the WTP for self-insurance is concave with respect to the baseline probability of experiencing adverse events: the diffusion of personalized information should reduce the total demand for self-insurance programs. Results are qualitatively unchanged when individual covariates are defined as continuous scales instead of binary variables (Tables A3 & A4 in appendix).

Among the individual covariates in the count part of the ZINB regression, only one is significantly non-null: workers are willing to pay less than students by a factor of 0.37[9]. It can also be noted from the zero-inflation part of the ZINB models for self-insurance that participants rating by 5/10 or more their eagerness to avoid the shocks and their fear of shocks are less likely to state structurally null WTPs, whereas those rating as very important the completion of the experiment were strongly more likely to do so. Although they are not statistically significant, the other coefficients are of the expected sign.

Note that we have performed sensitivity analyses excluding subjects who did not answer adequately a question testing their basic understanding of probabilities (N=5) and/or those who showed inconsistency in their WTP with respect to the effectiveness of prevention program (out of 6 potential violations, N=11 violated once and N=31 violated at least once first order stochastic dominance). Our results are qualitatively unchanged, as shown by Table A5 in the appendix.

5. Discussion

In our experiment, we find no effect of the probability of damage on the WTP for self-protection, but we find evidence that WTP for self-insurance increases at a decreasing rate with the probability of damage. These results need to be discussed in view both of our experimental design and the findings of risk theory.

Regarding the first point, it must be noted that our approach has several limitations that impede the generalization of the results. First, our sample is not representative of the general adult population, and we cannot rule out some selection bias due to the fact that we excluded subjects who showed important signs of anxiety or who expressed very low tolerance to electric shocks. Second, we assess WTP for reducing risks of pain, which is not equivalent to reducing risks of diseases or reducing non-financial risks in general. Especially, diseases have long lasting effects (on the patient himself/herself but also on his/her relatives) that bear no relation to those of electric shocks administered in a lab experiment (these effects are acute and short-lasting). However, the prospect of developing a disease and that of experiencing pain both lead to avoidance strategies. In our analysis, the values of the WTP for reductions in the risk of pain have no interest as such. What we are interested in is the difference between these WTP for different baseline probability levels. Therefore, the only assumption we make is that the WTP for reducing risks of adverse events – disease, pain or other non-financial risks – vary in a similar fashion with the baseline probability. Third, our approach considers baseline probabilities of harm between 0.3 and 0.7. The results may hence not generalize to extreme cases where some individuals have markers conferring very high probabilities of disease. Fourth, the subjects had to evaluate different scenarios in our experiment. WTP in this setting may differ from those stated when subjects are randomized into multiple experimental arms. Hsee (1996) indeed suggests that subjects attach less importance to attributes that are difficult to evaluate (such as the probability of an event) when these are evaluated in isolation rather than among several scenarios in which they take different values (so that comparisons can be established). As a result, WTP might be less sensitive to baseline probability differences in public policy analysis than in our experiment. Fifth, since our experiment exogenously manipulates baseline probability of harm, it does not raise the question of the appropriation of the information. It is for instance possible that prior beliefs play a role, conducing individuals to update more in response to personalized information than average information, as discussed in Hartzmark et al. (2021) in the context of owned versus non-owned goods.

[9] Similar effects are found in the OLS and NB specifications.

Regarding risk theory, our results can be analysed in light of the model developed by Crainich and Eeckhoudt (2017). To begin with, it must be noted that these authors highlight the role played by the interaction between wealth and health[10] in individuals' preferences (the sign of $u_{12}(w,h)$ *i.e.* the cross-derivative of the utility function[11]) when one evaluates how the WTP for prevention changes with the baseline probability of disease. More precisely, they show that the sign of $u_{12}(w,h)$ determines whether WTP for self-protection increases (when $u_{12}(w,h) > 0$) or decreases (when $u_{12}(w,h) < 0$) with the baseline probability of disease. Regarding self-insurance, $u_{12}(w,h) \geq 0$ is a sufficient condition for WTP being increasing and convex in the baseline probability of disease.

Experimental designs such as the one we conducted obviously cannot capture the long-term effects of diseases, notably the way they affect the marginal utility of wealth. However, some short-term cross-effects between wealth and pain may play a role in subjects' decision making in our experiment. If one assumes that the amount of money obtained by subjects during the experiment reduces the disutility of pain, then $u_{12}(w,h) < 0$ and the WTP for self-protection should fall as the baseline probability of being administered electrical shocks rises. If the opposite assumption is made (money increases the marginal disutility of pain so that $u_{12}(w,h) > 0$), we should notice that the WTP for self-protection increases with the baseline probability of experiencing pain. None of these assumptions are supported in our experiment since the baseline probability levels of experiencing pain seem to have no impact on the WTP for self-protection. The fact that we observe an increasing relationship between WTP for self-insurance and the baseline probability of experiencing pain does not say anything about the sign of $u_{12}(w,h)$ since $u_{12}(w,h) > 0$ is only a sufficient theoretical condition for this relationship. Moreover, the absence of significant cross-effects fits well with the observed increase in WTP for self-insurance as the baseline probability of experiencing pain rises since it is straightforward to show that, in the expected utility model and in the absence of cross-effects ($u_{12}(w,h) = 0$), the higher the baseline probability of experiencing pain, the higher the incentive to pay to reduce the number of pain doses.

That being said, we have to acknowledge that our experimental results are not in accordance with the theoretical predictions of Crainich and Eeckhoudt (2017) who find that, in the framework of expected utility theory, the WTP for self-protection is convex with the probability of disease and the WTP for self-insurance is convex provided that the marginal utility of wealth rises with health. The expected utility model is however not suitable for descriptive purposes, among other things because it assumes that the weight attached to each outcome of the distribution is the probability associated with that outcome, whereas in practice individuals tend to distort this probability[12]. To determine how the distortion of probabilities affects the link between the WTP for prevention and the baseline probability of disease, we adapt the method used by Crainich and Eeckhoudt (2017) to the rank-dependent expected utility model (Quiggin, 1981) that assumes that the weight attached to each outcome depends only on its probability and its ranking in the distribution. To capture the fact that the administration of electric shocks does not modify the marginal utility of wealth (see the point discussed above), we assume that the utilities attached to wealth and health (respectively represented by $u(w)$) and $s(h)$) are additive so that there are no cross-effects ($u_{12}(w,h) = 0$). Suppose that p and M respectively denote the probability and the severity of disease and that the probability weighting function is denoted by $\varphi(p)$ (with $\varphi(p) > p$ and $\varphi'(p) > 0$). We focus on the analysis of the WTP for self-insurance as it is the only prevention action for which we obtain significant results.

The WTP (denoted by z) for self-insurance programs reducing by Ψ ($\leq M$) the severity of disease is defined by the following expression:

[10] Or, more generally, any non-financial argument of the utility function.

[11] In what follows $u(w,h)$ denotes the utility function where w and h respectively stand for wealth and health; first derivatives of the utility function with respect to wealth and health are respectively denoted by $u_1(w,h)$ and $u_2(w,h)$. The cross derivative of this utility function is denoted by $u_{12}(w,h)$.

[12] An estimate of the probability weighting function is for instance provided in Abdellaoui et al. (2011).

$$\varphi(p)[u(w)+s(h-M)]+\big(1-\varphi(p)\big)[u(w)+s(h)]$$
$$=\ \varphi(p)[u(w-z)+s(h-M+\Psi)]+\big(1-\varphi(p)\big)[u(w-z)+s(h)]$$

so that the following changes in WTP as the baseline probability of disease rises should be obtained:

$$\frac{dz}{dp}=\frac{\varphi'(p)[s(h-M+\Psi)-s(h-M)]}{u'(w-z)}>0$$

and

$$\frac{d^2z}{dp^2}=\frac{\varphi''(p)[s(h-M+\Psi)-s(h-M)]}{u'(w-z)}<0$$

The data we collected from the experiment indicate that WTP for self-insurance significantly increases at a decreasing rate with the baseline probability of receiving electrical shocks. Therefore, our analysis – which is however solely based on three probability levels: 0.3, 0.5 and 0.7 – suggests that $\varphi''(p)<0$, which is consistent with the rank-dependent expected utility model where individuals exhibit pessimism.

6. Conclusion

The way individuals' WTP for prevention changes with the baseline probability of experiencing non-financial adverse events, such as diseases, has important implications from a public policy perspective as it determines how prevention expenditure is likely to be affected by the ongoing development of personalized information. This issue has been addressed from a theoretical perspective by Crainich and Eeckhoudt (2017) who analyzed the WTP for prevention in the expected utility framework. Doing so, they adopted a normative point of view which is useful when assessing the relevance of prevention programs resulting from collective decisions. However, the expected utility model fails to correctly describe individual behavior. The objective of our paper is to provide such a description through an experimental approach meant to determine how personalized information modifies the WTP for prevention actions. To do so, we first analyzed the way information influences individual WTP for two prevention actions (self-protection and self-insurance). We then determined its effect on the aggregate WTP in order to determine whether an increase in the implementation of prevention actions may result from the upcoming development of personalized information.

In our experiment, the adverse effect the subjects were exposed to took the form of painful transcutaneous electrical shocks that were administered on a probabilistic basis. Subjects had the opportunity to reduce either the probability of receiving the shocks or their severity. Our main result is that the WTP for self-insurance significantly rises at a decreasing rate as the baseline probability of experiencing pain increases. This is in accordance with the predictions of the rank-dependent expected utility model, provided that individuals display pessimism (i.e. they underweight the probabilities of good outcomes and overweight the probabilities of bad ones). And, more importantly, this indicates that the development of personalized information is likely to lead to a global decrease in the WTP for self-insurance programs.

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Figure 1. Number of null WTPs for 12 prevention schemes (N=106 subjects)

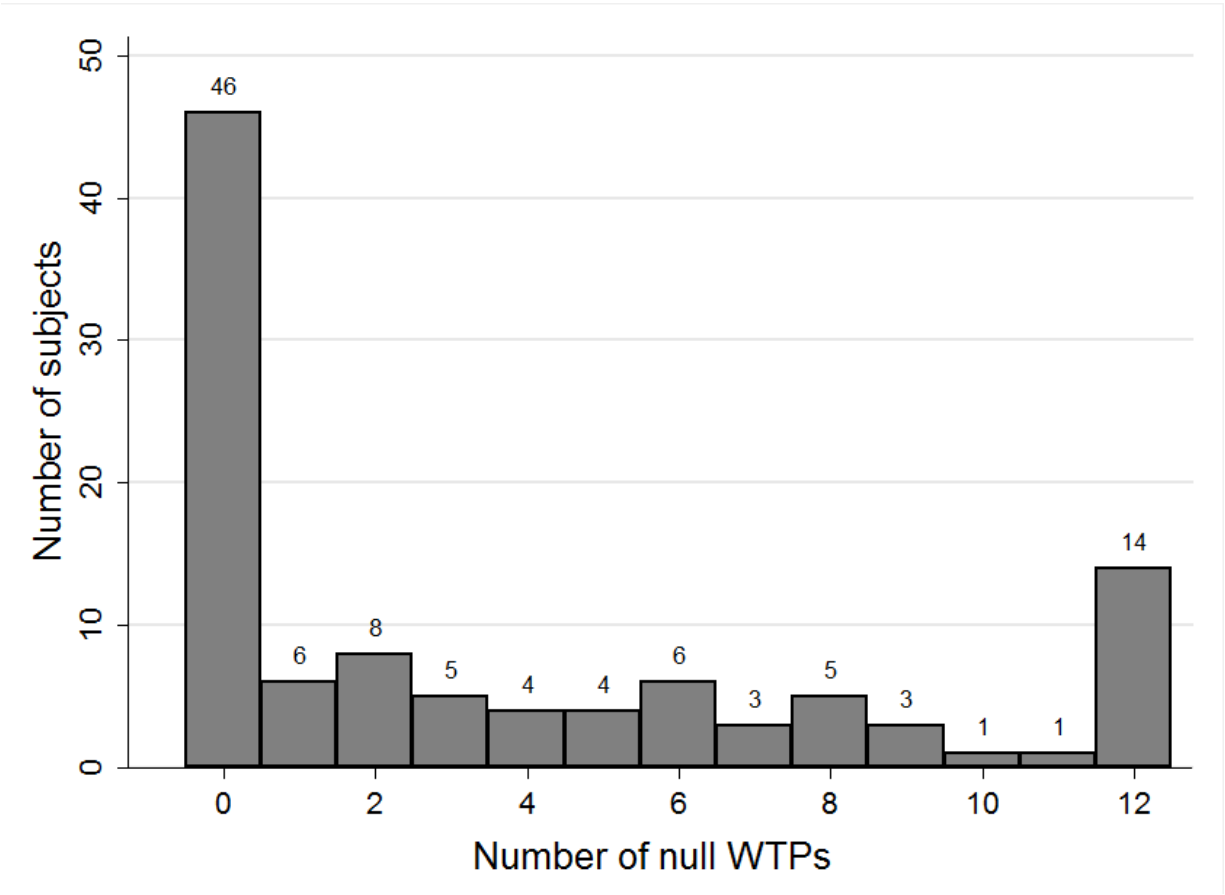

Figure 2. Distribution of WTPs for self-protection and self-insurance (N=1272: 106 subjects x 6 WTP x 2 prevention programs)

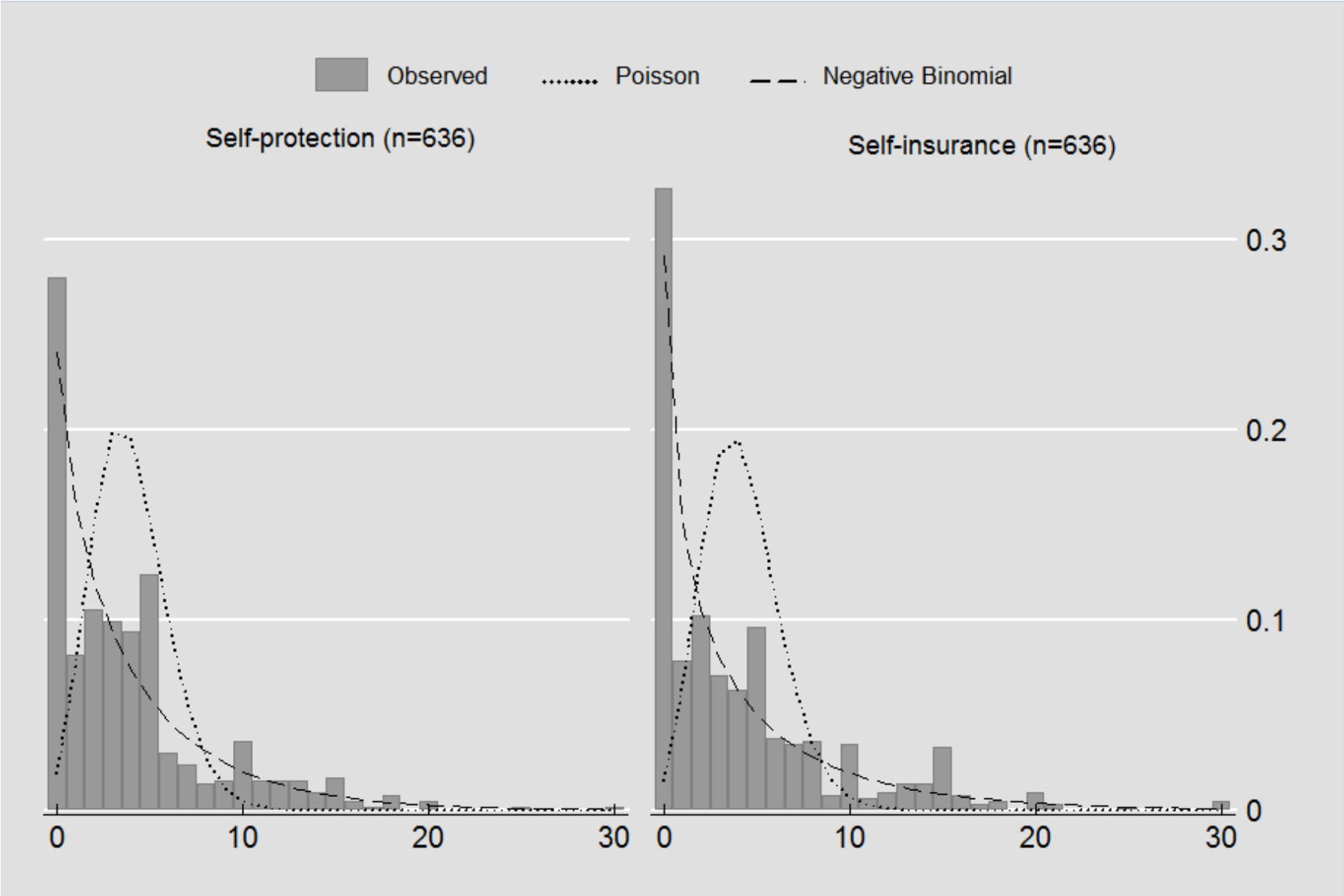

Figure 3. Demand curves for self-protection and self-insurance

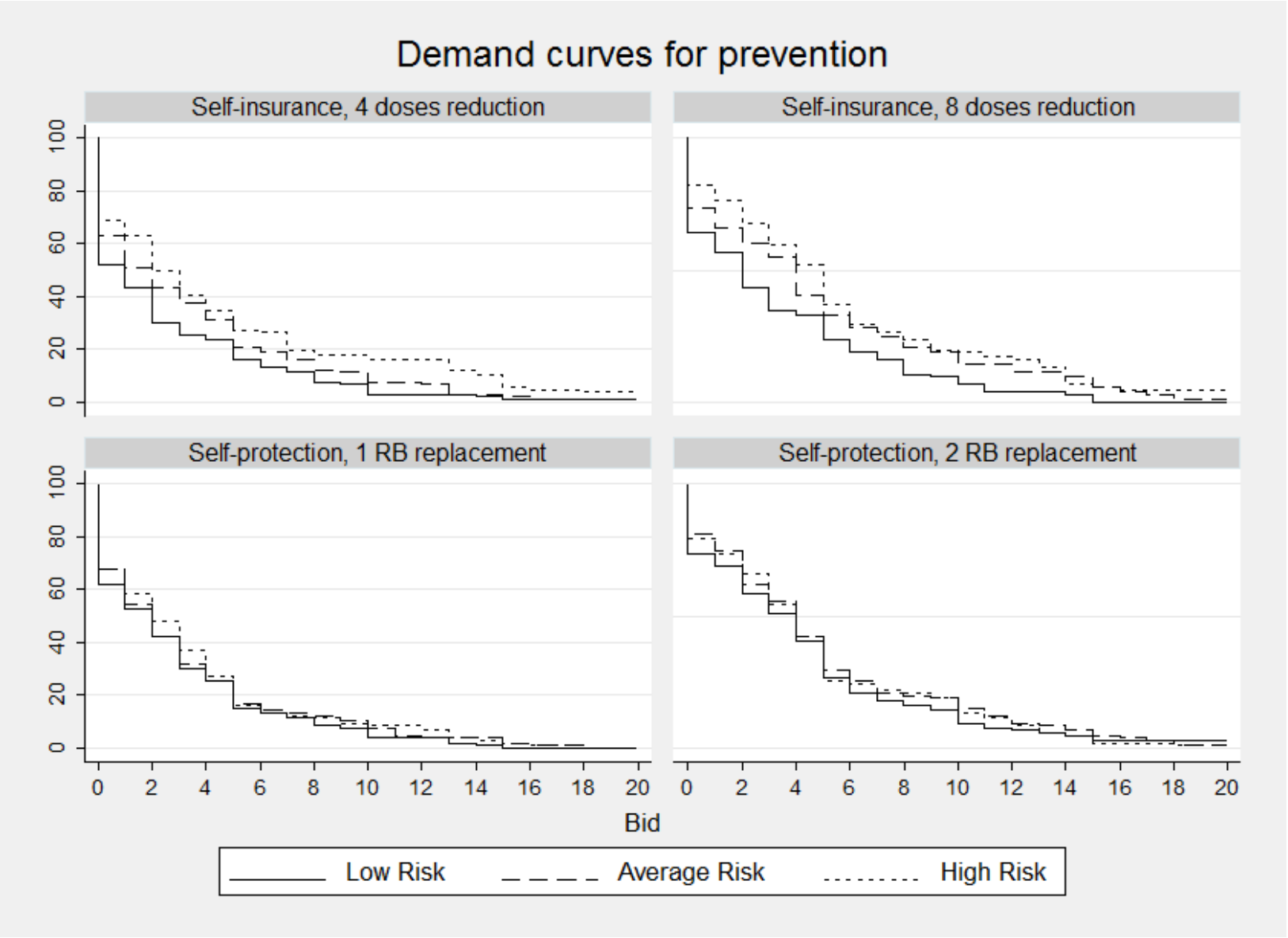

Table 1. Characteristics of participants (N=106 subjects)

Variable	Mean or %	Std. Dev.	Median	Min.	Max.
Age	22.2	3.1	22	18	36
Female	50.0%				
Student	91.5%				
Has less than 500€ each month for all current expenses (students only; N=97)	35.8%				
Risk attitude (score) [0: very prudent - 10: very adventurous]	5.9	2.1	6	0	10
Risk attitude (score>6)	48.1%				
Eager to complete the experiment (score) [0: not important - 10: very important]	8.8	1.5	9	2	10
Eager to complete the experiment (score>9)	45.3%				
Eager to avoid shocks (score) [0: not important - 10: very important]	4.1	2.5	4	0	10
Eager to avoid shocks (score>4)	46.2%				
Eager to maximize gains (score) [0: not important - 10: very important]	7.7	2.1	8	0	10
Eager to maximize gains (score>8)	40.6%				
Eager to leave quickly (score) [0: not important - 10: very important]	2.2	2.6	1	0	10
Eager to leave quickly (score>1)	49.1%				
Fear of shocks (score) [0: not fearful- 10: very fearful]	4.1	2.2	4	0	8
Fear of shocks (score>4)	46.2%				
Did not believe he/she would really undergo physical pain or pay for urn change	9.4%				
Honestly stated the maximum amount he/she was ready to pay in each task	80.2%				

Table 2. Baseline probabilities and WTP for prevention activities: unadjusted tests (N=106 subjects)

	Self-protection		Self-insurance	
	Replace 1 RB by 1 WB	Replace 2 RB by 2 WB	Reduce doses by 4	Reduce doses by 8
Average WTP with p=0.3	2.83 (3.49)	4.45 (5.00)	2.47 (3.73)	3.31 (3.89)
Average WTP with p=0.5	3.17 (3.97)	5.00 (4.98)	3.48 (4.74)	5.05 (5.51)
Average WTP with p=0.7	3.35 (4.04)	4.78 (4.54)	4.70 (5.93)	5.95 (5.79)
Mean diff of WTPs for p=0.5 and p=0.3	0.34 (0.29)	0.55 (0.36)	1.01 (0.38)***	1.74 (0.36)***
	[-0.23;0.91]	[-0.17;1.27]	[0.26; 1.76]	[1.01;2.46]
Mean diff of WTPs for p=0.7 and p=0.5	0.18 (0.18)	-0.22 (0.22)	1.22 (0.26)***	0.91 (0.27)***
	[-0.18;0.53]	[-0.65;0.22]	[0.70;1.73]	[0.37;1.44]
Pooled average WTP for p=0.3 and p=0.7	3.09 (3.4)	4.62 (4.36)	3.58 (4.26)	4.63 (4.52)
Effect of information (diff. btw rows 6 & 2)	-0.08 (0.18)	-0.38 (0.23)	0.10 (0.21)	-0.42 (0.26)
	[-0.43;0.27]	[-0.84;0.08]	[-0.33;0.53]	[-0.93;0.10]

Standard errors in parentheses. 95% confidence intervals in brackets. ***: p-value<1%; **: <5%; *: <10% (two-sided Student Tests)

Reading note: as an example, we describe column 5, *i.e.* the WTP to reduce the number of pain doses by 8 (high-efficacy self-insurance). The first three rows report the average WTP for the entire pool of subjects: €3.31 (resp. €5.05 and €5.95) when the probability to draw a RB is 0.3 (resp. 0.5 and 0.7). The next two rows indicate that the WTPs are on average €1.74 (resp. €0.91) higher when the probability to draw a RB is 0.5 instead of 0.3 (resp. 0.7 instead of 0.5). The first row of the lower panel contains the average of rows 1 and 3 (*i.e.* €4.63 = (€3.31 + €5.95)/2). Since €4.63 (the average WTP with personalized information) is lower than €5.05 (the average WTP in the absence of personalized information), personalized information reduces by €0.42 the average WTP in the population (one-sided p-value = 0.056).

Table 3. Multivariate results for self-protection (N=636 observations: 106 subjects x 6 WTP)

Explanatory variables	OLS	Negative binomial	ZINB
Low Prob. (β_1)	-0.443 (-1.48)	0.905 (-1.34)	0.958 (-0.55)
High Prob. (β_2)	-0.019 (-0.12)	1.015 (0.39)	1.025 (0.58)
High efficacy (δ)	1.629 (5.78) ***	1.564 (5.89) ***	1.370 (4.62) ***
Age	-0.072 (-0.52)	0.990 (-0.28)	0.969 (-0.89)
Female	1.090 (1.52)	1.276 (1.36)	1.191 (1.03)
Worker	-2.097 (-1.98) *	0.407 (-2.20) **	0.493* (-1.75)
Risk attitude (score>6)	-0.658 (-0.92)	0.823 (-1.08)	0.895 (-0.65)
Intercept	4.818 (1.57)	4.004 (1.74) *	8.409 (2.90) ***
Low + High Prob. (Δ)	-0.462 (-1.31)	0.919 (-0.98)	0.982 (-0.19)
First stage			Excess zeros
Low Prob. (β_1)			1.451 (1.53)
High Prob. (β_2)			1.084 (0.41)
High efficacy (δ)			0.498 (-3.52) ***
Age			0.912 (-0.74)
Female			1.146 (0.22)
Worker			1.730 (0.37)
Risk attitude (score>6)			0.884 (-0.21)
Eager to avoid shocks (score>9)			0.329* (-1.83)
Eager to maximize gains (score>4)			0.886 (-0.21)
Eager to complete the experiment (score>8)			5.332 (2.85) ***
Eager to leave quickly (score>1)			0.993 (-0.06)
Fear of shocks (score>4)			0.385 (-1.51)
Intercept			2.119 (0.28)
Overdispersion		1.089 [0.78;1.52]	0.435 [0.29-0.66]
Likelihood ratio Test vs Poisson		1128***	401***
Vuong's Test vs NB			6.02 ***

Reading note:
For OLS regressions: coefficients are reported.
For negative binomial and logistic regressions: exponentiated coefficients are reported.
Cluster-robust test statistics in parentheses.
The row "Low + High Prob." reports $\widehat{\beta_1} + \widehat{\beta_2}$ for OLS and $\exp(\widehat{\beta_1} + \widehat{\beta_2})$ for count regressions.

The row "Overdispersion" reports the estimates and [95%CI] of the random component's variance, $\mathrm{Var}(\Theta) = \frac{1}{a}$.
The row "Likelihood ratio Test" compares negative binomial to Poisson. Under the null, the statistic is Chi-square (1d.f.) distributed. The row "Vuong's Test" compares ZI vs. negative binomial. Under the null, the statistic is normally distributed. The two tests were conducted without cluster-robust S.E.

***: p-value<1%; **: <5%; *: <10%

Table 4. Multivariate results for self-insurance (N=636 observations: 106 subjects x 6 WTP)

Explanatory variables	OLS	Negative binomial	ZINB
Low Prob. (β_1)	-1.373 (-4.15) ***	0.663 (-4.08) ***	0.718 (-3.43) ***
High Prob. (β_2)	1.061 (4.51) ***	1.238 (4.39) ***	1.142 (2.59) ***
High efficacy (δ)	1.220 (7.60) ***	1.391 (6.66) ***	1.212 (3.53) ***
Age	-0.072 (-0.50)	0.990 (-0.24)	0.967 (-0.88)
Female	1.740 (2.11) **	1.421 (1.71) *	1.223 (1.07)
Worker	-2.927 (-2.71) ***	0.267 (-3.00) ***	0.373 (-2.67) ***
Risk attitude (score>6)	-1.118 (-1.35)	0.762 (-1.36)	0.825 (-1.06)
Intercept	5.175 (1.62)	4.470 (1.62)	11.096 (3.00) ***
Low + High Prob. (Δ)	-0.311 (-0.77)	0.821 (-1.64)	0.820 (-1.77) *
First stage			Excess zeros
Low Prob. (β_1)			1.495 (1.69) *
High Prob. (β_2)			0.597 (-2.22) **
High efficacy (δ)			0.494 (-3.45) ***
Age			0.912 (-0.65)
Female			0.882 (-0.17)
Worker			3.939 (0.95)
Risk attitude (score>6)			0.827 (-0.32)
Eager to avoid shocks (score>9)			0.266 (-2.21) **
Eager to maximize gains (score>4)			0.522 (-0.97)
Eager to complete the experiment (score>8)			8.106 (2.70) ***
Eager to leave quickly (score>1)			1.079 (0.71)
Fear of shocks (score>4)			0.261 (-2.07) **
Intercept			3.652 (0.42)
Overdispersion		1.382 [0.98;1.95]	0.526 [0.34;0.83]
Likelihood ratio Test vs Poisson		1482***	545***
Vuong's Test vs NB			7.12***

Reading note:
For OLS regressions: coefficients are reported.
For negative binomial and logistic regressions: exponentiated coefficients are reported.

Cluster-robust test statistics in parentheses.
The row "Low + High Prob." reports $\widehat{\beta_1} + \widehat{\beta_2}$ for OLS and $\exp(\widehat{\beta_1} + \widehat{\beta_2})$ for count regressions.

The row "Overdispersion" reports the estimates and [95%CI] of the random component's variance, $\mathrm{Var}(\Theta) = \frac{1}{a}$.
The row "Likelihood ratio Test" compares negative binomial to Poisson. Under the null, the statistic is Chi-square (1d.f.) distributed. The row "Vuong's Test" compares ZI vs. negative binomial. Under the null, the statistic is normally distributed. The two tests were conducted without cluster-robust S.E.

***: p-value<1%; **: <5%; *: <10%

Appendix - Table A1: Characteristics of non-purchasers (N=14) and of participants stating only positive bids (N=46)

Variable	Sample Means				Sample Means		Difference Test
	12 Null WTPs (n=14)	Others (n=92)	Difference Test		12 Positive WTPs (n=46)	Others (n=60)	
Stimulus amplitude (in mA)	16.93	15.47	-0.84	T	15.39	15.87	0.48
Age	21.93	22.22	0.31		21.87	22.42	0.93
Female	0.21	0.54	5.27**	χ^2	0.57	0.45	1.38
Student	0.86	0.92	0.70		0.93	0.90	0.41
Has less than 500€/month for current expenses (students only)	0.67	0.64	0.04		0.62	0.66	0.17
Risk attitude (score>6)	0.43	0.49	0.18		0.39	0.55	2.63
Eager to complete the experiment (score>9)	0.86	0.39	10.64***		0.26	0.60	12.09***
Eager to avoid shocks (score>4)	0.14	0.51	6.62***		0.57	0.38	3.47*
Eager to maximize gains (score>8)	0.43	0.40	0.04		0.35	0.45	1.13
Eager to leave quickly (score>1)	0.21	0.53	4.93**		0.57	0.43	1.81
Fear of shocks (score>4)	0.14	0.51	6.62***		0.54	0.40	2.16
Did not believe he/she would really undergo physical pain or pay for urn change	0.21	0.08	2.72		0.07	0.12	0.81
Honestly stated the maximum amount he/she was ready to pay in each task	0.79	0.80	0.03		0.80	0.80	0.00

Student tests (with unequal variance) were performed for quantitative variables.
Fisher's exact tests were conducted for factor variables.
The test statistics and the significance level are reported.
***: p-value<1%; **: <5%; *: <10%

Appendix - Table A2: Goodness of Fit

	Observed	OLS	Negative Binomial	ZINB
Self Protection				
WTP	3.931 (4.44)	3.931 (1.27) [-0.32; 6.17]	3.938 (1.33) [1.02; 6.66]	3.929 (1.55) [0.52; 7.53]
Pr. of zero bids	27.99%		23.38% [14.4%; 50.5%]	28.45% [6.0%;80.0%]
(incl. Structural zeros)				22.07% [1.2%; 73.8%]
Self Insurance				
WTP	4.16 (5.13)	4.160 (1.82) [-1.73; 7.82]	4.162 (1.88) [0.55; 9.01]	4.156 (2.17) [0.11; 9.81]
Pr. of zero bids	32.70%		28.00% [15.3%; 66.5%]	32.91% [4.3%; 93.3%]
(incl. Structural zeros)				26.25% [0.4%; 88.1%]

Notes:
The rows "WTP" report observed average WTP and average predicted WTP. Standard deviations in parentheses. Range of predictions in brackets.
The rows "Pr. of zero bids" report the observed % of zero bids and the average predicted probabilities of bidding zero (range of predictions in brackets).
For the ZINB regressions, the rows "incl. structural zeros" report the average predicted probabilities of WTPs being structural zeros (range in brackets).

Appendix -Table A3. Results for self-protection – Participants' scores as continuous. 636 obs.

Explanatory variables	OLS	Negative binomial	ZINB
Low Prob. (β_1)	-0.443 (-1.48)	0.899 (-1.41)	0.906 (-1.25)
High Prob. (β_2)	-0.019 (-0.12)	1.005 (0.13)	0.997 (-0.06)
High efficacy (δ)	1.629 (5.78) ***	1.545 (6.00) ***	1.433 (4.98) ***
Age	-0.053 (-0.38)	0.988 (-0.33)	0.977 (-0.64)
Female	1.151 (1.6)	1.333 (1.63)	1.230 (1.19)
Worker	-2.066 (-1.8) *	0.453 (-1.85) *	0.546 (-1.09)
Risk attitude (score)	0.086 (0.57)	1.025 (0.56)	1.041 (0.97)
Intercept	3.530 (1.09)	3.236 (1.42)	4.757 (2.06) **
Low + High Prob. (Δ)	-0.462 (-1.31)	0.904 (-1.11)	0.904 (-1.05)
First stage			Excess zeros
Low Prob. (β_1)			1.212 (0.31)
High Prob. (β_2)			0.900 (-0.24)
High efficacy (δ)			0.258 (-2.12) **
Age			0.707 (-0.76)
Female			0.956 (-0.04)
Worker			11.872 (0.32)
Risk attitude (score)			1.121 (0.57)
Eager to avoid shocks (score)			0.123 (-3.69) ***
Eager to maximize gains (score)			0.691 (-0.7)
Eager to complete the experiment (score)			1.347 (0.54)
Eager to leave quickly (score)			1.106 (0.57)
Fear of shocks (score)			0.73 (-1.64) *
Overdispersion		1.10 [0.79;1.51]	0.65 [0.45-0.94]
Likelihood ratio Test		1132***	453***
Vuong's Test			7.09 ***

Reading note:
For OLS regressions: coefficients are reported.
For negative binomial and logistic regressions: exponentiated coefficients are reported.
Cluster-robust test statistics in parentheses.
The row "Low + High Prob." reports $\widehat{\beta_1} + \widehat{\beta_2}$ for OLS and $\exp(\widehat{\beta_1} + \widehat{\beta_2})$ for count regressions.

The row "Overdispersion" reports the estimates and [95%CI] of the random component's variance, $\mathrm{Var}(\Theta) = \frac{1}{a}$.
The row "Likelihood ratio Test" compares negative binomial to Poisson. Under the null, the statistic is Chi-square (1d.f.) distributed. The row "Vuong's Test" compares ZI vs. negative binomial. Under the null, the statistic is normally distributed. The two tests were conducted without cluster-robust S.E.

***: p-value<1%; **: <5%; *: <10%

Appendix -Table A4. Results for self-insurance – Participants' scores as continuous. 636 obs.

Explanatory variables	OLS	Negative binomial	ZINB
Low Prob. (β_1)	-1.373 (-4.15) ***	0.671 (-4.15) ***	0.679 (-4.12) ***
High Prob. (β_2)	1.061 (4.51) ***	1.23 (4.45) ***	1.17 (3.29) ***
High efficacy (δ)	1.22 (7.6) ***	1.39 (6.64) ***	1.333 (5.65) ***
Age	-0.058 (-0.4)	0.988 (-0.29)	0.978 (-0.56)
Female	1.781 (2.14) **	1.483 (1.92) *	1.382 (1.72) *
Worker	-2.859 (-2.51) **	0.29 (-2.65) ***	0.407 (-2.16) **
Risk attitude (score)	-0.052 (-0.29)	0.994 (-0.11)	1.011 (0.27)
Intercept	4.612 (1.33)	4.155 (1.43)	6.041 (2) **
Low + High Prob. (Δ)	-0.311 (-0.77)	0.825 (-1.71) *	0.794 (-2.12) **
First stage			Excess zeros
Low Prob. (β_1)			1.203 (0.54)
High Prob. (β_2)			0.394 (-1.85) *
High efficacy (δ)			0.58 (-1.42)
Age			0.787 (-0.89)
Female			1.152 (0.15)
Worker			18.439 (0.74)
Risk attitude (score)			1.07 (0.36)
Eager to avoid shocks (score)			0.155 (-2.5) **
Eager to maximize gains (score)			0.6 (-1.04)
Eager to complete the experiment (score)			1.499 (0.76)
Eager to leave quickly (score)			1.324 (1.13)
Fear of shocks (score)			0.586 (-1.13)
Overdispersion		1.4 [1.01;1.95]	0.78 [0.54;1.12]
Likelihood ratio Test		1512***	595***
Vuong's Test			6.99***

Reading note:
For OLS regressions: coefficients are reported.
For negative binomial and logistic regressions: exponentiated coefficients are reported.
Cluster-robust test statistics in parentheses.
The row "Low + High Prob." reports $\widehat{\beta_1} + \widehat{\beta_2}$ for OLS and $\exp(\widehat{\beta_1} + \widehat{\beta_2})$ for count regressions.

The row "Overdispersion" reports the estimates and [95%CI] of the random component's variance, $\mathrm{Var}(\Theta) = \frac{1}{a}$.
The row "Likelihood ratio Test" compares negative binomial to Poisson. Under the null, the statistic is Chi-square (1d.f.) distributed. The row "Vuong's Test" compares ZI vs. negative binomial. Under the null, the statistic is normally distributed. The two tests were conducted without cluster-robust S.E.

***: p-value<1%; **: <5%; *: <10%

Appendix - Table A5: Sensitivity tests on restricted samples

Sample	Number of subjects	Number of observations	OLS	Negative binomial	ZINB
Analyses for self-protection					
Full sample (baseline results)	106	636	-0.462 (-1.31)	0.919 (-0.98)	0.982 (-0.19)
Subjects understanding probabilities	101	606	-0.480 (-1.32)	0.915 (-0.99)	0.952 (-0.51)
Subjects violating 1SD at most once	95	570	0.057 (0.20)	1.040 (0.46)	1.110 (1.20)
Subjects never violating 1SD	75	450	0.433 (1.63)	1.190 (1.92) *	1.266 (2.64) ***
Subjects understanding probabilities and violating 1SD at most once	90	540	0.067 (0.22)	1.042 (0.48)	1.075 (0.83)
Subjects understanding probabilities and never violating 1SD	70	420	0.471 (1.73) *	1.207 (1.98) **	1.229 (2.27) **
Analyses for self-insurance					
Full sample (baseline results)	106	636	-0.311 (-0.77)	0.821 (-1.64)	0.822 (-1.74) *
Subjects understanding probabilities	101	606	-0.505 (-1.24)	0.791 (-1.99) **	0.823 (-1.72) *
Subjects violating 1SD at most once	95	570	-0.274 (-0.63)	0.805 (-1.48)	0.785 (-1.73) *
Subjects never violating 1SD	75	450	-0.047 (-0.18)	0.861 (-1.44)	0.832 (-1.84) *
Subjects understanding probabilities and violating 1SD at most once	90	540	-0.489 (-1.12)	0.771 (-1.81) *	0.787 (-1.70) *
Subjects understanding probabilities and never violating 1SD	70	420	-0.307 (-1.35)	0.790 (-2.58) ***	0.811 (-2.10) **

Notes:
$\hat{\Delta} = \widehat{\beta_1} + \widehat{\beta_2}$ is reported for OLS regressions, whereas $\exp(\hat{\Delta})$ is reported for count regressions.
Analyses are adjusted on the same sets of covariates as in Tables 3 and 4 (main text).
Cluster-robust test statistics in parentheses.
***: p-value<1%; **: <5%; *: <10%