Predicting Insurance Demand from Risk Attitudes*

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Abstract

Can measured risk attitudes and associated structural models predict insurance demand? In an experiment (n = 1,730), we elicit measures of utility curvature, probability weighting, loss aversion, and preference for certainty and use them to parameterize seventeen common structural models (e.g., expected utility, cumulative prospect theory). Subjects also make twelve insurance choices over different loss probabilities and prices. The insurance choices show coherence and some correlation with various risk-attitude measures. Yet all the structural models predict insurance poorly, often less accurately than random predictions. This is because established structural models predict opposite reactions to probability changes and more sensitivity to prices than people display. Approaches that temper the price responsiveness of structural models show more promise for predicting insurance choices across different conditions.

Keywords: Insurance Demand · Behavioral Insurance · Risk Attitudes · Utility Models

JEL Classifications: D14 · D81 · G22

*We thank the Alfred P. Sloan Foundation for financial support under grant number G-2016-7312. This study was pre-registered with the American Economic Association's randomized controlled trial registry under ID AEARCTR-0002783 (https://doi.org/10.1257/rct.2783-1.0). For helpful feedback and comments, we thank Levon Barseghyan, Mark Browne, Sebastian Ebert, Glenn Harrison, Julian Reif, Barbara Simmons, Charles Sprenger and seminar participants at the University of Hannover, LMU Munich, University of Alabama, the MRIC Winter Workshop, and the American Risk and Insurance Association annual meeting. We also thank Josh Frederick and Joëlle Näger for research assistance. All remaining errors are ours.

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1 Introduction

In this paper, we use an incentivized lab study to examine the extent to which structural models of risk attitudes can effectively predict insurance demand.[1] Recent studies estimate models of risk preference from observed insurance choices in market settings (e.g., Cohen and Einav, 2007; Decarolis et al., 2020; Handel et al., 2015). The resulting models are often used to predict insurance demand in various economic environments and sometimes to conduct welfare analyses of different policy options. However, these studies infer risk attitudes from data assuming a particular structural model and have not systematically evaluated the quality of the predictions out-of-sample.

Prior literature provides a mixed message on whether individuals' insurance decisions are governed by a stable set of risk attitudes that could potentially be captured by structural models. Barseghyan et al. (2011) analyze customers' decisions about deductibles for home and automobile insurance and show that their decisions in the two domains can seldom be rationalized by a single level of risk aversion. Collier et al. (2020) study customers' flood insurance decisions regarding their deductible choices and their chosen coverage limits and come to a similar conclusion. Harrison and Ng (2016) use a lab experiment with lottery choices to estimate structural models of risk preferences and include a separate insurance take-up decision. They find that insurance choices rarely maximize consumer surplus given the estimated preferences. On the other hand, Einav et al. (2012) find that people show some rank-order correlation across different insurance decisions, suggesting there may be a stable underlying factor which might be captured by the correct structural model.

Our study aims to address three open questions emerging from this literature. First, is there a stable set of risk attitudes driving insurance demand which is masked by market-specific factors in empirical studies? Prior work has suggested that demand in market settings could be influenced by variations in subjective beliefs, default options, or menu effects (e.g., Sydnor, 2010). These effects are controlled in our laboratory setting. Second, are some models better able to capture insurance choices than others? There is evidence that a range of behavioral factors may affect insurance demand (e.g., Abaluck and Gruber, 2011; Abito and Salant, 2019; Barseghyan et al., 2013; Bhargava et al., 2017; Handel, 2013; Handel and Kolstad, 2015; Sydnor, 2010), yet most of the applied work using structural models has used models incorporating only classic risk aversion

[1] We pre-specified our research questions, experiment, and analysis in a randomized controlled trial registration with the American Economic Association (AEARCTR-0002783).

(i.e., concave utility). Considering additional motives may improve our ability to model insurance decisions. Barseghyan et al. (2013) and Collier et al. (2020), for example, both show that models incorporating probability distortions can better fit some patterns of insurance demand than models with only classic risk aversion. No study, though, has evaluated different models of insurance demand with respect to the quality of their out-of-sample predictions. Third, even if there is no domain-general structural model that predicts well across contexts, are structural models useful for predicting responses to changes in economic fundamentals (e.g., prices) considering only an insurance context?

We use an incentivized lab study to help answer these questions. The lab setting offers a controlled environment to isolate the links between underlying risk attitudes and insurance decisions. We conduct our study with students at the University of Wisconsin and in an online experiment via Amazon's Mechanical Turk, recruiting a total of 1,730 subjects across the two platforms. Participants earn money by doing a short effort task, but face a risk of losing part of these earnings. They then make a series of choices about the proportion of this potential loss they want to insure, under different loss probabilities and insurance prices (i.e., premiums).[2] In addition to the insurance choices, participants also make a series of choices over neutrally-framed lotteries. The lotteries are adapted from procedures used previously in the literature (e.g., Tanaka et al., 2010) and are designed to allow us to jointly measure different components of risk attitudes identified in prior literature: utility curvature, probability weighting, loss aversion, and a preference for certainty.

We use the lottery choices to parameterize seventeen different utility models that have been used previously in the literature, including classic expected utility theory, cumulative prospect theory, rank-dependent expected utility theory, and a number of other models.[3] This allows us to investigate how accurately any of these structural models of risk attitudes can predict insurance choices. The variation in price across our insurance scenarios also allows us to conduct exercises where we fit a more limited set of structural models from within a subset of the insurance choices (i.e., we focus solely on choices in an insurance context and ignore the neutral lottery choices).

[2]Specifically, subjects choose a coverage level between 0% and 100% of the potential loss (in 1% increments). Throughout the paper, we use the terms "coverage level," "amount insured," and "proportion insured" interchangeably to describe this coverage choice. When we refer to "insurance demand," we are referring to the coverage level chosen at a given price.

[3]For prospect theory, we consider a number of different reference points that might be employed when considering insurance decisions. All of the models we consider are "consequentialist" in the sense that (decision) utility is a function of the distribution of potential final wealth outcomes possible under a given choice.

Using those fitted models, we examine how accurately they predict reactions to variation in the economic fundamentals (e.g., prices).

Our experimental design is similar to Harrison and Ng (2016) who also use lottery choices to estimate a structural model of risk attitudes and involve a separate insurance-choice task.[4] The key difference between our work and theirs is that they assume a particular model structure (rank-dependent expected utility) and use it to evaluate the normative quality of insurance choices. In contrast, we investigate a range of potential preference models and examine each model's ability to predict insurance choices. Our insurance task also allows us to investigate the predictive power of structural models fit on a subset of insurance choices in a way that they do not.

Our first exercise of using lottery tasks to estimate risk attitudes shows that there is some correlation between measured risk attitudes and insurance choices. Our preference-elicitation task provides us with both a nonparametric ordinal measure and a parametric measure for each of the underlying preference motives.[5] Within an insurance-choice scenario, we observe modest correlations between the level of insurance chosen and utility curvature, loss aversion, and probability weighting.[6] For each of these three measures, we find that a one-standard deviation increase in the measured preference motive is associated with around a 4% increase in insurance demand. These findings support the idea that insurance choices are related to a number of different underlying preference motives and that better understanding motives such as loss aversion and probability weighting can have value for understanding insurance demand. None of the three main preference motives, however, is clearly more important than the others. Moreover, when evaluating all preference motives jointly, they explain only a small part of the variation in insurance choices.

The central finding in our study is that structural models of decisions under risk do a poor job of predicting insurance choices. Consistent with the modest correlations we observe when looking at primitive preference motives alone, the parameterized utility models have some ability to predict the *relative* amount of insurance that different subjects select within a scenario. However, in all cases the correlations are quite modest – in the utility model with the strongest within-scenario correlations,

[4]See also Harrison and Ng (2018) and Harrison et al. (2020), who use the same general design to study the welfare of insurance choices in situations with non-performance risk and basis risk, respectively.

[5]Our parametric measures are generally in line with estimates from other studies. For instance, we find that the majority of subjects display inverse-S probability weighting in both the gain domain and loss domain. We also observe a median coefficient of loss aversion of 2.7, which is broadly consistent with estimates in prior studies.

[6]We find no correlation between preference for certainty and insurance demand.

a 10 percentage-point increase in the predicted level of insurance purchased is associated with only a 0.8 percentage-point increase in actual insurance purchased. An arguably more important question for structural models applied to insurance demand, though, is whether the models are valuable for predicting the *level* of demand for insurance (as opposed to the *relative* demand) and whether they can do so well *across* different economic scenarios. Parameterized utility models are useful primarily if they allow one to predict behavior in a range of counterfactual environments. We find, however, that all of the utility models, including the ones incorporating loss aversion and probability weighting, have low overall correlation with insurance demand. In fact, each of the parameterized utility models performs worse than random choice in predicting the level of insurance purchased.

We attribute the poor predictive validity of these models to two primary inconsistencies between the model predictions and our subjects' choices. First, the models predict strong sensitivity to the price of insurance. Subjects' actual insurance choices, however, respond to price in the expected direction, but much more modestly. For example, a simple expected utility model calibrated from lottery choices predicts subjects to be more than six times as sensitive to price than they actually are. Second, all the models predict that a (weakly) higher share of the loss will be insured at low loss probabilities. Subjects' actual decisions show the reverse pattern – they purchase more insurance when the probability of loss is higher.

Are these results due to the limits of modeling risk attitudes across contexts (e.g., between abstract financial lotteries and insurance), or do they point to deeper issues in using common structural models to predict insurance choices? We explore this issue by looking within our insurance-choice data. For this exercise, we adopt the framework from Barseghyan et al. (2013) that allows for both classic risk aversion via a concave utility function and generalized probability distortions.[7] We fit the model on a subset of insurance choices with intermediate price levels and then use the fitted model to predict demand under both higher and lower prices, a common exercise of interest in studies of insurance demand. In order to account for potential individual-level noise in choice patterns, we do the fitting exercise at different levels of aggregation, ranging from a representative agent model (where all individuals get the same parameter estimates) down to the individual level. We benchmark the structural model predictions against two other simple approaches to estimating

[7] In the insurance choices we study, this framework is equivalent to multiple models which include rank-dependent expected utility theory (Quiggin, 1982), reference-dependent preferences with loss aversion and concave consumption utility (Kőszegi and Rabin, 2007), disappointment aversion (Gul, 1991), and salience theory (Bordalo et al., 2012).

out-of-sample demand at the same level of aggregation: (a) using the average demand observed under the in-sample prices and (b) using a simple linear extrapolation of demand across prices.

Of these three approaches, using average demand provides the best predictions overall, even though this strategy does not involve a price response. The structural models estimated using insurance choices perform better than the structural models fit on lottery choices, especially at intermediate levels of data aggregation. However, even in the cases where the structural model's out-of-sample predictions are reasonably good, the estimated parameters that best fit the in-sample data are extreme and would likely be inappropriate for any normative analysis. While structural models do not outperform the average-demand heuristic, we find that a convex combination of average demand and structural model predictions slightly outperform average demand alone.

Our findings offer new insights to the question of whether insurance demand reflects a stable underlying set of risk attitudes. Our results are consistent with the message that, while some underlying component seems to exist, insurance choices are not obviously governed by a simple model of risk preferences. We extend those findings by highlighting that the limitations in predicting insurance demand are shared by a wide range of structural models. Moreover, our results from a controlled experiment also imply that the limitations of structural models are not driven only by institutional factors that may affect decisions across real-world insurance settings. Our results are also broadly consistent with Harrison and Ng's (2016) findings that insurance choices are inconsistent with maximization of welfare when preferences are modeled based on lottery choices. Our study shows that even if one remains agnostic about their normative value, structural models do a poor job of predicting insurance choices across a range of modeling assumptions. The structural models also predict poorly whether they are fit from separate preference-elicitation tasks or fit from a subset of insurance choice data. There appears to be a fundamental failure of the established consequentialist models of risk attitudes to capture how people make decisions about insurance.

There are a few implications of our results both for applied policy work and for future research. For example, the Congressional Budget Office uses models to predict health insurance coverage under different policy environments (CBO, 2019). Historically, their models relied primarily on an "elasticity approach" that modeled the responsiveness to prices and other variables, but they have been moving toward an approach using structural models that incorporate risk preferences. Our results suggest a reason for caution in moving away from the elasticity approach. We believe our results should motivate further research into insurance decision models that incorporate features beyond consequentialist utility frameworks, such as decision frictions, limited consideration sets, and decision heuristics (e.g., Abaluck and Adams, 2017; Coughlin, 2020; Handel et al., 2015).

Finally, our results relate to growing evidence on the limited value and consistency of risk preference estimates in the lab (e.g., Chapman et al., 2018; Charness et al., 2020; Friedman et al., 2019; Friedman and Sunder, 2011). In our analysis, we do see correlation between the preference motives elicited in lottery choices and insurance demand. This is in line with recent evidence suggesting that there is a context-independent, underlying risk preference in human decisions (Vieider et al., 2015).[8] However, this correlation disappears once we utilize the preference motives in fully-specified structural models, showing that such models – in contrast to their individual components – have essentially no external validity for insurance choices. Taken together, our findings are inconsistent with the idea that risk preferences are fully context-dependent. Instead, they highlight that the restrictions implied by structural models reduce, and in our case even eliminate, the predictive power of these risk preferences for insurance demand.

The remainder of the paper proceeds as follows. We lay out the underlying theoretical structure for our exercise in Section 2. In Section 3, we discuss the experimental design and the choice patterns we observe for lottery choices and insurance choices separately. We provide our main results on the predictions of insurance choices from the risk attitudes and structural models estimated from lottery choices in Section 4. In Section 5, we present the results of estimating the structural model within the insurance choices. We conclude and discuss in Section 6.

2 Theoretical Basis

2.1 Preference Motives

To elicit primitive preference motives, we first construct a decision model such that these motives have both a definition and implications for decision-making behavior.[9] We begin with a standard cumulative prospect theory (CPT, Tversky and Kahneman, 1992) preference functional. We also consider an extended version of this model that adds a parameter which can regulate a preference for

[8] Those authors report the results of a laboratory study. For evidence from insurance choices in the field, see Barseghyan et al. (2011) and Einav et al. (2012).

[9] Parts of the following section and Section 3.2 resemble the theoretical considerations of a companion paper to this (Jaspersen et al., 2020). The companion paper considers a question distinct from the analysis here but is based on the same experimental data and thus utilizes the same approach to preference elicitation.

(or against) certainty. This general model allows for the most common preference motives in risky decision-making, including those hypothesized to drive insurance demand (see, e.g., Barseghyan et al., 2013; Callen et al., 2014; Sydnor, 2010). The model is also useful because, for the decisions faced by subjects in our experiment, it nests several other models (see Section 3.2).

We represent risk as lotteries with n outcomes. Each outcome $x_i \in \mathbb{R}$ has a probability p_i and outcomes are indexed such that $x_1 \geq ... \geq x_n$. We describe a lottery with the notation $(x_1, p_1; ...; x_n, p_n)$. Preferences over lotteries are represented by the function

$$V(\tilde{x}) = \sum_{i=1}^{n} \pi_i U(x_i). \tag{1}$$

Here, outcomes are evaluated by the function

$$U(x) = \begin{cases} u^+(x-r) & \text{for } x \geq r \\ \lambda u^-(x-r) & \text{for } x < r \end{cases} \tag{2}$$

in which r describes the reference point, u^+ is the utility function over gains, u^- is the utility function over losses and λ is a loss aversion parameter. u^+ and u^- are assumed to be strictly increasing and $u^+(0) = 0$. The probability weights π_i are formed according to

$$\pi_i = \begin{cases} w^+(\sum_{j=1}^{i} p_j) - w^+(\sum_{j=1}^{i-1} p_j) & \text{if } x_i \geq r \\ w^-(\sum_{j=i}^{n} p_j) - w^-(\sum_{j=i+1}^{n} p_j) & \text{if } x_i < r. \end{cases} \tag{3}$$

If one assumes current wealth is the reference point, the standard CPT preference functional includes five behavioral motives that influence behavior in decisions under risk and thus insurance demand. We begin by outlining our "nonparametric" measures of these motives (denoted by capital letters), which do not assume a specific underlying functional form. If the utility function is not linear, it shapes an attitude towards risk. We denote this concept of utility curvature in the gain and loss domains as UC^+ and UC^-, respectively. The shape of the probability weighting functions in the gain and loss domain similarly influence risk attitudes (Schmidt and Zank, 2008). We assume that deviations from the identity line are in the form of either S shaped or inverse-S shaped probability weighting functions, with an inflection point around the middle of the unit interval.[10] Our measure PW^+ denotes the extent to which the gain domain probability weighting function is inverse-S shaped. The loss domain is analogous with PW^-. Lower values of these measures imply an S shape of the functions, while higher values imply an inverse-S shape. Lastly, a slope difference between utility in the gain domain and utility in the loss domain denotes loss aversion (LA). Higher values of LA indicate a steeper slope in the loss domain than in the gain domain.

In addition to these five standard CPT preference motives, we add a potential sixth motive, a preference for certainty. We model this after Schmidt (1998), who axiomatizes a decision model and develops a measure for certainty preference.[11] While payouts of risky prospects are evaluated with utility functions u^+ or u^-, payouts of certain prospects are evaluated by a function v. Because we are within a CPT framework, $u^+(0) = v(0) = 0$ must hold. We model the value function as

$$v(x) = \kappa u^+(x). \tag{4}$$

Here, $\kappa > 1$ implies a preference for certainty, while $\kappa < 1$ implies a preference for risk. We model and elicit the certainty preference CP in the gain domain. CP is elicited with the help of a separate choice table. All other preference motives are elicited as if a standard CPT preference functional was assumed (i.e., they are measured independently of CP).

The motives introduced above are not parametric in nature because we have not yet assumed a fully parametric structure for the utility function or the probability weighting function. Our elicitation procedure allows us to assess these motives ordinally using statements in which preference motives change *ceteris paribus* in subjects' answers to our preference elicitation task. The specific assumptions allowing us to do so are given in Section 3.2. Formal derivations of the elicitation procedures are provided in Appendix B.

In addition to the nonparametric motives, we also calibrate a parametric structure of the preference functional. The parameters shaping the structure are our "parametric" measures of the six preference motives, and we refer to them with Greek letters. Our parametric structure involves assumptions similar to Tanaka et al. (2010), after which our preference elicitation procedure is

[10] This assumption is likely a slight simplification. More sophisticated models have been proposed, e.g., by Prelec (1998). We make the assumption to ease elicitation of preference parameters.

[11] Note that this motive has distinct implications from the preference for certainty already inherent in probability weighting (Andreoni and Sprenger, 2012).

modeled. Specifically, we assume a utility function shaped by γ

$$U(x) = \begin{cases} \frac{(x+1)^{1-\gamma^+}}{1-\gamma^+} - \frac{1}{1-\gamma^+} & \text{for } x \geq 0 \\ -\lambda\left(\frac{(1-x)^{1+\gamma^-}}{1+\gamma^-} - \frac{1}{1+\gamma^-}\right) & \text{for } x < 0. \end{cases} \tag{5}$$

and a probability weighting function shaped by β

$$w^{+/-}(p) = exp\left(-(-ln(p))^{2-\beta^{+/-}}\right). \tag{6}$$

The two forms are similar but not equal to standard assumptions in the literature. The utility function closely resembles the iso-elastic form, which has been the workhorse of preference elicitation (e.g., Andersen et al., 2008; Tanaka et al., 2010).[12] For interpretation's sake, the γ coefficients can be seen as approximate coefficients of relative risk aversion.[13] We code γ^- such that a higher value implies more concave curvature, allowing congruent interpretation of the nonparametric UC^- and the parametric γ^-. Equation (6) is a slight modification of the one-parameter Prelec (1998) probability weighting function, with $\beta^{+/-} = 1$ giving the identity (no probability weighting), $\beta^{+/-} > 1$ implying the typical inverse-S shape, and $\beta^{+/-} < 1$ implying S shaped probability weighting.[14]

Measuring loss aversion is not trivial and several measures have been proposed in the literature (Abdellaoui et al., 2007). The parameter λ has an intuitive interpretation only when using power utility. In the utility function used here, γ^+ and γ^- also shape the absolute values of the utility function in the gain and in the loss domain such that λ must be interpreted in combination with these parameters (Balcombe et al., 2019). We thus create an index $\hat{\lambda}$, equal to the average absolute ratio of utility values over a range $[-x_{max}, x_{max}]$ such that

$$\hat{\lambda} = -\int_0^{x_{max}} \frac{\lambda u^-(-x)}{u^+(x)} dx. \tag{7}$$

[12]Many papers in the literature use the power formulation $u(x) = x^\gamma$, which is a special case of the iso-elastic function. The power function, however, is limited to modeling relative risk aversion less than or equal to one, which is insufficient to grasp the utility curvature of many individuals over laboratory stakes. The general form of the iso-elastic utility function, $u(x) = \frac{x^{1-\gamma}}{1-\gamma}$, can model higher coefficients of relative risk aversion but is not appropriate for prospect theory, because the model requires $u(0) = 0$ and the iso-elastic form is not always defined at $x = 0$. We thus opt for the expression in (5), which is very close to iso-elastic but does not match the structure perfectly.

[13]The exact coefficient of relative risk aversion is $\gamma^+ \frac{x}{x+1}$.

[14]In Prelec's original formulation, inverse-S probability weighting is decreasing in β. Our modification makes inverse-S probability weighting increasing in β, so that all primitive preference motives are increasing in their measures. The adjustment does not affect the properties of the weighting function.

Similarly, the preference for certainty is not fully captured by κ in the certainty value function $v(x)$. We adapt the index $\hat{\kappa}$ developed by Schmidt (1998), where

$$\hat{\kappa} = \frac{v(x) - u^{+}(x)}{xu'^{+}(x)}. \tag{8}$$

This index measures the difference between the two utility functions in units of marginal utility over lottery outcomes.

2.2 Structural Models

In addition to analyzing how the primitive motives explain insurance demand, we assemble the preference motives in various structural decision models to predict insurance demand. The models involve individuals with wealth y who face a loss L with probability p. They can purchase insurance with a coverage level $\alpha \in [0, 1]$. Once purchased, the policy covers a share α of the loss if it occurs. The insurance premium for coverage level α is calculated as αqpL, where q is a relative loading factor. At $q = 1$, the premium is actuarially fair. If q exceeds one, the premium includes a risk premium. A structural model predicts insurance demand by determining the level of α at which the model's objective function is maximized. In the experiment, subjects choose α in twelve different insurance scenarios with varying levels of p and q. The models are thus used to make twelve predictions of α^* for each subject.

We test seventeen different structural models which have been proposed in the literature. The models, their generalized objective functions, and their possible variants are summarized in Table 1. This is a comprehensive list of the possible structural models for which our preference elicitation procedure provides us information. All of these models are context-independent—the evaluation of one action does not depend on the other available actions.[15] For each model, we assume that individuals are narrowly focusing on the decision at hand in our experiment and do not integrate the outcomes of this experiment with background wealth.

We begin with a simple expected value calculation (EV) and then consider increasingly complex models that increase the number of parameters involved. The first three models, expected utility

[15]Because they involve psychologically distinct concepts, context-dependent models, the most prominent of which are regret theory (Loomes and Sugden, 1982) and salience theory (Bordalo et al., 2012), cannot easily be parameterized with our elicitation procedure. The preference elicitation tables in our experiment, which are detailed in Tables A.1 and A.2, render six indifference relationships between prospects which would enable us to calibrate both a regret theory and a salience theory preference functional within some margin of error. However, the tables were not designed with this goal in mind, which might lead to framing and boundary effects. We thus refrain from the exercise.

Table 1: Summary of structural models

Model	Objective Function	Variants
Exp. Value	$p(y-(1-\alpha)L-\alpha qpL)+(1-p)(y-\alpha qpL)$	EV
Exp. Utility	$pu(y-(1-\alpha)L-\alpha qpL)+(1-p)u(y-\alpha qpL)$	EU^+, EU^-
Dual Theory	$w(p)(y-(1-\alpha)L-\alpha qpL)+(1-w(p))(y-\alpha qpL)$	DT^+, DT^-
Reference Dependent Preferences	$y-pL-(q-1)\alpha pL+p(1-p)(1-\lambda)(1-\alpha)L$ Axiom A3' of Kőszegi and Rabin (2007). Model: CPE Stoch. ref. point $\{p, y-\alpha qpL-(1-\alpha)L; 1-p, y-\alpha qpL\}$	KR
Rank Dependent Exp. Utility	$w(p)u(y-(1-\alpha)L-\alpha qpL)+(1-w(p))u(y-\alpha qpL)$	RDEU^+, RDEU^-
CPT (loss domain)	$w^-(p)u^-(-(1-\alpha)L-\alpha qpL)+(1-w^-(p))u^-(-\alpha qpL)$ Reference point $r=y$	CPT^-
CPT (no loss in buying)	$w^+(1-p)u^+((1-\alpha)qpL)+\lambda w^-(p)u^-((\alpha-1)L+(1-\alpha)qpL)$ Reference point $r=y-qpL$	CPT^{NLIB}
Certainty Preference	Above models with $\kappa(y-\alpha qpL)$ for $\alpha=1$	EV_{CP}, DT^+_{CP}, DT^-_{CP}
	Above models with $\kappa u(y-\alpha qpL)$ for $\alpha=1$	EU^+_{CP}, EU^-_{CP}, $\text{RDEU}^+_{\text{CP}}$, $\text{RDEU}^-_{\text{CP}}$

Note: The table lists the seventeen structural models tested in this study. p denotes loss probability. y denotes wealth. L denotes loss amount. α is the proportion of the loss insured. q is the relative premium loading factor. Superindices + and − on the model abbreviations indicate whether preference parameters are elicited in the gain domain or in the loss domain. The subindex CP indicates that the otherwise unchanged model evaluates certain outcomes with utility function v instead of u. The two CPT models are listed separately because the difference in the reference point changes the objective function.

(EU), dual theory (DT) and reference-dependent preferences under property A3' of Kőszegi and Rabin (KR, 2007) each feature one primitive preference motive. These are utility curvature, probability weighting, and loss aversion, respectively.[16] Rank-dependent expected utility (RDEU) and cumulative prospect theory in the loss domain (CPT^-) combine the two motives of utility curvature and probability weighting. Other combinations of two motives have seldom been proposed in the literature.[17] All three preference motives are combined in the CPT^{NLIB} model, where purchasing

[16]For modeling probability weighting in DT and RDEU, we use the lower Choquet integral such that the probability of the loss event is weighted first. This seems appropriate as insurance decisions regard so called "bad news events" (Sarin and Wakker, 1998).

[17]More general reference-dependent preferences of Kőszegi and Rabin (2007, property A3) can be seen as a model combining utility curvature and loss aversion. The model, however, requires further assumptions to calibrate using our data (Argyris et al., 2019).

full insurance is set as a reference point (see Novemsky and Kahneman, 2005, for a psychological rationale of this reference point).

For some of the models, we include different variants. We elicit utility curvature and probability weighting in the gain domain and in the loss domain, and consider EU, DT, and RDEU using parameters in both domains. For most models, we also add a variant with a preference for certainty. In the reference dependence model, adding a preference for certainty seems infeasible and there are no prior implementations of the concept.[18]

It is worth noting that the parameters of the utility function, the probability weighting function, and loss aversion are not the same for the different structural models. While CPT^{NLIB} can simply utilize the parameters of the model in Equation (1), all other structural models restrict some elements of (1). In expected utility theory, for example, the probability weighting function is restricted to the identity line. Similarly, some theories only draw from a select number of preference elicitation questions, such as considering only choices among lottery prospects in the gain domain. When these issues apply, we adjust the mapping of lottery choices to preference parameters accordingly (see also Section 3.2.2).

3 Experimental Design and Resulting Choice Patterns

3.1 General Structure and Subject Recruitment

Our experiment was implemented using the online Qualtrics platform. After an initial screen with a consent form (and a bot check for online participants), our experiment consists of the five stages. All subjects begin with the typing task, where they can earn \$5.00 in virtual currency by correctly typing two passages of text from an image into a text box. Subjects are told they must correctly transcribe each passage to earn their payment and continue to the next stage (we allowed transcriptions with errors to continue after three minutes). Subjects then complete the "preference task" and the "insurance task" as described in following subsections.[19]

[18]If such a preference motive were to be added, it seems in the spirit of the model to add it in the gain-loss utility function. However, we use the choice-acclimated personal equilibrium (CPE) to predict insurance demand in this model, as suggested by Kőszegi and Rabin (2007, p. 1058). In this equilibrium, gain-loss utility disappears if full insurance is bought, and so a preference for certainty would not affect the purchasing decision. In CPT^{NLIB}, purchasing full insurance is the reference point and thus implies a value of 0 by definition, also implying no role for certainty preferences.

[19]We randomly vary whether the preference task or the insurance task is presented first. Each task begins with a set of instructions, a practice task, and several questions to ensure subjects understand the instructions.

After both tasks are complete, the computer randomly selects one question to play out, collecting the insurance premium (if applicable) and drawing a virtual ball to determine whether any additional money is gained or lost. After the outcomes are determined, subjects complete a questionnaire including the "general risk question" of Dohmen et al. (2011) and demographic information (namely, age, sex, location, income, and education). Finally, we provide a validation code to enter in mTurk or provide to the experimenter.

Experimental sessions with a total 1,730 subjects were conducted in March of 2018. 1,352 subjects were recruited on the online recruitment platform Amazon Mechanical Turk and conducted the experiment online.[20] The other 378 subjects were recruited without any restrictions from the subject pool of the university laboratory.[21] Subjects were on average 33 years old and 53% of subjects were male. Summary statistics of demographic characteristics and other experimental data are provided in Appendix D. On average, experimental sessions were about 25 minutes long and subjects earned $6.27.[22]

3.2 Preference Task

Our preference measurement tasks are based on the lottery tables of Tanaka et al. (2010). The Tanaka et al. study involved three lottery tables designed to elicit probability weighting and utility curvature in the gain domain, as well as loss aversion. We make two primary adjustments to elicit additional preference motives and make fewer assumptions. First, we change the stakes and probabilities to permit a greater range of elicitable utility curvature and probability weighting. Second, we add three additional lottery tables. Our preference elicitation task thus includes six lottery tables. As in Tanaka et al. (2010), we have two tables that allow us to measure utility curvature and probability weighting in the gain domain (GD1 and GD2) and one table with mixed gambles for eliciting loss aversion (LA). Two of the additional tables allow us to elicit utility curvature and probability weighting in the loss domain, separately from those measures in the gain

[20]To participate in our mTurk human intelligence task (HIT), mTurk workers must have completed at least 100 prior HITs with an approval rate of 95% or greater. There were no other filters, though some participants failed a browser compatibility check at the beginning of our experiment. While our experiment was live, we monitored the popular mTurk worker forums (e.g., TurkerHub, mTurkCrowd) and found no threads discussing our experiment to any other degree than that it was a good opportunity to earn money.

[21]The sample sizes were based on an *ex ante* power calculation which rendered target sizes of 1,350 and 350 subjects for mTurk and in-person experiments, respectively. These targets were registered in the American Economic Association Randomized Control Trial Registry.

[22]Subjects in the in-person experiments were additionally paid a flat fee of $6 to comply with laboratory standards. To avoid income effects, this additional payment was not mentioned until the end of the experiment.

domain (LD1 and LD2). The other table (CP) allows us to elicit a preference for (or against) certainty in the sense of Schmidt (1998).

Lottery stakes involve potential gains between \$0.50 and \$60.00 and potential losses between \$0.10 and \$4.00 (taken from the \$5.00 typing task earnings). In five of the six tables, the probabilities for the possible outcomes do not change between different rows. In these tables the probabilities are all multiples of 10 percentage points. In the last table, intended for measuring loss aversion, the possible outcomes do not change, but their probabilities change in increments of 5 percentage points in each row. In the experiment, each of the six tables is provided on one screen, with probabilities illustrated with urns containing colored balls. For each row on one screen, subjects click radio buttons between the lotteries to indicate their choice. To encourage subjects to think carefully about their choices, the "Next" button is hidden for twenty seconds. We randomize the order of the six tables, the left-right display of the lotteries, and whether the stakes are ascending or descending. The full choice tables as well as rank-order correlations of the choices in the tables are provided in Appendix A. Screen captures from the experiment are in Appendix I.

There are a total of 101 choices across the six tables. To lower the cognitive load from making so many decisions, we automate monotonic choices—if a subject switches from Lottery A to Lottery B, we automatically select Lottery B for all subsequent choices on the screen. If the subject switches a Lottery B choice back to Lottery A, we automatically switch all higher choices back to Lottery A as well. We also simplify the choice sets by specifying the same probabilities for Lottery A and Lottery B (except for the table which measures the preference for certainty). Each lottery table, with the exception of the certainty preference table, includes a choice with a first-order stochastically dominated (FOSD) option. Choosing these options may indicate a lack of attention by participants. We construct an indicator for whether a subject violated FOSD in any of these five tables and use this as a proxy for inattentive participants.

We use the subjects' answers in the preference task to construct the "nonparametric" and "parametric" preference measures mentioned in Section 2.1. Below, we describe the construction of both measures from the choice tables and the resulting choice patterns in detail. In Appendix B, we offer formal derivations of each preference measure under our elicitation procedure.

3.2.1 Nonparametric Preference Measures

In the nonparametric approach, we refrain from making further structural assumptions on the elements of Equations (1) through (4) and use a *ceteris paribus* approach for the elicitation. That is, we assume for the sake of measuring each preference motive that choices in the corresponding tables are guided *only* by that preference motive. For example, we assume that subjects have a more concave utility function if they choose the less risky Lottery A in tables GD1 and GD2 more often. The nonparametric measure of gain-domain utility curvature (UC^+) is constructed as $UC^+ = GD1_A + GD2_A$. (Subscripts A and B indicate the number of choices in Lotteries A and B, respectively. For reference, the caption in Figure 1 summarizes the construction and interpretation of each measure.) The only necessary structural assumption on the gain-domain utility function u^+ is that there is a single parameter regulating its global risk aversion. Under the corresponding assumptions, more concave loss-domain utility is implied by more Lottery B choices in LD1 and LD2 and thus $UC^- = LD1_B + LD2_B$.

For the nonparametric measure of probability weighting, we assume that the probability weighting function has an inflection point towards the middle of the unit interval and is either S shaped or inverse-S shaped. For the gain domain, the shape is dictated by a single parameter such that the degree of inverse-S shape of the function can be measured by adding those choices in the gain domain tables which have a better outcome with a low probability (i.e., which would be overweighted if the probability weighting function was inverse-S shaped). The measure is calculated as $PW^+ = GD1_B + GD2_A$. The corresponding loss domain measure is determined according to the same logic, so $PW^- = LD1_B + LD2_A$.

To measure a preference for or against certainty, we adopt a procedure similar to that of Callen et al. (2014), who recently highlighted this preference motive. Subjects face table CP which is equal to table GD1 except that the less risky Lottery A in table CP is a certain payment of the lower outcome of Lottery A in table GD1. If a subject makes more Lottery A choices in CP than in GD1, we can conclude that an outcome paid with certainty has a higher value than that outcome has in a lottery setting. The nonparametric measure for certainty is calculated as $CP = CP_A - GD1_A$.

Our loss aversion table LA differs from the other preference tables—rather than varying outcomes along its rows, the table varies the probabilities of fixed outcomes. This allows us to elicit loss aversion from a greater possible range. Lottery A involves a small gain and a small loss, while both gain and loss are multiplied by 10 for Lottery B. The probability of the gain increases down the rows, increasing the difference in expected value between the lotteries. Under our *ceteris paribus* approach, the more loss averse a subject is, the larger will be the required difference in expected value to switch from Lottery A to Lottery B, so $LA = LA_A$.

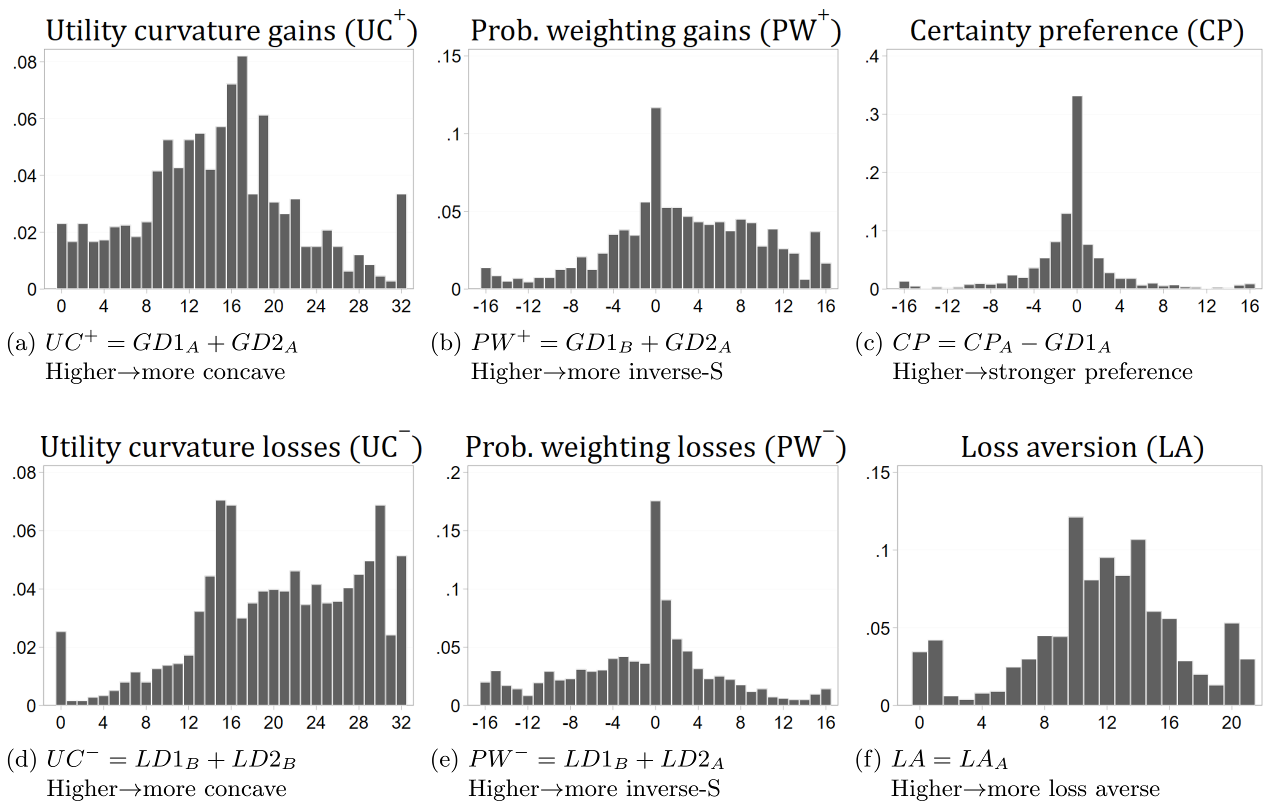
Figure 1 shows the distributions of our nonparametric preference measures based on the subjects' choices in the experiment. The distributions show few extreme or corner values, and most seem to be single-peaked. Recall that the gain (loss) utility curvature measure is a simple sum of the number of safe choices in tables GD1 and GD2 (LD1 and LD2). If we had chosen a too-narrow spectrum of the riskiness of the lotteries in those tables, we would observe high frequencies of subjects with UC^+ and UC^- at either 0 or 32. While such values occur, they are infrequent compared to other choice patterns and alternative measurement scales in the literature. The measures of PW^+, PW^-, and CP subtract the choices in two tables and thus could lead to a bunching around 0 if subjects chose the same number of safe choices in multiple tables. While such an effect only seems to occur in 10–20% of the probability weighting measures, more than 30% of subjects have a CP value of 0. Such an answer pattern in CP, however, is not necessarily a sign of inattentive choices by the subjects. In the CP measure, a value of 0 implies that subjects have no distinct preference for or against certainty, which makes a concentration of answers on this point natural. The nonparametric measure of loss aversion results from a single lottery table, which may raise concerns about corner solutions and a tendency of subjects to switch in the middle of the table. Both tendencies can be observed to a small degree but neither of them appear to dominate the choices of most subjects.

3.2.2 Parametric Preference Measures

For the parametric preference measures, we assume the functional forms detailed in Equations (5) and (6). With the help of these functional forms, a subject's choices in the preference measurement tables imply six indifference statements with six open parameters (γ^+, γ^-, β^+, β^-, λ and κ).[23] The tables are designed so that any combination of choices in the six tables will lead to a solvable system of equations as long as the subject did not make a choice that violated FOSD.

[23]We make the assumption that switching from Lottery A in one line to Lottery B in the next line implies indifference for a hypothetical lottery statement between those two lines. Consider, for example, a subject who chooses Lottery A in the first four rows of GD1 and Lottery B in all subsequent rows. This implies the preference relations $(2.50, 0.8, 2.00) \succ (5.00, 0.2, 1.00)$ and $(2.50, 0.8, 2.00) \prec (5.50, 0.2, 1.00)$. By our assumption, it also implies $(2.50, 0.8, 2.00) \sim (5.25, 0.2, 1.00)$.

Figure 1: Distributions of nonparametric preference measures



(a) $UC^+ = GD1_A + GD2_A$
Higher→more concave

(b) $PW^+ = GD1_B + GD2_A$
Higher→more inverse-S

(c) $CP = CP_A - GD1_A$
Higher→stronger preference

(d) $UC^- = LD1_B + LD2_B$
Higher→more concave

(e) $PW^- = LD1_B + LD2_A$
Higher→more inverse-S

(f) $LA = LA_A$
Higher→more loss averse

Note: Histograms include observations for all 1,730 subjects (both online and in-person) who completed the experiment. In each histogram, the y-axis is the fraction of subjects. Note that the scales of the y-axes differ for the different preference motives.

We solve the system by first determining (γ^+, β^+) and (γ^-, β^-) from the indifference relation implied by the choices in the gain domain tables and the loss domain tables, respectively. We designed the tables with two goals in mind. First, we want to identify a sufficiently broad range of parameter values such that utility could be both concave and convex and that probability weighting could be both inverse-S and S shaped. Second, we want to minimize the required number of decisions while also limiting the number of corner choices made by subjects. We thus calibrate our tables such that the implied parameters are centered around previous measures from the literature (e.g., Harbaugh et al., 2010; Tanaka et al., 2010; Tversky and Kahneman, 1992). Choices in the middle of the tables thus imply concave utility and inverse-S shaped probability weighting in the gain domain and linear utility and inverse-S shaped probability weighting in the loss domain. Once γ^+, γ^-, β^+ and β^- are calibrated from the choices in GD1, GD2, LD1, and LD2, we use the indifference relationships implied by choices in LA and CP to calculate λ and κ as well as the corresponding indices $\hat{\lambda}$ and $\hat{\kappa}$ (Equations (7) and (8)). Because these two parameters are dependent on the prior values of utility curvature and probability weighting, there is no clear range for them preset by the choice tables.

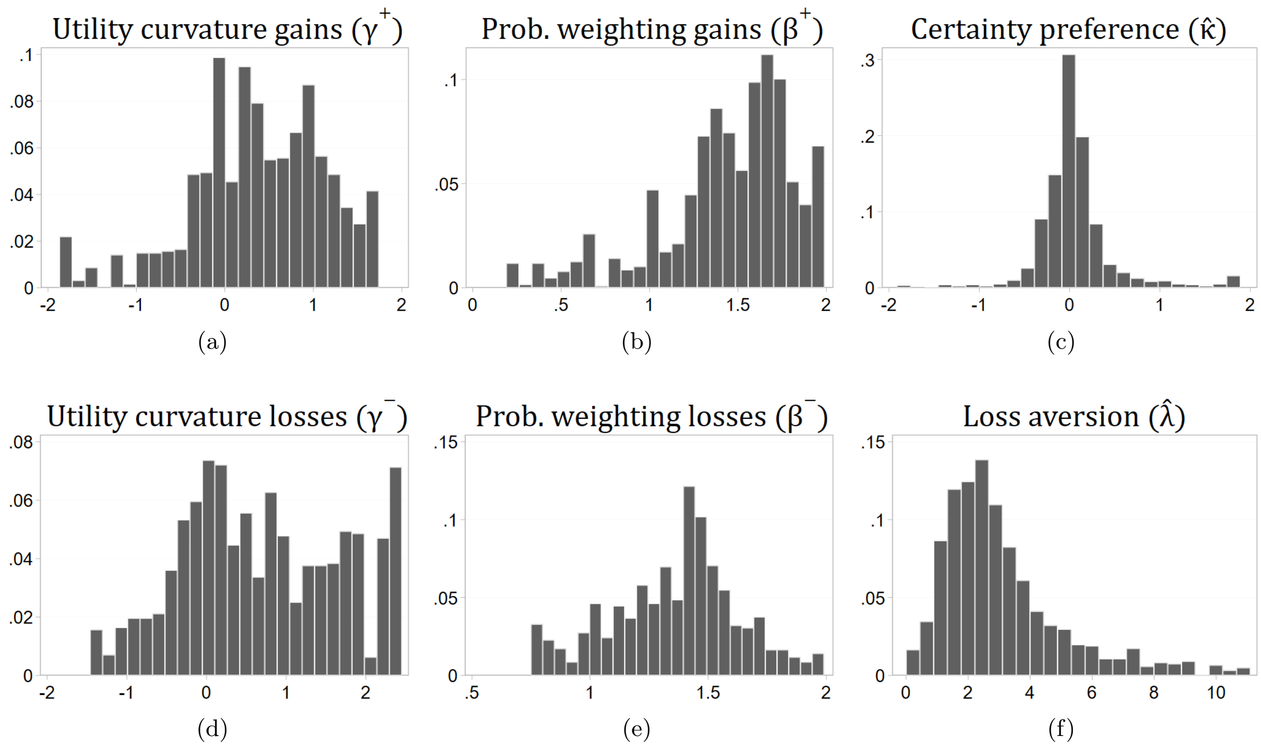
Distributions of the parametric preference measures are displayed in Figure 2. As with the nonparametric measures, they show relatively few corner solutions and subjects do not seem to be biased strongly towards choosing in the middle of the table. The distributions appear single-peaked. In the gain domain, we observe concave utility functions ($\gamma^+ > 0$) and inverse-S shaped probability weighting functions ($\beta^+ > 1$) for most subjects. In the loss domain, probability weighting is commonly inverse-S shaped ($\beta^- > 1$), but fewer subjects show concave utility ($\gamma^- > 0$). Nevertheless, the majority of subjects still display risk aversion due to utility curvature in the loss domain, which makes our results at odds with the common assumptions in models such as cumulative prospect theory. As expected from the nonparametric CP measure, the index of marginal preference for certainty is near zero for most subjects, indicating that this preference motive plays a minor role.[24] We report means and medians of the parametric preference measures in Table 2.[25] The means and medians for the mTurk sample and the university sample appear similar. Overall, the median subject has concave utility and inverse-S shaped probability weighting in both domains, is loss averse with $\hat{\lambda}$ of approximately 2.7, and does not have a distinct preference for or against certainty. These parameters are broadly consistent with other estimates in the literature.

We report the pairwise Pearson correlations of the parametric preference measures in Table 3. For these and all other inductive statistics using the preference measures, we standardize the measures such that they are measured in units of standard deviations (indicated by the subscript std). As would be expected from a behavioral perspective, the probability weighting parameters are positively and significantly correlated between the two domains ($\rho_{\beta^+,\beta^-} = 0.338$). For utility curvature, we observe a similarly strong, but negative correlation between domains ($\rho_{\gamma^+,\gamma^-} = -0.230$). This

[24] Other studies have found a preference for certainty among their subjects (e.g., Callen et al., 2014; Stango and Zinman, 2019). However, Vieider (2018) suggests that this could stem from randomness in subject responses. We are susceptible to this criticism as well—if choices were made randomly, roughly 65% of our subjects would be classified as having a preference for certainty. This is evident in Table 2, which shows that the mTurk sample (which is susceptible to more noisy decision making) demonstrates a slightly higher preference for certainty on average than the in-person sample. In addition, our elicitation procedure varies payouts while the elicitation procedure of Callen et al. (2014) varies probabilities, so differences in the elicitation tasks might also be the cause of the discrepancy in results.

[25] Summary statistics of the nonparametric measures are not particularly informative because the motives are ordinally scaled. We provide those summary statistics in Table D.1 of Appendix D. We also report the pairwise Pearson correlations of the nonparametric preference measures in Table D.2.

Figure 2: Distributions of parametric preference measures



Note: Histograms include observations for the 1,276 subjects (both online and in-person) who did not violate FOSD in their preference measurement choices. In plots (c) and (f), a small number of outliers make the central part of the distribution difficult to see. For display purposes, we exclude outliers from these plots. Certainty preference is plotted from -2 (2^{nd} percentile) to 2 (96^{th} percentile). We also omit loss aversion parameters above 11 (95^{th} percentile). In each histogram, the y-axis is the fraction of subjects. Note that the scales of the y-axes differ for the different preference measures.

Table 2: Summary statistics for parametric preference measures

	University Only $n = 326$		mTurk Only $n = 950$		Full Sample $n = 1,276$	
	Mean	Median	Mean	Median	Mean	Median
γ^+	0.38	0.45	0.37	0.39	0.38	0.39
β^+	1.36	1.46	1.47	1.54	1.44	1.53
$\hat{\kappa}$	0.06	0.01	0.23	-0.01	0.19	-0.00
γ^-	0.64	0.47	0.72	0.68	0.70	0.59
β^-	1.29	1.29	1.38	1.42	1.36	1.41
$\hat{\lambda}$	3.22	2.47	4.25	2.79	3.98	2.68

Note: The parameters $\gamma, \beta, \hat{\kappa},$ and $\hat{\lambda}$ denote our measures of utility curvature, probability weighting, certainty preference, and loss aversion, respectively. Superscripts $^+$ ($^-$) indicate that the parameter was elicited in the gain (loss) domain. The number of subjects summarized above is less than the total 1,730 experiment subjects because parametric measures are not calculable for subjects who make FOSD-violating choices. Due to the elicitation procedure and its associated calculations, some extreme values could appear for both $\hat{\kappa}$ and $\hat{\lambda}$. To limit the influence of such outliers on our results, we winsorize both measures at the 99^{th} percentile and $\hat{\kappa}$ values additionally at the 1^{st} percentile. We report summary statistics for the nonparametric preference measures in Appendix D.

Table 3: Correlation table for standardized parametric preference measures

		γ^+_{std}	β^+_{std}	$\hat{\kappa}_{std}$	γ^-_{std}	β^-_{std}	$\hat{\lambda}_{std}$
Utility curvature gains	γ^+_{std}	1.000	.	.	.	.	.
Probability weighting gains	β^+_{std}	0.288	1.000	.	.	.	.
Certainty preference	$\hat{\kappa}_{std}$	-0.043	0.039	1.000	.	.	.
Utility curvature losses	γ^-_{std}	-0.230	0.008	-0.045	1.000	.	.
Probability weighting losses	β^-_{std}	-0.002	0.338	-0.007	0.249	1.000	.
Loss aversion index	$\hat{\lambda}_{std}$	-0.292	-0.258	-0.004	0.195	-0.101	1.000

Note: Preference motives are standardized by subtracting the mean and dividing by standard deviation. For our sample size of 1,276 subjects with estimable parametric preferences, a correlation is statistically significant at the 10% level if it is larger than 0.047, at the 5% level if it is larger than 0.055, and at the 1% level if it is larger than 0.073 (in absolute values). We report correlations for the nonparametric preference measures in Appendix D.

provides evidence that there is an underlying motive of diminishing marginal sensitivity for some subjects (Tversky and Kahneman, 1992). However, this motive is not strong enough to lead to convex utility in the loss domain for most subjects. A more concave utility function is typically accompanied by more inverse S probability weighting ($\rho_{\gamma^+,\beta^+} = 0.288, \rho_{\gamma^-,\beta^-} = 0.249$), while loss aversion is negatively correlated with probability weighting and has a mixed association with utility curvature.

The calibrated parameters are also used in the structural models introduced in Section 2.2. As stated above, some of the models (namely RDEU and CPT) can utilize the elicited preference parameters directly, while others restrict some elements of the preference functional (such as setting $\beta = 1$ in the case of EU). For these restrictive models, we derive model-specific parameters taking the restriction(s) into account. Applying such restrictions can, however, lead to situations in which two choices by a subject imply different values for the same preference parameter. For example, in EU, a choice in GD1 can imply one value of γ^+_{EU}, while a choice in GD2 can imply a different value of γ^+_{EU}. A similar inconsistency can occur in DT models with conflicting estimates of β^+_{DT}. If such inconsistencies arise, we calculate the parameter separately for each relevant lottery table and use the average parameter value in the structural model.

Eliciting preference parameters from choice lists allows for a quick elicitation procedure based on relatively few choices of the subjects. One potential drawback is that using few choices to elicit risk preferences can lead to inference from noise in the decision process. Alternative procedures use a larger set of choices and base preference inference on maximum likelihood estimation (e.g., l'Haridon and Vieider, 2019). Such procedures, however, have the risk of leading to fatigue by experimental subjects which is an especially important consideration for experiments carried out online. We thus follow much of the recent literature (Callen et al., 2014; Sprenger, 2015; Tanaka et al., 2010) and use fewer choices with the potential drawback of over-interpreting noise. We discuss the robustness of our main findings in light of the potential for noisy decisions by subjects at the end of Section 4.2.

3.3 Insurance Task

In the insurance task, subjects make twelve insurance decisions. For each decision, they face the potential to lose \$3 of their \$5 typing task earnings under various loss probabilities. Loss probabilities are stated in percentage terms and visualized with an urn of 20 white and red balls, where drawing a red ball results in a loss. Subjects can buy a level of insurance ranging from 0% to 100% of the potential loss, in one-percent increments. In the event of a loss, the insurance covers the selected percentage of the \$3 loss.[26] Subjects change their insurance choice by moving a slider on the screen (screenshots of the task are in Appendix I. Every time the slider is set to a value, the screen displays the chosen level of insurance coverage, the corresponding insurance premium, and the covered and uncovered loss amounts in case of a loss.

We present the twelve insurance scenarios in random order. These scenarios differ in the loss probability and the relative loading charged for insurance. The combinations of loss probability and loading in our experiment are outlined in Table 4. In each insurance scenario, we hide and disable the "Next" button for ten seconds to encourage subjects to explore various coverage levels.

We plot the distributions of chosen coverage levels for each scenario in Figure 3. It is apparent that insurance for low-probability losses tends to result in subjects choosing corner solutions of full or no insurance. For the scenarios with a 5% (10%) loss probability, 36.8% (27.1%) of choices are for 0% coverage and 18.6% (17.5%) are for 100% coverage. This is consistent with prior studies showing a bimodal distribution of insurance demand at low probabilities (McClelland et al., 1993). As loss probabilities (and thus absolute premiums) increase, subjects choose corner solutions less often—at 70% loss probability, 71.7% of choices were for partial coverage. Insurance demand also appears

[26] One could be concerned that this response format, while being consistent with theoretical analyses of optimal insurance demand (see Schlesinger, 2013), is different from those insurance decisions commonly observed in real insurance markets where individuals typically choose between a small set of available policies. We also conduct the main analyses of this paper treating insurance demand more discretely by (i) rounding subjects' replies into bins of 25% coverage and (ii) rounding them into either no or full insurance coverage. For both discrete formats, we make a new set of structural model predictions. Results are consistent with the main text across all analyses. A more detailed description of these analyses and their results is given in Appendix G.

Table 4: Insurance scenarios faced by the experimental subjects.

		Loading factor (q)				
		0.80	1.00	1.25	1.50	2.50
Probability of loss (p)	5%				×	×
	10%		×	×	×	×
	20%			×	×	
	40%				×	
	70%	×	×	×		

Note: Subjects faced twelve insurance scenarios with a potential loss of \$3 and the probability of loss and loading factor displayed above.

to decrease as loading increases—the mean coverage level is 71.3% at a load of 0.80 and decreases monotonically to a mean of 31.5% at a load of 2.50. Interestingly, when loading is actuarially fair or better, subjects choose partial (no) insurance 65.1% (12.1%) of the time.

In Appendix D, we report the Spearman rank correlations of the coverage level selected for each insurance scenario. All coverage level choices are positively correlated with each other. Generally, choices over scenarios with a common probability have the highest correlation and correlations decrease as the difference in loss probabilities increases. Scenarios with common loading factors do not appear to be substantially more correlated than scenarios with different loading factors.

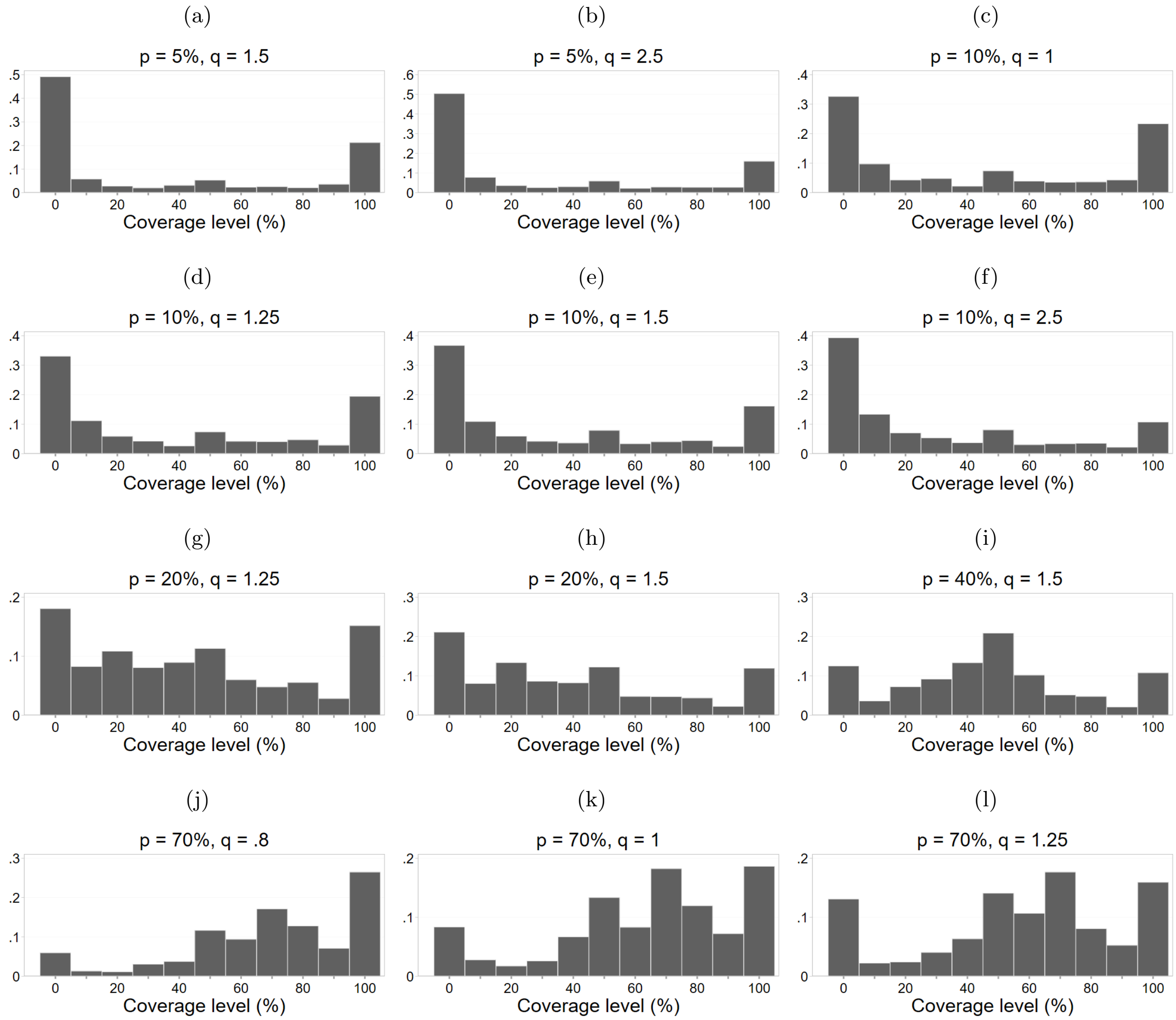
To illustrate the demand response to price explicitly, we plot average insurance demand as a function of the loading in Figure 4. Average insurance demand is downward-sloping in price at all loss probabilities, showing general adherence to the law of demand by our subjects. Further, insurance demand increases with loss probability at all loads except for a load of 2.50, where average insurance demand for loss probabilities of 5% and 10% is virtually identical. These graphical observations are corroborated by statistical analysis. A simple pooled OLS model estimated on all insurance choices (Table 5) shows statistically significant effects of both loading factor (negative) and loss probability (positive) on insurance demand.

4 Results

4.1 Predicting Insurance Demand from Preference Motives

We now consider whether the preference motives are correlated with insurance demand. For this purpose, we run a series of linear regressions with coverage level as the dependent variable (integers

Figure 3: Distributions of observed coverage levels chosen by scenario



Note: Histograms include observations for all 1,730 subjects (both online and in-person) who completed the experiment. In each histogram, the y-axis is the fraction of subjects. Note that the scales of the y-axes differ for the different scenarios.

between 0 and 100).[27] In the first analysis, reported in Table 6, we regress the coverage level on each preference motive separately, clustering standard errors by subject and correcting p-values for multiple hypothesis tests.[28] We include a fixed effect for each of the twelve insurance scenarios, so the coefficient estimates indicate whether a given preference motive can explain variation of the subjects' insurance demand within each scenario. The results indicate that utility curvature

[27]It could be argued both theoretically and from the empirical distributions that the dependent variable insurance demand is left- and right-truncated. When this is taken into account via a Tobit estimator, the results remain virtually unchanged in sign and significance as can be seen in Appendix E.

[28]In all our regressions involving multiple hypotheses, we correct p-values using the Šidák (1967) method. Details of each adjustment are in the respective table note.

Figure 4: Insurance demand reactions to loading and loss probabilities

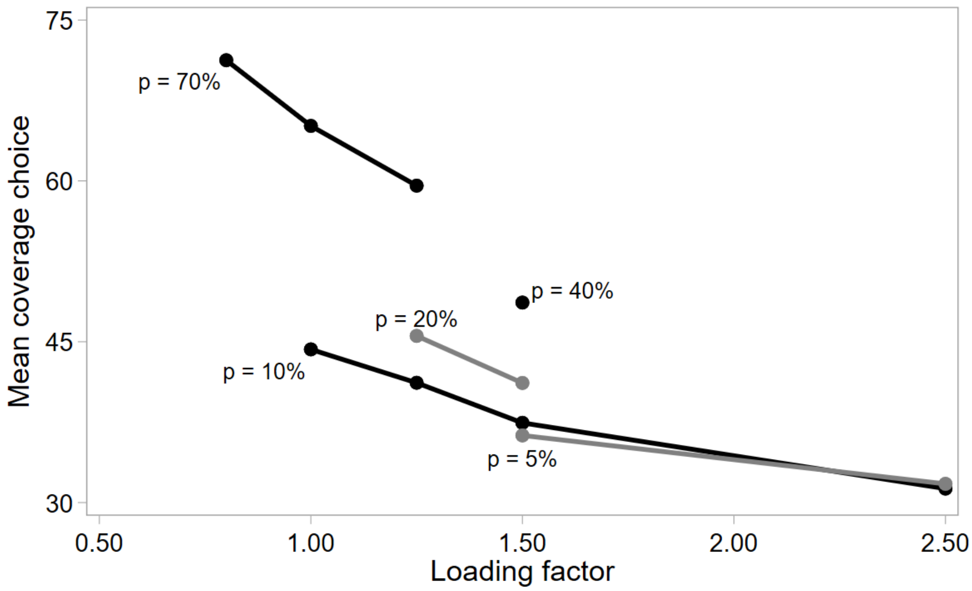


Table 5: Regression of coverage level on loss probability and insurance loading

	Coefficient	Std. err.
Probability of loss	0.365***	(0.016)
Loading factor	−8.185***	(0.400)
Constant	47.753***	(1.242)
R^2	0.11	
N choices	20,760	
N subjects	1,730	

Note: Dependent variable is the coverage level selected by the subject in the given insurance scenario. Coverage level ranges from 0 to 100 with a mean of 46.2. Probability of loss is 5, 10, 20, 40, or 70. Loading factors are 0.80, 1.00, 1.25, 1.50, or 2.50. Standard errors clustered by subject are in parentheses. Stars *** denote statistical significance at the 0.01 level.

in both domains, loss domain probability weighting, and loss aversion have statistically significant correlations with insurance demand, whether they are measured nonparametrically (Panel (a)) or parametrically (Panel (b)). For probability weighting in the gain domain, we also observe a significant positive effect when it is measured parametrically. A preference for certainty does not seem to have any significant effect on insurance demand. These results are in accordance with theory for most behavioral models which have been proposed in the literature, as long as these models do not feature a preference for certainty.

These regressions, however, do not account for the correlation between different preference motives. This can pose a significant bias for inference especially for the parametric measures,

Table 6: Regressions of coverage level on standardized preference motives separately

Panel (a): Nonparam. measures	(1)	(2)	(3)	(4)	(5)	(6)
Motive	UC^+_{std}	PW^+_{std}	CP_{std}	UC^-_{std}	PW^-_{std}	LA_{std}
Coefficient	1.36*	0.61	−0.63	1.49*	2.30***	2.09***
	(0.62)	(0.61)	(0.58)	(0.63)	(0.58)	(0.67)
FOSD violators	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.11	0.11	0.11	0.11	0.11	0.11
N choices	20,760	20,760	20,760	20,760	20,760	20,760
N subjects	1,730	1,730	1,730	1,730	1,730	1,730

Panel (b): Param. measures	(7)	(8)	(9)	(10)	(11)	(12)
Motive	γ^+_{std}	β^+_{std}	$\hat{\kappa}_{std}$	γ^-_{std}	β^-_{std}	$\hat{\lambda}_{std}$
Coefficient	1.70**	1.92**	−1.26	1.96**	1.90**	1.72*
	(0.68)	(0.69)	(0.78)	(0.72)	(0.66)	(0.80)
FOSD violators	No	No	No	No	No	No
R^2	0.13	0.13	0.12	0.13	0.13	0.13
N choices	15,312	15,312	15,312	15,312	15,312	15,312
N subjects	1,276	1,276	1,276	1,276	1,276	1,276

Note: Dependent variable is the coverage level selected by the subject in the given insurance scenario. The preference motive used as an explanatory variable is denoted in the first row of each panel. Motives are standardized by subtracting the mean and dividing by standard deviation. Parametric preference measures cannot be calculated for subjects who make FOSD-violating choices, so those subjects are excluded from regressions involving the parametric preference measures. For comparison, we also exclude FOSD violators from regressions using nonparametric preference measures, with results in Appendix F. All models contain fixed effects for each of the 12 insurance scenarios. In each panel, p-values have been adjusted using the Šidák (1967) method for the six hypotheses tested. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

which are calibrated dependent on the values of the other parameters. To address this, we conduct regressions in which all preference motives are included together. As with the regressions in Table 6, we include insurance scenario fixed effects and cluster standard errors by subject.

We report the results of these estimations in Table 7, with the nonparametric measures in columns (1) and (2) and the parametric measures in columns (3) and (4). In column (1), loss domain probability weighting and loss aversion significantly correlate with insurance demand. A linear term for probability weighting, however, does not correctly capture the theoretical prediction that those with S-shaped probability weighting should overweight lower probabilities but underweight higher probabilities. To account for this dynamic, in column (2) we introduce an interaction between probability weighting measures and an indicator for whether the probability of loss was greater than or equal to 40%. Consistent with theoretical predictions for inverse-S probability weighting, we find that probability weighting has a positive and significant correlation with insurance demand for scenarios with a low probability of loss. The effect is offset once the probability of loss is greater than or equal to 40%. This construction also leads to a negative and significant effect of gain domain probability weighting on insurance demand in high loss probability scenarios. There is, however, no significant effect in low probability scenarios.[29]

The results for the nonparametric preference motives are corroborated and extended by the results for the parametric preference motives, reported in columns (3) and (4) of Table 7. In these regressions, we only consider those subjects who do not violate FOSD because we cannot calibrate a preference functional for those who violate FOSD. For most preference motives, the coefficients increase in their value indicating a higher predictive power for the (standardized) parametric preference motives. The exceptions are the preference for certainty and probability weighting in the loss domain. However, when considering the estimation including the interaction structure in column (4), it is clear that probability weighting in both domains has the predicted effect on insurance demand. The biggest difference between the nonparametric and the parametric preference motives is the significant effect of gain domain utility curvature on insurance demand in the latter. The predictive power of this element is higher because we exclude FOSD-violating subjects and because the parametric structure imposes a nonlinear transformation.[30]

While the statistical significance of the coefficients in Tables 6 and 7 seems generally encouraging for the predictive power of behavioral decision theories on insurance demand, the estimated coefficients are modest in scale. Using coefficient estimates from Tables 5 and 7 allows for some back-of-the-envelope calculations regarding effect size. Increasing the loss aversion of a subject by one standard deviation has the same positive effect on insurance demand as decreasing the loading q by about 32 percentage points (2.60/8.18).

[29] One interpretation of this joint result is that there is a single underlying probability weighting motive which does not differ between the gain and loss domains. Our measures exhibit similar distributions between the two domains and correlate strongly with each other ($\rho = 0.338$, see Table 3), providing evidence of this relationship. Under this interpretation, our joint result implies a positive and significant effect of probability weighting on insurance demand at low probabilities and a negative and significant effect at high probabilities.

[30] For comparison, we conduct the nonparametric regressions from Tables 6 and 7 and restrict the sample to non-FOSD violating subjects. We report our estimations in Table F.1 of Appendix F. There is no substantial difference in results.

Table 7: Regressions of coverage level on all standardized preference motives jointly

Nonparam./Param.	Nonparametric		Parametric	
measures	(1)	(2)	(3)	(4)
$UC^+_{std}/\gamma^+_{std}$	0.81	0.81	2.34***	2.34**
	(0.69)	(0.69)	(0.74)	(0.74)
PW^+_{std}/β^+_{std}	−0.07	1.00	1.53	2.68**
	(0.68)	(0.85)	(0.76)	(0.95)
$CP_{std}/\hat{\kappa}_{std}$	−0.39	−0.39	−1.13	−1.13
	(0.65)	(0.65)	(0.79)	(0.79)
$UC^-_{std}/\gamma^-_{std}$	1.12	1.12	1.62	1.62
	(0.65)	(0.65)	(0.75)	(0.75)
PW^-_{std}/β^-_{std}	2.15***	3.28***	1.24	2.30*
	(0.62)	(0.79)	(0.72)	(0.93)
$LA_{std}/\hat{\lambda}_{std}$	1.91**	1.91**	2.60**	2.60**
	(0.69)	(0.69)	(0.87)	(0.87)
Prob ≥ 40		34.99***		37.05***
		(1.12)		(1.28)
Prob $\geq 40 \times PW^+_{std}/\beta^+_{std}$		−3.20***		−3.47***
		(0.83)		(0.96)
Prob $\geq 40 \times PW^-_{std}/\beta^-_{std}$		−3.41***		−3.18**
		(0.84)		(0.99)
FOSD violators	Yes	Yes	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject
R^2	0.12	0.12	0.14	0.14
N choices	20,760	20,760	15,312	15,312
N subjects	1,730	1,730	1,276	1,276

Note: Dependent variable is the coverage level selected by the subject in the given insurance scenario. Preference motives are standardized by subtracting the mean and dividing by standard deviation. Parametric preference measures cannot be calculated for subjects who make FOSD-violating choices, so those subjects are excluded from regressions involving the parametric preference measures. For comparison, we also exclude FOSD violators from regressions using nonparametric preference measures, with results in Appendix F. All models contain fixed effects for each of the 12 insurance scenarios. Column 1 contains only the nonparametric preference measures. Column 2 adds an interaction between the PW preferences and a dummy for "high probability" (Prob $\geq 40 = 1$ if the probability of loss is 40% or 70%). Columns 3 and 4 replicate columns 1 and 2 using the parametric preference measures. In each column, p-values have been adjusted using the Šidák (1967) method. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

4.2 Predicting Insurance Demand from Structural Models

We next assemble the preference motives into the seventeen structural models outlined in Table 1 and see how well these models predict insurance demand. For each model, we calculate the subject's optimal coverage level in each of the twelve insurance scenarios. The mean and standard deviation for the observed insurance demand and for each model's prediction are given in the first two columns of Table 8. Cursory observation shows that while some models predict fairly accurate average demand levels (such as EU, DT, RDEU, and CPT$^-$), other models predict too much (KR, CPT$^{\text{NLIB}}$, and almost all models with a preference for certainty) or too little (EV) demand.

To assess each model's predictive validity at the individual level, we first examine the correlation between the prediction and the observed insurance demand. The Pearson correlation coefficients over all 1,276 non-FOSD violating subjects are provided in column (3) of Table 8. The results show a positive and significant correlation between model predictions and observed demand for all decision models which do not feature probability weighting (EV, EU, and KR). Models with probability weighting do not significantly correlate with observed demand or even have a negative correlation. Adding a preference for certainty to any of the models decreases the correlation with observed demand. This corroborates the results in Section 4.1, which show that CP has little explanatory value in our setting. The correlations also show that using preference parameters elicited in the loss domain often leads to a slight increase in the explanatory value of a given structural model.

Positive and significant correlations show that some of the models can explain part of the variation in observed insurance demand. However, positive correlations do not imply predictive accuracy—for example, they ignore the absolute level of the prediction. An alternative procedure is to compare the models' predictions with randomly generated ones in a "horse race" (Gathergood et al., 2019). In our horse race (columns (4) to (6) of Table 8), we compare the predictive ability of three non-behavioral benchmarks to each of the structural models. In each column, we report the proportion of choices where the structural model denoted in the row outperforms a particular benchmark (i.e., is closer to the observed coverage level). The structural model is superior if the proportion exceeds 0.5. Our benchmark in column (4) is choosing a random coverage level from a uniform distribution, which we perform 1,000 times for each choice. None of the seventeen models we analyze can predict insurance demand better than a random number generator the majority of the time. Those models with a higher correlation coefficient generally perform better (with KR being the exception), but even EV and EU$^-$—the models with the highest correlation coefficients—do not outperform predicting coverage levels randomly. Columns (5) and (6) of Table 8 report similar horse race analyses, where the benchmark predictions are the overall average insurance demand (46.5%) or the average insurance demand within a scenario (ranging from 30.8% to 73.5%, depending on

Table 8: Goodness of fit analysis for structural models

				Horse Race		
	(1)	(2)	(3)	(4)	(5)	(6)
Model	Mean	SD	Correlation with observed	Random choice	Overall average	Scenario average
Observed	46.51	37.35	1.000	–	–	–
EV	16.67	31.18	0.261	0.461	0.469	0.398
EU^+	43.94	39.70	0.189	0.480	0.426	0.384
EU^-	38.47	40.93	0.205	0.470	0.429	0.385
DT^+	40.85	49.16	0.015	0.345	0.343	0.327
DT^-	44.87	49.74	−0.002	0.336	0.331	0.320
KR	88.83	31.50	0.053	0.319	0.320	0.291
$RDEU^+$	55.61	47.57	−0.064	0.331	0.314	0.304
$RDEU^-$	54.85	46.40	0.010	0.372	0.352	0.332
CPT^-	57.98	45.27	0.017	0.382	0.354	0.335
CPT^{NLIB}	73.61	38.31	−0.008	0.370	0.340	0.314
EV_{CP}	48.21	48.76	0.098	0.385	0.381	0.345
DT^+_{CP}	70.43	45.44	−0.025	0.312	0.310	0.293
DT^-_{CP}	70.77	45.28	−0.023	0.313	0.310	0.293
EU^+_{CP}	81.58	37.59	0.050	0.336	0.331	0.300
EU^-_{CP}	83.20	34.95	0.042	0.340	0.328	0.297
$RDEU^+_{CP}$	69.42	44.65	−0.069	0.311	0.299	0.285
$RDEU^-_{CP}$	71.16	43.06	−0.019	0.335	0.324	0.303

Note: For our sample size of 1,276 subjects for whom we can make parametric predictions, the correlation in column (3) is statistically significant at the 10% level if it is larger than 0.047, at the 5% level if it is larger than 0.055, and at the 1% level if it is larger than 0.073 (in absolute values). Table cells in the "Horse Race" columns are the frequency with which the specified model in each row predicts coverage level choice at least as well as the prediction rule in the column header. "Random choice" specifies a random uniform distribution of predicted coverage from 0 to 100, which we repeated 1,000 times for each choice (the average random prediction across repetitions ranged from 46.3% to 53.6%). "Overall average" specifies the average coverage level of 46.5% for every prediction. "Scenario average" specifies the average coverage level in each of the 12 scenarios as the prediction for all choices in that scenario. This ranges from 30.8% in the scenario with 10% loss probability and a loading of 2.5 to 73.5% in the scenario with 70% loss probability and a loading of 0.8.

the scenario), respectively. Both of these benchmark predictions perform better than the random choice benchmark and thus none of the structural models outperform them either.

The horse race results in Table 8 seemingly imply two contradictions. First, even models that show a correlation above 20% with observed insurance demand are not better at predicting demand than random choice. Second, the primitive probability weighting motive shows some explanatory power when correlated with insurance demand (Tables 6 and 7), but significantly decreases predictive power once it is integrated into a structural model. The reasons for both of these observations in part stem from the way the structural models respond to changes in loading

(q) and probability (p). We examine these responses in Figure 5, where we compare observed insurance demand to predicted demand over values of q and p (holding the other constant).

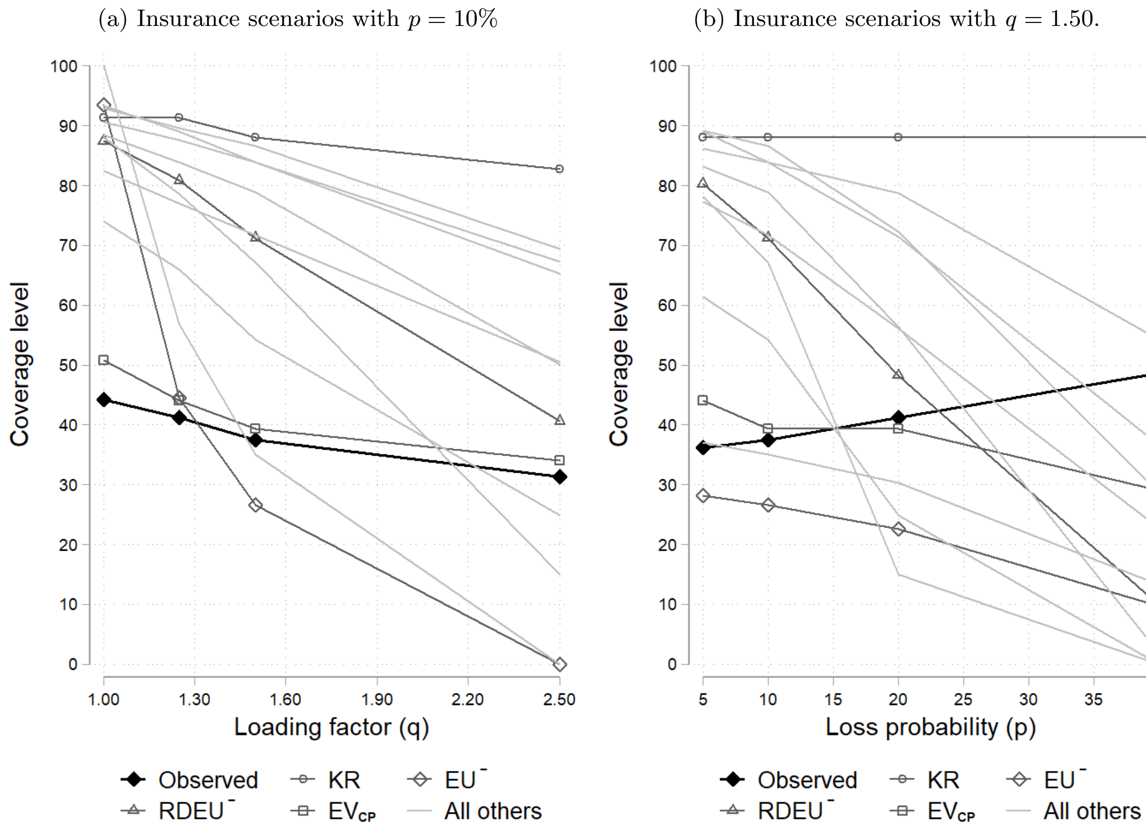
The first contradiction—a disconnect between correlations and horse race performance—is the result of models predicting a more extreme price response than what our subjects exhibit. Panel (a) of Figure 5 shows the change in insurance demand due to an increase in loading if the loss probability is fixed at $p = 10\%$. Both observed insurance demand and predicted insurance demand are downward-sloping as loading increases. This leads to a positive correlation between observed demand and model predictions. The magnitude of the price response, however, differs substantially—the observed demand curve is relatively flat, while many of the structural models (such as the highlighted EU^-) predict a much stronger reaction.[31] The predicted reaction will thus be more extreme than the observed reaction. Our data support this effect, as many of the models which perform badly in the horse race analysis also predict a higher proportion of corner solutions (0% and 100% coverage) than are observed empirically.

The extreme demand response is compounded by structural models which predict only corner solutions. Of the models analyzed here, only those featuring utility curvature (EU, RDEU, and CPT) can lead to an interior solution for optimal insurance demand. All other models will always predict either 0% or 100% coverage, which strongly disadvantages them in a horse race analysis.[32] This is also the reason why the average prediction of the EV_{CP} model looks very close to average observed demand (Figure 5), but individual predictions of the EV_{CP} model perform poorly in the horse race analysis. While the average prediction might be close to the average observed demand, all individual predictions will be corner solutions. Even in models which allow for interior predictions, corner solutions can still appear frequently. If insurance is simply too expensive (and the coverage level is predicted to be 0%) or when probability weighting or loss aversion feature strongly (and the coverage level is predicted to be 100%), the structural models will overshoot observed demand reactions and perform poorly in the horse race. Another contributing factor is that correlation

[31] To compare these price responses numerically, we regress predicted and observed insurance demand on loss probability p and loading q as in Table 5. In the "Predicted" regression, the dependent variable is the predicted demand according to EU^- and the estimated coefficient on Loading is -55.69. In the "Observed" regression, the dependent variable is the observed insurance demand (excluding FOSD violating subjects) and the estimated coefficient on Loading is -9.16. Thus, the predicted reaction to price is 6.08 times what is observed.

[32] To see this, observe in Table 1 that models without utility curvature have linear target functions in α and will thus always lead to corner solutions. Utility curvature makes the target functions non-linear and potentially concave in α, allowing for interior solutions.

Figure 5: Observed insurance demand and model predictions over values of q and p



Note: Figure displays observed and predicted insurance demand as a function of premium loading q when the loss probability is fixed at $p = 10\%$ (panel (a)) and as a function of loss probability p when the premium loading is fixed at $q = 1.50$ (panel (b)). Observed demand (thick black line) is reported for all 1,276 non FOSD-violating subjects. The other lines in the figure show the average predictions of the seventeen structural models listed in Table 1 using the individual parameters for each of the 1,276 subjects.

coefficients are not affected by the absolute levels of the predicted insurance demand. In the horse race analysis, however, absolute levels directly affect the relative performance of each model. As such, any model which on average predicts too much or too little insurance demand correlates positively with observed demand, but performs poorly in the horse race.

The second contradiction—probability weighting performing well until it is integrated into a structural model—stems from the difference in explaining demand variation between subjects and explaining demand variation between scenarios. In panel (b) of Figure 5, we display the observed and predicted demand response to changes in the loss probability at a fixed premium loading of $q = 1.50$. As demonstrated in Figure 4, observed insurance demand increases with the loss probability. However, in models with probability weighting (such as the highlighted RDEU$^-$) predicted insurance demand decreases with increasing loss probability as long as the probability weighting function is inverse-S shaped.[33] This is the most common shape of the weighting function elicited from our preference elicitation tasks, so all structural models featuring probability weighing predict people will buy more insurance when the probability of loss is low. This discrepancy is the reason for low or even negative correlations between the models' predictions and observed demand. The structural models without probability weighting do not predict a negative influence of loss probability on insurance demand (such as KR) or do so to a smaller extent (such as EU). Their predictions thus correlate positively with observed demand across scenarios.

The analyses of Table 6 and columns (1) and (3) of Table 7 show a positive correlation between probability weighting and insurance demand. However, because probability weighting in those analyses is a fixed parameter for each subject and does not further interact with the decision situation, they only examine whether the preference motive can explain variation in insurance demand between subjects within each scenario. Even when an interaction structure with the loss probability is specified in columns (2) and (4) of Table 7, the analysis features insurance scenario fixed effects such that again only between-subject variation is studied. For between-subject variation, probability weighting has explanatory power. When considering the results of the two analyses in combination, we can thus conclude that probability weighting does influence insurance demand, but that an additional mechanism connected to loss probabilities is likely also at work. The nature of this additional mechanism is a compelling question for future research.

One possible explanation for the low observed correlations could be randomness in the insurance decisions. To investigate this, we divide the subjects in our sample into four groups based on the number of times the subject violated the law of demand (increasing insurance demand at higher loads). We consider subjects who never violated the law of demand as exhibiting the most consistent choices, and subjects who violated three or more times as making the least consistent choices (the other two groups being subjects who violated only once and subjects who violated twice). Each group comprises about a quarter of the full sample. For each subsample, we calculate the correlation between observed demand and each structural model's predicted demand, as in column (3) of Table 8. Our findings are in Table F.2 of Appendix F. Even for the most consistent group, the relationships between observed and predicted insurance demand are moderate and, in line with

[33]Technically, the required condition is not an inverse-S shape, but decreasing relative overweighting of the probability weighting function. See Jaspersen, Peter, and Ragin (2020) for a discussion of this property and a formal derivation in the RDEU framework.

our analysis above, no model has a higher correlation than expected value maximization. The only difference we find is that insurance demand for the most consistent subjects now has small positive correlations with models incorporating probability weighting. The least consistent subjects (i.e., those who violate the law of demand three or more times) tend to make decisions which have much less correlation with structural model predictions.

5 Robustness: Eliciting Preferences Using Insurance Choices

Our results show that structural models estimated from lottery choices have limited ability to predict insurance choices. This suggests that we cannot yet identify a portable model of risk attitudes that can be applied across these contexts.

An open question, though, is whether this is because structural models do not adequately capture insurance decisions or because preferences do not translate well across domains. Our setting addresses some obvious concerns with using models across domains by having the choices made in the same experiment, at nearly the same time and for similar financial stakes. Nonetheless, it is possible that other issues limit the portability across contexts, and the structural models have strong predictive power within a particular financial context (e.g., lottery choices or insurance).

In this section, we test this possibility by analyzing the predictive power of structural models using only the insurance choice data. This exercise was not part of our original pre-specified research plan, but strikes us as valuable for exploring the implications of our main results. However, we focus our attention on estimating a more limited set of structural models than in our main analysis because the design of insurance questions does not cleanly identify the full range of models considered, and because this analysis was not pre-specified.

Our goal is to identify a subset of the insurance choices made by subjects that can be used to fit a structural model and then use the resulting fitted model to predict the choices that subject made under other insurance conditions. We focus on the choices subjects made when the probability of loss was 10%, for which they saw prices with four different loading factors: 1.00, 1.25, 1.50 and 2.50 (i.e., ranging from actuarially fair to "high load" insurance). We use the choices the subjects made at the middle two loads of 1.25 and 1.50 as our observed data for the modeling exercise, and then use the model to predict the choices under the other two loads of 1.00 and 2.50. We adopt the structural model of Barseghyan et al. (2013), which incorporates both a standard utility function and generalized probability distortions without assuming a form on the probability weighting function. The model of the (decision) utility for an insurance choice in this framework is

$$\Omega(p)u\left(w-(1-\alpha)L-\alpha qpL\right)+\left(1-\Omega(p)\right)u(w-\alpha qpL), \tag{9}$$

where $\Omega(p)$ is the generalized probability distortion.

If we maintain our assumptions from the original analysis that subjects' choices are non-stochastic, we can use an individual's choices at the two intermediate levels to identify the model at the individual level. Specifically, we use the result of Jaspersen et al. (2020), who show that two coverage level decisions at two different values of $q > 1$ are sufficient to elicit $\Omega(p)$ and u, provided that u can be described by a parametric form with a single parameter that is monotonically related to the function's curvature. The condition for this identification strategy is that subjects purchase more insurance at lower levels of q. There are three cases where this strategy does not work. First, for subjects who choose full insurance at both of the intermediate loads, the model cannot separately identify a probability distortion and utility curvature. For these cases, we code the choice in the $q = 1.25$ scenario as 99% coverage and the choice when $q = 1.50$ as 98% coverage. This results in a strong level of utility curvature and almost no probability distortion (i.e., Ω is close to p). Second, subjects who choose higher levels of insurance at the 1.50 load than the 1.25 load cannot be rationalized by any parameter combination in Equation (9). For these cases, we use the value of Ω which leads to the smallest distance between the two utility curvature parameters implied by the insurance choices. Third, for the corner solution of no insurance coverage at both intermediate loads, we set $\Omega = p$ and utility curvature to the parameter which implies $\alpha^* = 0$ at $q = 1.25$. In Appendix H, we show that all the results in this section hold if we instead restrict our attention to the subset of participants whose choices can be easily rationalized with the model.

Of course, in reality individual insurance decisions likely reflect some noise in the decision process. As a result, structural models fit at the individual level may make excessively noisy out-of-sample predictions as well. In order to allow for that possibility, while keeping our approach simple and transparent, we also present results at higher levels of aggregation. Specifically, we group subsets of participants together and then fit the model to the average level of insurance at each load across the subjects in that subgroup. We use three different levels of aggregation:

(a) representative agent using all participants, (b) averaging coverage levels between $q = 1.25$ and $q = 1.50$ at the individual level and then separating the distribution into quintiles, and (c) plotting each subject's coverage choices for $q = 1.25$ and $q = 1.50$ and dividing the plot into a 5x5 grid based on 20% coverage level intervals. Combining these aggregated approaches with the individual-level parameters allows us to span a range of models from complete homogeneity where all variation in choices is assumed to be individual-level noise (the representative agent model) to a fully heterogeneous model with an assumption of zero noise.

We compare the out-of-sample predictions from these fitted structural models to two simpler approaches: (a) predictions based on average demand under the intermediate loads (i.e., no differentiation by load) and (b) predictions based on a linear extrapolation of demand with respect to load.[34] We find that the simple predictions based on average demand have the best fit, but that the structural model predictions at high levels of aggregation have very similar fit statistics. The results of this analysis can be seen in Table 9. The three "Individual Distance" columns show the mean squared deviations between predicted and selected insurance under each of the three prediction approaches (average, linear extrapolation, Equation (9)) for the different levels of aggregation. Here we see that the best fit is rendered by predictions based on average choices on the individual-level of aggregation. However, using average predictions gives very similar fit at either the grid or quintiles level of aggregation as well. The structural model at the individual level fits much worse than any other prediction approach. Yet when the structural model is fit at the level of quintiles (where each prediction approach is making only five distinct predictions for each out-of-sample load), it achieves a level of individual fit very similar to the average-demand predictions. The linear extrapolation outperforms the structural model at the individual level and slightly underperforms it at higher levels of aggregation. The three "Population Distance" columns show that these basic patterns hold if instead we use a population-level measure of goodness of fit based on comparing the actual and predicted CDF rather than individual-level deviations.

[34] If the third derivative of the utility function is negligible, insurance demand according to Equation (9) can be approximated by $\alpha^* = 1 + \frac{1}{r(1-\Omega(p))L} - \frac{p}{(r\Omega(p)(1-\Omega(p))L)}q$ which is equivalent to the linear extrapolation model. Because the approximation is fairly accurate in our setting, linear extrapolation based on the load and Equation (9) are close in their predictions of insurance demand in many cases. However, there are some important limitations to this. When insurance demand is low and the slope of demand in loading is flat, the approximation does not work and the models will make substantially different predictions. Further, in cases where we observe people who show demand that *increases* with load, the linear extrapolation will extrapolate that pattern, while Equation (9) requires predictions that obey the law of demand. See Appendix C for a more detailed discussion.

Table 9: Goodness of fit analysis at 10% loss probability for structural models calibrated with insurance choices

	Individual Distance			Population Distance		
Prediction Approach:	Average	Linear	Eq. (9)	Average	Linear	Eq. (9)
Aggregation Level						
Representative Agent	0.150	0.149	0.147	0.584	0.547	0.558
Quintiles	0.081	0.094	0.084	0.231	0.283	0.261
Grid	0.080	0.136	0.128	0.308	0.229	0.335
Individual	0.078	0.137	0.266	0.127	0.116	0.396

Note: The table reports the results of our calibration analysis in which we use the coverage level decisions in the scenarios with loss probability 10% and loading factors 1.25 and 1.50 to calibrate the decision model in Equation (9) and use it to predict insurance demand in the scenarios with loss probability 10% and loading factors 1.00 and 2.50. We offer two non-utility models for comparison. The first non-utility model uses the average demand for loading factors 1.25 and 1.50 to predict demand in the other two scenarios. The second non-utility model calibrates an individual linear demand function $\alpha = bq + c$ for predictions. Individual distances are Euclidean distances, population distances are Kolmogorov-Smirnoff distances.

This evidence provides a mixed message for the potential value of structural models estimated using only insurance data. On the one hand, these results suggest that structural models which use aggregation and other approaches to allow for individual-level noise can make reasonably good predictions. On the other hand, the structural approach never outperforms the simple average predictions, even though those average predictions do not change with the loading. So the structural model does not add predictive value beyond the underlying data being used to estimate the model.

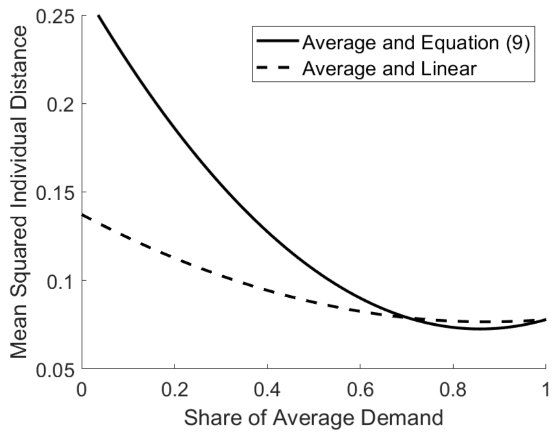
The fact that the best out-of-sample predictions come from simply using the average observed demand is disappointing, since the ultimate goal of any modeling exercise is to say something meaningful about how demand responds to changes in the economic environment. An interesting question is whether predictions could be enhanced by combining the noisier structural model or linear extrapolation predictions with the stable average predictions. Figure 6 shows the average individual-level squared deviations for predictions that are a convex combination of the average prediction and one of these two other price-responsive predictions. The graph shows that the best out-of-sample fit actually comes from a mix that is predominantly the simple average but has a small mix of the structural model. Of course, knowing how much to mix requires out-of-sample data, limiting the value of this exact approach for counterfactual prediction exercises. However, it suggests that there could be some value in modeling approaches that temper structural predictions that are responsive to economic environments with some form of average "stickiness."

It is also worth highlighting, though, that even when the structural model makes reasonable out-of-sample predictions, the estimated parameters of the model are rather extreme. In Appendix Figure H.2, we show scatter plots of the estimated utility curvature and probability distortion terms for the structural model at the different levels of aggregation. In the aggregate to quintiles, where the structural model has the best out-of-sample predictive fit, the fitted parameter pairs generally involve high levels of risk aversion and significantly underweighted probability distortions. That pattern is not consistent with the findings of Barseghyan et al. (2013), who estimated strongly overweighted probability distortions and modest amounts of risk aversion.[35] The key issue is that in our setting, the model is being asked to fit a pattern where many participants show little responsiveness to prices and moderate overall levels of insurance coverage. The low price responsiveness pushes the structural model to require more risk aversion. However, at high levels of risk aversion we would also expect people to purchase nearly full insurance, so the model compensates by estimating strong probability underweighting. While that combination creates a reasonable fit to our data, it is unlikely to have meaningful normative content. More generally, this observation combined with the rest of the analysis in this section suggests to us that the path forward for structural modeling of insurance decisions should likely incorporate hybrid approaches that model decisions as coming from some combination of economic fundamentals and simpler heuristics.

Finally, one might wonder how valuable the structural modeling approach is if we focus on the subset of subjects who make choice patterns that are most consistent with the structural model assumptions. In our setting, these are subjects who have a clear downward-sloping demand curve over the two intermediate loads. In Appendix H, we show that all of the patterns we just discussed for the full sample hold even when we limit to this group of subjects. In fact, in this subset the average demand outperforms the structural model more clearly. Ultimately, we conclude that the structural model applied within insurance choices can make reasonable predictions at the right level of aggregation to account for noise, but does not add value beyond simply using the underlying data used to estimate the model.

[35]Our setting where people make decisions about a continuous level of insurance coverage provides more data on the degree of responsiveness to prices than the discrete choices over a limited set of deductibles that are available in the empirical setting analyzed by Barseghyan et al. (2013)

Figure 6: Evaluation of predictive accuracy for mixture of models



Note: Figure displays the distance between predicted insurance demand and empirically-observed choices of two mixture models for possible values of the mixture parameter. Individual distance is measured as the Euclidean distance.

6 Discussion and Conclusion

The results of our experiment call into question the ability of common consequentialist structural models of risk preferences to predict insurance demand. We find moderately-sized and statistically significant predictive power for the three most commonly discussed primitive preference motives of insurance demand: utility curvature, probability weighting, and loss aversion. Despite these correlations, however, assembling these motives into structural decision models leads to poor predictions in our setting, particularly across different insurance scenarios. We find somewhat more promising results for structural models fit within insurance data, but even in those cases simpler approaches that extrapolate from the raw data perform at least as well.

Until we have a better understanding of the decision processes at play in insurance choices, some caution is warranted in using structural models of insurance demand. Yet this does not imply that there is no role for counterfactual predictions in insurance markets. Prior research has shown that insurance choices correlate to some degree across contexts. Our work adds to that point and helps to highlight that it may be possible to use data on insurance choices to predict choices in somewhat different economic conditions. The key implication, though, is that these predictions may be better if they are based on the direct patterns of observed choices rather than structural models of risk attitudes.

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Appendices

A Choice tables for preference elicitation

Table A.1: Preference motive elicitation tables for certainty preference and loss aversion

	Certainty Preference Table (CP)				**Loss Aversion Table (LA)**			
	Lottery A	Lottery B			Lottery A		Lottery B	
p	1.00	0.20	0.80	\$	+0.50	−0.20	+5.00	−2.00
\$	2.00	2.50	1.00	p	*0.00*	*1.00*	*0.00*	*1.00*
	2.00	4.50	1.00		0.05	0.95	0.05	0.95
	2.00	4.75	1.00		0.10	0.90	0.10	0.90
	2.00	5.00	1.00		0.15	0.85	0.15	0.85
	2.00	5.50	1.00		0.20	0.80	0.20	0.80
	2.00	6.00	1.00		0.25	0.75	0.25	0.75
	2.00	6.50	1.00		0.30	0.70	0.30	0.70
	2.00	7.00	1.00		0.35	0.65	0.35	0.65
	2.00	8.00	1.00		0.40	0.60	0.40	0.60
	2.00	9.00	1.00		0.45	0.55	0.45	0.55
	2.00	10.00	1.00		0.50	0.50	0.50	0.50
	2.00	12.00	1.00		0.55	0.45	0.55	0.45
	2.00	15.00	1.00		0.60	0.40	0.60	0.40
	2.00	20.00	1.00		0.65	0.35	0.65	0.35
	2.00	30.00	1.00		0.70	0.30	0.70	0.30
	2.00	60.00	1.00		0.75	0.25	0.75	0.25
					0.80	0.20	0.80	0.20
					0.85	0.15	0.85	0.15
					0.90	0.10	0.90	0.10
					0.95	0.05	0.95	0.05
					1.00	*0.00*	*1.00*	*0.00*

Note: A row in each of the two tables above represents a choice set presented to the subject. In the certainty preference table (left), row values are the possible dollar outcomes and column headings are the probabilities of obtaining the given outcome. In the loss aversion table (right), column headings are the dollar outcomes and row values are the probabilities of obtaining each outcome. Losses and gains are relative to the \$5.00 earned in the real effort task to begin the experiment. Italicized rows indicate a stochastically-dominated choice.

Table A.2: Preference motive elicitation tables for utility curvature and probability weighting in the gain and loss domains

	Gain Domain Table 1 (GD1)					**Gain Domain Table 2 (GD2)**			
	Lottery A		Lottery B			Lottery A		Lottery B	
p	0.2	0.8	0.2	0.8	p	0.9	0.1	0.9	0.1
$	*2.50*	*2.00*	*2.50*	*1.00*	$	*2.00*	*1.50*	*2.00*	*0.50*
	2.50	2.00	4.50	1.00		2.00	1.50	2.05	0.50
	2.50	2.00	4.75	1.00		2.00	1.50	2.10	0.50
	2.50	2.00	5.00	1.00		2.00	1.50	2.15	0.50
	2.50	2.00	5.50	1.00		2.00	1.50	2.20	0.50
	2.50	2.00	6.00	1.00		2.00	1.50	2.25	0.50
	2.50	2.00	6.50	1.00		2.00	1.50	2.30	0.50
	2.50	2.00	7.00	1.00		2.00	1.50	2.35	0.50
	2.50	2.00	8.00	1.00		2.00	1.50	2.45	0.50
	2.50	2.00	9.00	1.00		2.00	1.50	2.55	0.50
	2.50	2.00	10.00	1.00		2.00	1.50	2.65	0.50
	2.50	2.00	12.00	1.00		2.00	1.50	2.80	0.50
	2.50	2.00	15.00	1.00		2.00	1.50	3.00	0.50
	2.50	2.00	20.00	1.00		2.00	1.50	3.25	0.50
	2.50	2.00	30.00	1.00		2.00	1.50	3.50	0.50
	2.50	2.00	60.00	1.00		2.00	1.50	3.75	0.50
	Loss Domain Table 1 (LD1)					**Loss Domain Table 2 (LD2)**			
	Lottery A		Lottery B			Lottery A		Lottery B	
p	0.1	0.9	0.1	0.9	p	0.8	0.2	0.8	0.2
$	*-0.75*	*-0.25*	*-0.75*	*-0.50*	$	*-1.75*	*-0.10*	*-1.75*	*-0.50*
	-1.20	-0.25	-0.75	-0.50		-1.95	-0.10	-1.75	-0.50
	-1.25	-0.25	-0.75	-0.50		-2.00	-0.10	-1.75	-0.50
	-1.30	-0.25	-0.75	-0.50		-2.05	-0.10	-1.75	-0.50
	-1.40	-0.25	-0.75	-0.50		-2.10	-0.10	-1.75	-0.50
	-1.50	-0.25	-0.75	-0.50		-2.15	-0.10	-1.75	-0.50
	-1.60	-0.25	-0.75	-0.50		-2.20	-0.10	-1.75	-0.50
	-1.70	-0.25	-0.75	-0.50		-2.30	-0.10	-1.75	-0.50
	-1.85	-0.25	-0.75	-0.50		-2.40	-0.10	-1.75	-0.50
	-2.00	-0.25	-0.75	-0.50		-2.50	-0.10	-1.75	-0.50
	-2.15	-0.25	-0.75	-0.50		-2.60	-0.10	-1.75	-0.50
	-2.35	-0.25	-0.75	-0.50		-2.75	-0.10	-1.75	-0.50
	-2.65	-0.25	-0.75	-0.50		-2.90	-0.10	-1.75	-0.50
	-3.00	-0.25	-0.75	-0.50		-3.05	-0.10	-1.75	-0.50
	-3.40	-0.25	-0.75	-0.50		-3.25	-0.10	-1.75	-0.50
	-4.00	-0.25	-0.75	-0.50		-3.50	-0.10	-1.75	-0.50

Note: A row in each of the four tables above represents a choice set presented to the subject. Row values are the possible dollar outcomes from the displayed lotteries. Column headings are the probability of obtaining the given outcome. Gains and losses are relative to the $5.00 earned in the real effort task to begin the experiment. Italicized rows indicate a stochastically-dominated choice.

In Table A.3, we report the Spearman rank correlations of the lottery choices. We designed the tables so that they measure different aspects of the preference functional, so the correlations are relatively low. One might be concerned that low correlations are the result of random choice. The high correlation between the choices in the GD1 and CP lottery tables, however, indicates deliberate behavior by subjects, as the lotteries in these two tables are similar.

Table A.3: Spearman rank correlations of lottery choices

	GD1	GD2	LD1	LD2	LA
GD1	1.000	.	.	.	.
GD2	0.046	1.000	.	.	.
LD1	-0.266	0.110	1.000	.	.
LD2	-0.010	-0.161	0.148	1.000	.
LA	0.197	0.202	0.011	0.037	1.000
CP	0.605	0.015	-0.231	0.028	0.182

Note: For our sample size of 1,730 subjects, a correlation is statistically significant at the 10% level if it is larger than 0.040, at the 5% level if it is larger than 0.047, and at the 1% level if it is larger than 0.062 (in absolute values).

B Theory on preference elicitation

This paper uses the same experimental data and preference measures as the study in Jaspersen, Ragin, and Sydnor (2020). Since the analysis there does not consider the insurance demand tasks, both studies analyze distinct research questions. However, because they both use the same preference measures, the contents of this appendix are to a large part identical to a corresponding appendix in Jaspersen, Ragin, and Sydnor (2020).

B.1 Nonparametric Preference Measures

There are six tables in the elicitation procedure: GD1, GD2, LD1, LD2, LA and CP. The first five are repeated choices between two binary lotteries, the last one is the choice between a binary lottery and a certain outcome. The choices are depicted in Figure B.1.

In accordance with Section 2.1, $i = 1$ and $j = 2$ in tables GD1, GD2, and LA and $i = 2$ and $j = 1$ in tables LD1 and LD2.

B.1.1 Utility Curvature and Probability Weighting in the Gain Domain

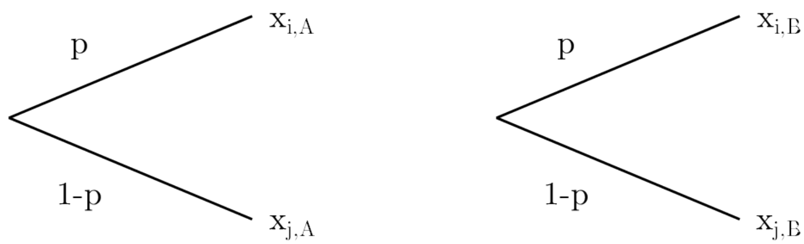
Assuming a full CPT preference functional, we evaluate the lotteries in the GD1/ GD2 tables as $EV = w^+(p)u^+(large\ gain) + (1 - w^+(p))u^+(small\ gain)$. In these tables, only the large gain of Lottery B changes. Adopting the notation that the large gain is x_2 and the small gain is x_1, the indifference large gain on Lottery B fulfills

$$w^+(p)u^+(x_{2,A}) + (1 - w^+(p))u^+(x_{1,A}) = w^+(p)u^+(x_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \tag{B.1}$$

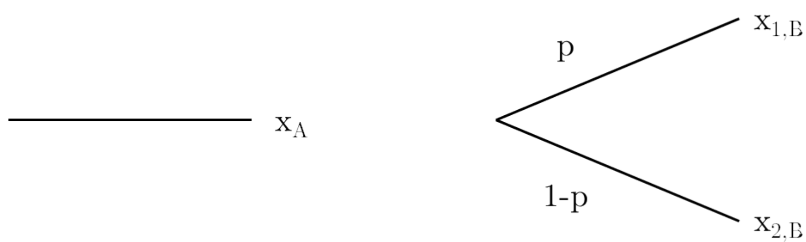
We first consider the *ceteris paribus* elicitation of utility curvature. When changing the indifference value for $x_{2,B}$ to $\hat{x}_{2,B}$ and keeping everything but the utility function fixed, we signify the change in the utility function by the transformation $g(\cdot)$ of which we know that it must be increasing. The new indifference relationship implies

$$w^+(p)g(u^+(x_{2,A})) + (1 - w^+(p))g(u^+(x_{1,A})) = w^+(p)g(u^+(\hat{x}_{2,B})) + (1 - w^+(p))g(u^+(x_{1,B})). \tag{B.2}$$

Figure B.1: Graphical illustrations of the different choice tables



(a) Schematic representation of choices in the GD1, GD2, LD1, LD2 and LA tables.



(b) Schematic representation of choices in the CP table

From $g'(\cdot) > 0$, we know that $g(u^+(\hat{x}_{2,B})) - g(u^+(x_{2,B})) > 0$. We can thus see from (B.2) that

$$w^+(p)g(u^+(x_{2,A})) + (1 - w^+(p))g(u^+(x_{1,A})) > w^+(p)g(u^+(x_{2,B})) + (1 - w^+(p))g(u^+(x_{1,B})). \quad \text{(B.3)}$$

We proceed by using w^+ to define ω as a probability measure of the random variables $\tilde{x}$ and, respectively, $u^+(\tilde{x})$. This can be done because $w^+(p) \in [0, 1]$ and all payoffs are in the gain domain, so the decision weights add to one. Under this probability measure, we know from (B.1) that the expectation of $u^+(\tilde{x})$ is equal between lotteries A and B. From p being equal for both lotteries, we further know the skewness of $u^+(\tilde{x})$ under the probability measure ω to be equal between both lotteries (Ebert, 2015). From Chiu (2010) we thus know that Lottery B is a mean-preserving spread in $u^+(\tilde{x})$ under the probability measure ω. As such $\mathbb{E}_\omega[g(u^+(\tilde{x}_A))] > \mathbb{E}_\omega[g(u^+(\tilde{x}_B))]$ is true if and only if $g'' < 0$. Thus, a higher value of $x_{2,B}$ in GD1 and GD2 implies more concave utility curvature.

For the *ceteris paribus* elicitation of the probability weighting function, we again consider the indifference relationship at two points $x_{2,B}$ and $\hat{x}_{2,B}$ with $x_{2,B} < \hat{x}_{2,B}$. The respective probability weighting functions for the two indifference relationships are w^+ and $\hat{w}^+$. We have the two equalities:

$$w^+(p)u^+(x_{2,A}) + (1 - w^+(p))u^+(x_{1,A}) = w^+(p)u^+(x_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \quad \text{(B.4)}$$

$$\hat{w}^+(p)u^+(x_{2,A}) + (1 - \hat{w}^+(p))u^+(x_{1,A}) = \hat{w}^+(p)u^+(\hat{x}_{2,B}) + (1 - \hat{w}^+(p))u^+(x_{1,B}). \quad \text{(B.5)}$$

We subtract (B.4) from (B.5) and add $\hat{w}^+(p)[u(x_{2,B}) - u(x_{2,B})]$ on the right hand side to obtain

$$\begin{aligned}[\hat{w}^+(p) - w^+(p)][u^+(x_{2,A}) - u^+(x_{1,A}))] = \quad & [\hat{w}^+(p) - w^+(p)][u^+(x_{2,B}) - u^+(x_{1,B}))] \\ & + \hat{w}^+(p)[u^+(\hat{x}_{2,B}) - u^+(x_{2,B}))]. \quad \text{(B.6)}\end{aligned}$$

Since $\hat{w}^+(p)[u^+(\hat{x}_{2,B}) - u^+(x_{2,B})) > 0$, (B.6) becomes

$$[\hat{w}^+(p) - w^+(p)][u^+(x_{2,A}) - u^+(x_{1,A}))] > [\hat{w}^+(p) - w^+(p)][u^+(x_{2,B}) - u^+(x_{1,B}))]. \tag{B.7}$$

From the construction of the table, we know $u^+(x_{2,A}) - u^+(x_{1,A})) < u^+(x_{2,B}) - u^+(x_{1,B}))$. (B.7) thus implies $\hat{w}^+(p) < w^+(p)$. A switching row lower in the GD1/GD2 tables thus leads to a smaller decision weight on the large outcome of each lottery.

We have structured the tables such that $p^{GD1} < p^{GD2}$ and assume the inflection point of the probability weighting function to be between these two probabilities. Under this construction, if the decision weight on p^{GD1} becomes smaller, we have less inverse S-shape or more S-shape in the weighting function. If the decision weight on p^{GD2} becomes smaller, we have more inverse S-shape or less S-shape in the weighting function.

B.1.2 Utility Curvature and Probability Weighting in the Loss Domain

Assuming a full CPT preference functional, we evaluate the lotteries in the LD1/LD2 tables as $EV = w^-(p)u^-(large\ loss) + (1 - w^-(p))u^-(small\ loss)$. In these tables only the large loss in Lottery A changes. The indifference gain fulfills

$$w^-(p)u^-(x_{2,A}) + (1 - w^-(p))u^-(x_{1,A}) = w^-(p)u^-(x_{2,B}) + (1 - w^-(p))u^-(x_{1,B}). \tag{B.8}$$

We change the indifference value to $\hat{x}_{2,A} < x_{2,A}$ and the utility function gets transformed by function $g(\cdot)$. The new indifference value now fulfills

$$w^-(p)g(u^-(\hat{x}_{2,A})) + (1 - w^-(p))g(u^-(x_{1,A})) = w^-(p)g(u^-(x_{2,B}) + (1 - w^-(p))g(u^-(x_{1,B})). \tag{B.9}$$

We again use the positive first derivatives of $u(\cdot)$ and $g(\cdot)$ and transform (B.9) such that

$$w^-(p)g(u^-(x_{2,A})) + (1 - w^-(p))g(u^-(x_{1,A})) > w^-(p)g(u^-(x_{2,B}) + (1 - w^-(p))g(u^-(x_{1,B})). \tag{B.10}$$

We proceed as in the gain domain. Under the probability measure ω defined by w^-, the utility lottery of Lottery A is a mean-preserving spread of that of Lottery B. As such, $\mathbb{E}_\omega[g(u^-(\tilde{x}_A))] > \mathbb{E}_\omega[g(u^-(\tilde{x}_B))]$ if and only if $g'' < 0$. Thus, a more negative value of $x_{2,A}$ (and thus a later switching row) is, ceteris paribus, associated with more convex utility curvature/ less risk aversion.

For probability weighting, we again consider two different indifference relationships. One at $x_{A,2}$ and one at $\hat{x}_{A,2}$ with $\hat{x}_{A,2} < x_{A,2}$ and different probability weighting functions w^- and $\hat{w}^-$. We have the two equalities:

$$w^-(p)u^-(x_{2,A}) + (1 - w^-(p))u^-(x_{1,A}) = w^-(p)u^-(x_{2,B}) + (1 - w^-(p))u^-(x_{1,B}). \tag{B.11}$$

$$\hat{w}^-(p)u^-(\hat{x}_{2,A}) + (1 - \hat{w}^-(p))u^-(x_{1,A}) = \hat{w}^-(p)u^-(x_{2,B}) + (1 - \hat{w}^-(p))u^-(x_{1,B}). \tag{B.12}$$

We subtract (B.11) from (B.12) and add $\hat{w}(p)[u(x_{2,A}) - u(x_{2,A})]$ on the left hand side to obtain

$$\begin{aligned}[\hat{w}^-(p) - w^-(p)][u^-(x_{2,A}) - u^-(x_{1,A}))] = \quad & [\hat{w}^-(p) - w^-(p)][u^-(x_{2,B}) - u^-(x_{1,B}))]. \\ +\hat{w}^-(p)[u^-(\hat{x}_{2,A}) - u^-(x_{2,A}))] \quad & \end{aligned} \tag{B.13}$$

Since $\hat{w}^-(p)[u^-(\hat{x}_{2,A}) - u^-(x_{2,A})) < 0$, (B.13) becomes

$$[\hat{w}^-(p) - w^-(p)][u^-(x_{2,A}) - u^-(x_{1,A}))] > [\hat{w}^-(p) - w^-(p)][u^-(x_{2,B}) - u^-(x_{1,B}))]. \tag{B.14}$$

From the construction of the table, we know $u^-(x_{2,A}) - u^-(x_{1,A})) < u^-(x_{2,B}) - u^-(x_{1,B})) < 0$. (B.7) thus implies $\hat{w}^-(p) < w^-(p)$. A switching row lower in the LD1/LD2 tables thus leads to a smaller decision weight on the more negative outcome of each lottery.

Since in CPT, the probability weighting function uses the upper Choquet integral in the gain domain and the lower Choquet integral in the loss domain, the implications of this theoretical result can be interpreted as for the gain domain described above. We have structured the tables such that $p^{LD1} < p^{LD2}$ and assume the inflection point of the probability weighting function to be between these two probabilities. Under this construction, if the decision weight on p^{LD1} becomes smaller, we have less inverse S-shape or more S-shape in the weighting function. If the decision weight on p^{LD2} becomes smaller, we have more inverse S-shape or less S-shape in the weighting function.

B.1.3 Loss Aversion

Assuming a full CPT preference functional, we evaluate the lotteries in the LA table as $EV = w^+(p)u^+(gain) + \lambda w^-(1-p)u^-(loss)$. As such, the probability of the gain leading to indifference fulfills

$$w^+(p)u^+(x_{2,A}) + \lambda w^-(1-p)u^-(x_{1,A}) = w^+(p)u^+(x_{2,B}) + \lambda w^-(1-p)u^-(x_{1,B}) \tag{B.15}$$

or equivalently

$$\lambda = \frac{w^+(p)(u^+(x_{2,B}) - u^+(x_{2,A}))}{w^-(1-p)(u^-(x_{1,A}) - u^-(x_{1,B}))}. \tag{B.16}$$

Given functions w^+, w^-, u^+, u^-, we can see that a higher indifference probability always leads to a higher λ. Observe

$$\frac{\partial\lambda}{\partial p} = \frac{\frac{\partial w^+(p)}{\partial p}(u^+(x_{2,B}) - u^+(x_{2,A}))}{w^-(1-p)(u^-(x_{1,A}) - u^-(x_{1,B}))} - \frac{\partial w^-(1-p)}{\partial p}\frac{w^+(p)(u^+(x_{2,B}) - u^+(x_{2,A}))}{[w^-(1-p)(u^-(x_{1,A}) - u^-(x_{1,B}))]^2} > 0. \tag{B.17}$$

B.1.4 Certainty Preference

To accommodate a preference for certainty, we utilize the model of Schmidt (1998). We integrate this model into CPT similarly as he has integrated it into EU. All evaluations of uncertain payments are made by a utility function $u(x)$ and evaluations of certain payments are made by a value function $v(x)$.[36] For a preference regarding certainty to appear, the utility and value functions must differ, whereas the difference is usually assumed to be monotonic for all values of x (Vieider, 2018). As such, when we can observe $v(x) > u(x)$ ($v(x) < u(x)$) for some value of x, we assume the preference for (against) certainty to persist everywhere in the preferences of the individual except at zero. Zero is excluded such that the prospect-theoretic convention that the utility/value function crosses at the origin is upheld.

The only table in which a certain payment appears is the CP table. It is structured such that $x_{2,B} > x_A > x_{1,B} > 0$. It is obvious that when we assume that $u(x)$ does not change, a higher value of $x_{2,B}$ implies a stronger certainty effect. Consider the two equalities implied by indifference values $x_{2,B}$ and $\hat{x}_{2,B}$ with $\hat{x}_{2,B} > x_{2,B}$ and the corresponding value functions $v(x)$ and $\hat{v}(x)$.

$$v(x_A) = w^+(p)u^+(x_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \tag{B.18}$$

$$\hat{v}(x_A) = w^+(p)u^+(\hat{x}_{2,B}) + (1 - w^+(p))u^+(x_{1,B}). \tag{B.19}$$

[36] See Schmidt (1998) for a discussion of the terminology "utility function" and "value function."

Subtracting (B.18) from (B.19), we gain

$$\hat{v}(x_A) - v(x_A) = w^+(p)[u^+(\hat{x}_{2,B}) - u^+(x_{2,B})]. \tag{B.20}$$

By assumption, $\hat{x}_{2,B} > x_{2,B}$ renders $\hat{v}(x_A) > v(x_A)$ and thus with a fixed utility function of $u(x)$ an increase in the certainty preference.

B.2 Analysis Using Parametric Preference Measures

For the parametric measures of the preference parameters, we assume that a switch from Lottery A to Lottery B at row h implies that the subject would be indifferent between the average lotteries A and B between rows $h-1$ and h. In every table, only one value varies with each row. As such, the average lotteries are the simple mid-point between the two different values. We signify this indifference value with a bar. When the switch occurred at a corner solution (which did not violate FOSD), then we assume the indifference value to be the same distance below the value indicated in the row as it would be above it if the switch occurred one row before the corner solution.

For the utility function and the probability weighting function, we assume the parametric forms summarized in Section 2.1. Using these assumptions, we identify the values of γ^+, γ^-, β^+, β^-, λ and κ which solve the six equations

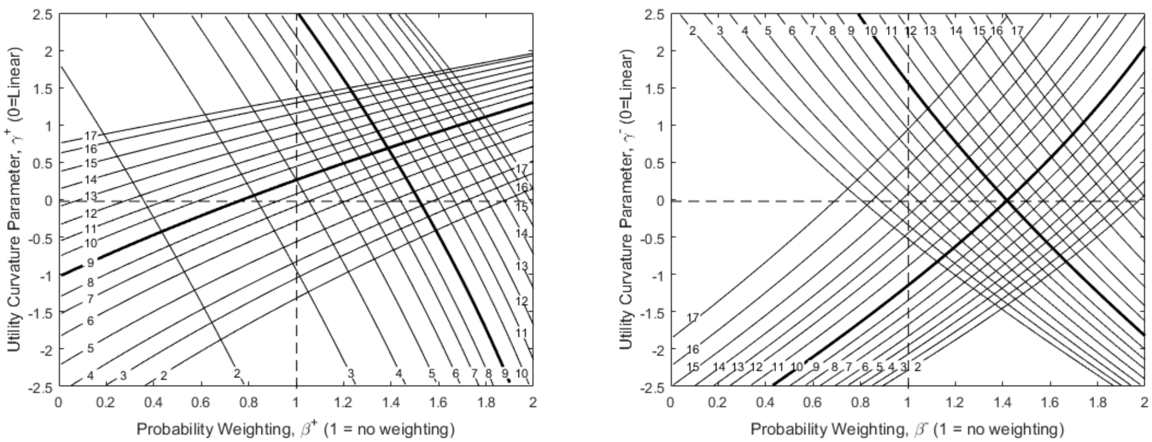
$$\begin{array}{lcl}
w^+(p^{GD1})u^+(x^{GD1}_{1,A}) + (1-w^+(p^{GD1}))u^+(x^{GD1}_{2,A}) & = & w^+(p^{GD1})u^+(\bar{x}^{GD1}_{1,B}) + (1-w^+(p^{GD1}))u^+(x^{GD1}_{2,B}) \\
w^+(p^{GD2})u^+(x^{GD2}_{1,A}) + (1-w^+(p^{GD2}))u^+(x^{GD2}_{2,A}) & = & w^+(p^{GD2})u^+(\bar{x}^{GD2}_{1,B}) + (1-w^+(p^{GD2}))u^+(x^{GD2}_{2,B}) \\
w^-(p^{LD1})u^-(\bar{x}^{LD1}_{1,A}) + (1-w^-(p^{LD1}))u^-(x^{LD1}_{2,A}) & = & w^-(p^{LD1})u^-(x^{LD1}_{1,B}) + (1-w^-(p^{LD1}))u^-(x^{LD1}_{2,B}) \\
w^-(p^{LD2})u^-(\bar{x}^{LD2}_{1,A}) + (1-w^-(p^{LD2}))u^-(x^{LD2}_{2,A}) & = & w^-(p^{LD2})u^-(x^{LD2}_{1,B}) + (1-w^-(p^{LD2}))u^-(x^{LD2}_{2,B}) \\
w^+(\bar{p}^{LA})u^+(x^{LA}_{1,A}) + \lambda w^-(1-\bar{p}^{LA})u^-(x^{LA}_{2,A}) & = & w^+(\bar{p}^{LA})u^+(x^{LA}_{1,B}) + \lambda w^-(1-\bar{p}^{LA})u^-(x^{LA}_{2,B}) \\
v(x^{CP}_{A}) & = & w^+(p^{CP})u^+(\bar{x}^{CP}_{1,B}) + (1-w^+(p^{CP}))u^+(x^{CP}_{2,B}).
\end{array} \tag{B.21}$$

Subjects who chose a lottery which was first-order dominated by another one were excluded from the analysis. The first two equations jointly determine γ^+ and β^+. Every pair of choices in both tables lead to a unique vector of these two variables. Similarly, the third and fourth equation jointly determine γ^- and β^-. The implied values from the possible combinations of answers both in the gain domain and in the loss domain are displayed in Figure B.2. Here, the upward-sloping lines indicate choices in Table GD1 (LD2) and downward-sloping lines indicate choices in GD2 (LD1). We designed the tables such that switching in the middle is consistent with common elicited values of the respective parameters, and we indicate these choices with thick lines. The lines for the tables differ in the sign of their slope because in tables GD1 and LD2 the safer lottery has a worse outcome in the low-probability event than the riskier lottery while in tables GD2 and LD1, the safer lottery has a better outcome in the low-probability event than the risky lottery. As such, more safe choices in GD1 and LD2 can either be caused by more concave utility or by less inverse-S probability weighting, while more safe choices in GD2 and LD1 can either be caused by more concave utility or by more inverse-S probability weighting. The difference in slopes along with the chosen parameters for the tables ensure that each choice combination has exactly one intersection in Figure B.2 and thus implies a unique utility curvature/probability weighting pair.

Based on the inferred values of γ^+, β^+, γ^- and β^- and the known parametric forms of u^+, w^+, u^- and w^-, λ and κ can be inferred from the equations

$$\lambda = \frac{w^+(\bar{p}^{LA})(u^+(x^{LA}_{2,B}) - u^+(x^{LA}_{2,A}))}{w^-(1-\bar{p}^{LA})(u^-(x^{LA}_{1,A}) - u^-(x^{LA}_{1,B}))} \tag{B.22}$$

Figure B.2: Range of elicitable parameters for utility curvature and probability weighting



(a) Possible gain domain preferences implied by the number of safe choices in Tables GD1 (upward-sloping lines) and GD2 (downward-sloping lines).

(b) Possible loss domain preferences implied by the number of safe choices in Tables LD1 (downward-sloping lines) and LD2 (upward-sloping lines).

Note: The figure displays the parameters for utility curvature and probability weighting implied by the choices in Tables GD1 and GD2 (panel(a)) and LD1 and LD2 (panel (b)). The number on each line denotes the number of safe lottery choices in the respective table. The intersection of two lines sets the parameter pair.

and

$$\kappa^{1-\gamma} = \frac{w^+(p^{CP/GD1})u^+(\bar{x}_{2,B}^{CP}) + (1 - w^+(p^{CP/GD1}))u^+(x_{1,B}^{CP/GD1})}{w^+(p^{CP/GD1})u^+(\bar{x}_{2,B}^{GD1}) + (1 - w^+(p^{CP/GD1}))u^+(x_{1,B}^{CP/GD1})}. \tag{B.23}$$

In Equation (B.23), the index $CP/GD1$ indicates that the values are equal in both tables.

Directly eliciting values of λ and κ results in bad measures of loss aversion and certainty preference (Abdellaoui et al., 2007; Schmidt, 1998). For loss aversion, the shapes of u^+ and u^- also influence how utility is traded off between the gain domain and the loss domain. We thus use an index for loss aversion that takes this into account. We use the negative average ratio of utility in the loss domain and the gain domain over the spectrum of relevant values for the LA table. Formally, our loss aversion index is described by

$$\hat{\lambda} = -\int_0^5 \frac{\lambda u^-(-x)}{u^+(x)dx} dx. \tag{B.24}$$

For certainty preferences, we use the marginal certainty preference index suggested by Schmidt (1998):

$$\hat{\kappa} = \frac{v(x) - u(x)}{u'(x)}. \tag{B.25}$$

C Accuracy of linear approximation

The agent faces lottery $(w - \alpha pqL - (1-\alpha)L, \quad p; \quad w - \alpha pqL, \quad 1-p)$. Under the subjective probability distortion Ω, this implies mean $\mu_\Omega = w - \alpha pqL - \Omega(1-\alpha)L$ and variance $\sigma_\Omega^2 = ((1-\alpha)L)^2\Omega(1-\Omega)$. The second-order Taylor approximation states that $\mathbb{E}_\Omega[U] = \mu_\Omega - \frac{1}{2}r\sigma_\Omega^2$ and thus $\mathbb{E}_\Omega[U] = w - \alpha pqL - \Omega(1-\alpha)L - \frac{r}{2}\Omega(1-\Omega)((1-\alpha)L)^2$. Rearranging renders the approximated solution

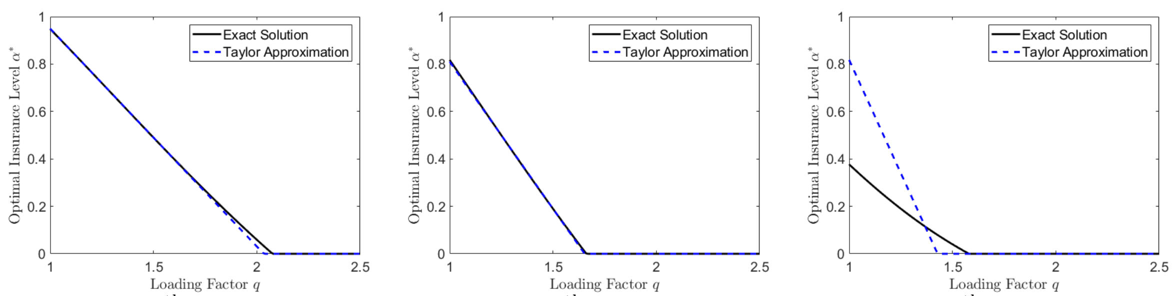
$$\alpha^* = 1 + \frac{1}{r(1-\Omega)L} - \frac{p}{r\Omega(1-\Omega)L}q. \tag{C.1}$$

This function is linear in q. However, this does not imply that optimal insurance demand under quadratic utility is linear in the loading, because Taylor approximations are only exact when the risk is normally distributed – which is not the case in our setting. Using Equation (9) and quadratic utility of the form $U(x) = ax - bx^2$ with $a, b > 0$, we can express the exact solution to optimal insurance demand as

$$\alpha^* = \frac{(a - 2bw)(\Omega - qp) + 2b(1 - qp)\Omega L}{2bL[(qp)^2 + (1 - 2qp)\Omega]}. \tag{C.2}$$

This term is not linear in q. However, the Taylor approximation is still close to the exact solution in many cases. To evaluate the quality of the approximation, we use the 25^{th}, 50^{th}, and 75^{th} percentile of responses for $q = 1.25$ and $q = 1.50$. Based on these values and setting $a = 1$ without loss of generality, we solve Equation (C.1) numerically for r and Ω.[37] Similarly, we use the two given choices and solve equation (C.2) for the implied values of b and Ω. Based on these solutions, we plot the implied demand by the b, Ω pair for the exact solution and by the r, Ω pair for the approximation over $q \in [1, 2.5]$ in Figure C.1.

Figure C.1: Graphical evaluation of the Taylor approximation in insurance choices with $p = 10\%$ for different percentiles of $\alpha_{1.25}$ and $\alpha_{1.50}$ in the insurance demand data



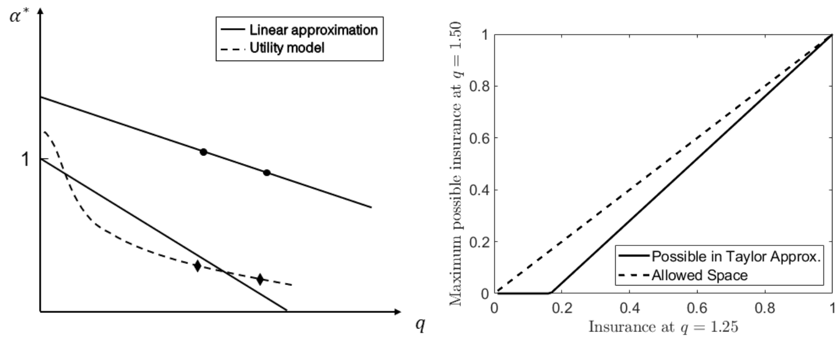
(a) 75^{th} percentile (b) 50^{th} percentile (c) 25^{th} percentile

As we can see in the figure, the approximation fares well when evaluating the 75^{th} or 50^{th} percentile. However, it breaks down for the 25^{th} percentile. The linear approximation in Equation (C.1) implies a minimum intercept of 1 for $q = 0$. The idea is that no matter what level of risk aversion the individual has, they will still accept free insurance coverage if it is offered. In addition, the slope of α^* in the approximation is linear in q. Thus, the approximation cannot model very flat reactions to the loading with very low initial levels of insurance at $q = 1.25$. We illustrate this concept in panel (a) of Figure C.2. While the linear approximation (indicated by the solid line) can model the two dots on the demand curve, it cannot model the two diamonds because of its restrictions. The utility model in Equation C.2 (indicated by the dashed line), however, can model the two diamonds (as is shown in Jaspersen et al., 2020), because it has the ability to slope upwards before the intercept.

Equation (C.1) shows that given any level of insurance demand at $q = 1.25$, the maximum possible slope is $-\frac{1-\alpha_{1.25}}{1.25}$. Thus, any level of $\alpha_{1.25}$ sets an upper bound on the level of $\alpha_{1.50}$ that can be accommodated by the model. Specifically, the maximal level is $\alpha_{1.50}^{max} = 1 - \frac{1-\alpha_{1.25}}{1.25}1.5$. Thus, for lower values of $\alpha_{1.25}$, only fairly low values of $\alpha_{1.50}^{max}$ are possible. To illustrate the extent of this issue, the dashed line in panel (b) of Figure C.2 shows the allowed space of insurance demand at $q = 1.25$ and $q = 1.50$ in the probability distortion model of Equation (9). The space can be

[37] The model in Equation (9) is invariant in its predictions towards positive affine transformations of $U(\cdot)$, and thus we maintain generality.

Figure C.2: Problematic aspects of the Taylor approximation in insurance decisions with binary risks



(a) Illustration of insurance choices impossible to approximate with a second-order Taylor approximation

(b) Possible $\alpha_{1.25}/\ \alpha_{1.50}$ combinations for second-order Taylor approximation

Note: Lines for the diamonds in panel (a) are exemplary sketches and do not necessarily display the exact demand functions implied by Equations (C.1) and (C.2).

approximated by $\alpha_{1.25} \geq \alpha_{1.50}$. In contrast, the solid line in the same panel shows the solutions possible in the linear approximation. The area between the two lines is the set of $\alpha_{1.25}, \alpha_{1.50}$ combinations for which the linear approximation breaks down. Since we observe a sizable number of insurance choices in this wedge, the linear model and the predictions from Equation (9) differ substantially in the analysis reported in Section 5.

D Summary statistics

Table D.1: Summary statistics for nonparametric preference measures

	University Only $n = 378$		mTurk Only $n = 1,352$		Full Sample $n = 1,730$	
	Mean	Median	Mean	Median	Mean	Median
UC^+	14.83	15.00	14.77	15.00	14.78	15.00
PW^+	1.04	1.00	2.91	2.00	2.50	2.00
CP	-0.51	0.00	-0.51	0.00	-0.51	0.00
UC^-	20.06	20.00	20.59	21.00	20.47	21.00
PW^-	-3.00	-3.00	-0.67	0.00	-1.18	0.00
LA	11.30	11.00	11.83	12.00	11.71	12.00

Note: The labels UC, PW, CP, and LA denote our measures of utility curvature, probability weighting, certainty preference, and loss aversion, respectively. Superscripts $^+$ ($^-$) indicate that the measure was elicited in the gain (loss) domain.

Table D.2: Correlation table for nonparametric preference measures

	UC^{+}_{std}	PW^{+}_{std}	CP_{std}	UC^{-}_{std}	PW^{-}_{std}	LA_{std}
UC^{+}_{std}	1.000	.	.	.	.	.
PW^{+}_{std}	0.044	1.000	.	.	.	.
CP_{std}	-0.304	0.268	1.000	.	.	.
UC^{-}_{std}	-0.120	0.120	0.034	1.000	.	.
PW^{-}_{std}	0.008	0.294	0.005	0.214	1.000	.
LA_{std}	0.289	-0.010	-0.015	0.016	-0.038	1.000

Note: For our sample size of 1,730 subjects, a correlation is statistically significant at the 10% level if it is larger than 0.040, at the 5% level if it is larger than 0.047, and at the 1% level if it is larger than 0.062 (in absolute values).

Table D.3: Summary statistics for demographic and experiment variables

	University		mTurk		Total	
	Mean	SD	Mean	SD	Mean	SD
Age	21.48	2.34	36.14	10.81	32.94	11.37
Dummy for female	0.72	0.45	0.40	0.49	0.47	0.50
Dummy for US	1.00	0.00	0.85	0.36	0.88	0.32
Dummy for white	0.69	0.46	0.69	0.46	0.69	0.46
Dummy for black	0.04	0.20	0.06	0.24	0.06	0.23
Dummy for asian	0.29	0.45	0.21	0.41	0.23	0.42
Dummy for latino	0.02	0.15	0.06	0.25	0.06	0.23
GRQ	5.28	2.13	5.23	2.76	5.24	2.63
Final payment to subject	6.41	4.65	6.23	5.05	6.27	4.97
Dummy for made ≥ 1 FOSD choice	0.14	0.34	0.30	0.46	0.26	0.44
Num times violated FOSD	1.44	0.73	1.75	0.98	1.72	0.96
Dummy for pref task instr wrong	0.12	0.32	0.14	0.35	0.13	0.34
Dummy for ins task instr wrong	0.17	0.37	0.18	0.38	0.18	0.38
Understanding score	1.94	0.80	1.76	0.82	1.80	0.82
Education:						
Less than high school	0.00		0.01		0.00	
High school graduate	0.24		0.10		0.13	
Some college, no degree	0.57		0.20		0.28	
Associate's college degree	0.02		0.11		0.09	
Bachelor's college degree	0.13		0.44		0.37	
Master's degree	0.03		0.12		0.10	
Doctoral degree	0.00		0.01		0.01	
Professional degree (JD, MD)	0.00		0.02		0.01	
Income ($ USD):						
Less than 5,000	0.00		0.06		0.04	
5,000–9,999	0.00		0.06		0.04	
10,000–24,999	0.00		0.16		0.13	
25,000–49,999	0.00		0.28		0.22	
50,000–74,999	0.00		0.20		0.16	
75,000–99,999	0.00		0.13		0.10	
100,000–149,999	0.00		0.08		0.06	
150,000 or greater	0.00		0.04		0.03	

Note: Summary statistics are presented for the 378 in-person subjects at a university laboratory, the 1,352 online subjects recruited through Amazon mTurk, and all 1,730 subjects together. GRQ is the self-reported risk aversion measure of Dohmen et al. (2011). Final payment to the subject does not include the $6 "show-up fee" paid to university participants. Num times violated FOSD is conditional on having violated FOSD at least once. Understanding score is the subject's rating of how easy or difficult the study was to understand, with 1 indicating very easy, 5 indicating very difficult, and 3 indicating a neutral response.

Table D.4: Spearman rank correlations of coverage levels

Loss prob	5%		10%				20%		40%	70%	
Loading	1.50	2.50	1.00	1.25	1.50	2.50	1.25	1.50	1.50	0.80	1.00
	P5L150	P5L250	P10L100	P10L125	P10L150	P10L250	P20L125	P20L150	P40L150	P70L080	P70L100
P5L150	1.000	.	.	.	.	.	.	.	.	.	.
P5L250	0.729	1.000	.	.	.	.	.	.	.	.	.
P10L100	0.676	0.631	1.000	.	.	.	.	.	.	.	.
P10L125	0.699	0.670	0.706	1.000	.	.	.	.	.	.	.
P10L150	0.709	0.705	0.689	0.739	1.000	.	.	.	.	.	.
P10L250	0.660	0.706	0.641	0.687	0.719	1.000	.	.	.	.	.
P20L125	0.583	0.566	0.628	0.677	0.631	0.623	1.000	.	.	.	.
P20L150	0.576	0.564	0.632	0.686	0.654	0.646	0.732	1.000	.	.	.
P40L150	0.347	0.329	0.386	0.432	0.414	0.433	0.557	0.591	1.000	.	.
P70L080	0.102	0.068	0.211	0.189	0.139	0.149	0.279	0.296	0.443	1.000	.
P70L100	0.076	0.048	0.147	0.131	0.120	0.154	0.233	0.289	0.495	0.644	1.000
P70L125	0.035	0.053	0.066	0.107	0.106	0.113	0.204	0.255	0.485	0.519	0.642

Note: Insurance scenarios are labeled in the first column and the third row as P[probability]L[loading * 100]. For our sample size of 1,730 subjects, a correlation is statistically significant at the 10% level if it is larger than 0.040, at the 5% level if it is larger than 0.047, and at the 1% level if it is larger than 0.062 (in absolute values).

E Tobit regressions

Table E.1: Tobit regressions of coverage level on standardized preference motives separately

Panel (a): Nonparam. measures	(1)	(2)	(3)	(4)	(5)	(6)
Motive	UC^{+}_{std}	PW^{+}_{std}	CP_{std}	UC^{-}_{std}	PW^{-}_{std}	LA_{std}
Coefficient	2.31*	0.69	−0.93	2.45*	3.86***	3.17**
	(0.98)	(0.99)	(0.90)	(1.00)	(0.92)	(1.04)
FOSD violators	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.01	0.01	0.01	0.01	0.01	0.01
N subjects	1,730	1,730	1,730	1,730	1,730	1,730
N choices	20,760	20,760	20,760	20,760	20,760	20,760
N left-censored	4,321	4,321	4,321	4,321	4,321	4,321
N uncensored	12,871	12,871	12,871	12,871	12,871	12,871
N right-censored	3,568	3,568	3,568	3,568	3,568	3,568
Panel (b): Param. measures	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Motive	γ^{+}_{std}	β^{+}_{std}	$\hat{\kappa}_{std}$	γ^{-}_{std}	β^{-}_{std}	$\hat{\lambda}_{std}$
Coeff	2.90**	2.85**	−1.92	3.04**	3.44***	2.79*
	(1.11)	(1.14)	(1.22)	(1.14)	(1.07)	(1.31)
FOSD violators	No	No	No	No	No	No
Pseudo R^2	0.01	0.01	0.01	0.01	0.01	0.01
N subjects	1,276	1,276	1,276	1,276	1,276	1,276
N choices	15,312	15,312	15,312	15,312	15,312	15,312
N left-censored	3,220	3,220	3,220	3,220	3,220	3,220
N uncensored	9,456	9,456	9,456	9,456	9,456	9,456
N right-censored	2,636	2,636	2,636	2,636	2,636	2,636

Note: Tobit regressions are specified with a left-censored limit of 0 and a right-censored limit of 100. Dependent variable is the coverage level selected by subject i. All models contain fixed effects for each of the 12 insurance scenarios. Regressions of parametric preference motives are limited to the 1,276 non FOSD-violating subjects. In each panel, p-values have been adjusted using the Šidák (1967) method, adjusting for the six hypotheses tested in each panel. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table E.2: Tobit regressions of coverage level on joint preferences

Nonparam./Param.	Nonparametric		Parametric	
	(1)	(2)	(3)	(4)
$UC^{+}_{std}/\gamma^{+}_{std}$	1.62	1.63	4.01***	4.03***
	(1.07)	(1.07)	(1.20)	(1.20)
$PW^{+}_{std}/\beta^{+}_{std}$	−0.57	0.96	1.92	3.86*
	(1.10)	(1.37)	(1.25)	(1.59)
$CP_{std}/\hat{k}_{std}$	−0.33	−0.34	−1.67	−1.67
	(1.02)	(1.02)	(1.23)	(1.23)
$UC^{-}_{std}/\gamma^{-}_{std}$	1.91	1.92	2.40	2.41
	(1.02)	(1.02)	(1.20)	(1.20)
$PW^{-}_{std}/\beta^{-}_{std}$	3.73***	5.76***	2.62*	4.52**
	(0.99)	(1.27)	(1.15)	(1.51)
$LA_{std}/\hat{\lambda}_{std}$	2.82**	2.81*	4.21**	4.20**
	(1.06)	(1.05)	(1.41)	(1.42)
Prob ≥ 40		49.95***		53.24***
		(1.88)		(2.17)
Prob $\geq 40 \times PW^{+}_{std}/\beta^{+}_{std}$		−4.48***		−5.63***
		(1.32)		(1.55)
Prob $\geq 40 \times PW^{-}_{std}/\beta^{-}_{std}$		−5.92***		−5.51***
		(1.33)		(1.59)
FOSD violators	Yes	Yes	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject
Pseudo R^2	0.01	0.01	0.02	0.02
N subjects	1,730	1,730	1,276	1,276
N choices	20,760	20,760	15,312	15,312
N left-censored	4,321	4,321	3,220	3,220
N uncensored	12,871	12,871	9,456	9,456
N right-censored	3,568	3,568	2,636	2,636

Note: Tobit regressions are specified with a left-censored limit of 0 and a right-censored limit of 100. Dependent variable is the coverage level selected by subject i. All models contain fixed effects for each of the 12 insurance scenarios. Column 1 contains only the nonparametric preference scales. Column 2 adds an interaction between the PW preferences and a dummy for "high probability" (Prob $\geq 40 = 1$ if the probability of loss is 40% or 70%). Columns 3 and 4 replicate columns 1 and 2 using the parametric preferences. In each column, p-values have been adjusted using the Šidák (1967) method. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

F Analysis with alternative samples

Table F.1: Regression of coverage level on nonparametric preferences, excluding subjects who made FOSD-violating choices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
UC^{+}_{std}	1.99**						1.32	1.32
	(0.78)						(0.86)	(0.86)
PW^{+}_{std}		1.10					0.65	1.83
		(0.77)					(0.82)	(1.05)
CP_{std}			−0.76				−0.72	−0.72
			(0.81)				(0.90)	(0.90)
UC^{-}_{std}				2.25**			1.99*	1.99
				(0.79)			(0.82)	(0.82)
PW^{-}_{std}					2.00**		1.13	2.25
					(0.70)		(0.78)	(1.00)
LA_{std}						4.57***	4.20***	4.20***
						(0.91)	(0.92)	(0.92)
Prob ≥ 40								37.00***
								(1.28)
Prob $\geq 40 \times PW^{+}_{std}$								−3.54***
								(1.06)
Prob $\geq 40 \times PW^{-}_{std}$								−3.38**
								(1.06)
FOSD violators	No	No	No	No	No	No	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject	Subject	Subject	Subject	Subject
R^2	0.13	0.12	0.12	0.13	0.13	0.13	0.14	0.14
N choices	15,312	15,312	15,312	15,312	15,312	15,312	15,312	15,312
N subjects	1,276	1,276	1,276	1,276	1,276	1,276	1,276	1,276

Note: Sample is restricted to subjects who did not violate FOSD. Dependent variable is the coverage level selected by subject i. All models contain fixed effects for each of the 12 insurance scenarios. Columns 1-6 replicate columns 1-6 in Panel A of Table 6, with p-values adjusted for six hypotheses using the Šidák (1967) method. Columns 7 and 8 replicate columns 1 and 2 in Table 7, with Šidák-adjusted p-values for the hypotheses in each column. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table F.2: Correlation between actual and predicted coverage levels, by number of law of demand violations

Model	0 violations (24.4%)	1 violation (26.4%)	2 violations (22.5%)	3+ violations (26.6%)
EV	0.249	0.288	0.261	0.252
EU^+	0.185	0.217	0.230	0.131
EU^-	0.220	0.245	0.204	0.148
DT^+	0.049	0.029	−0.001	−0.028
DT^-	0.055	0.028	0.021	−0.127
KR	0.063	0.024	0.108	0.029
$RDEU^+$	0.026	−0.070	−0.087	−0.146
$RDEU^-$	0.094	0.029	0.022	−0.126
CPT^-	0.105	0.033	0.017	−0.108
CPT^{NLIB}	0.069	−0.019	0.019	−0.110
EV_{CP}	0.098	0.114	0.089	0.096
DT^+_{CP}	−0.003	−0.028	−0.042	−0.034
DT^-_{CP}	−0.007	−0.007	−0.010	−0.079
EU^+_{CP}	0.006	0.066	0.101	0.041
EU^-_{CP}	0.003	0.067	0.090	0.021
$RDEU^+_{CP}$	−0.012	−0.074	−0.093	−0.114
$RDEU^-_{CP}$	0.020	−0.008	−0.011	−0.085

G Alternatively scaled insurance choices

The analysis in the main text treats insurance demand as a continuous and cardinal scaled measure. This appendix demonstrates that our results are robust to alternative assumptions about the scale of the variable. The first two columns of Table G.1 compare the correlations between observed demand and model predictions when treating insurance demand as cardinal (column 1, equal to analysis in main text) and treating it as ordinal (column 2).

The other analyses reported in this appendix treat insurance demand as a discrete measure. In the first analysis, we round answers of subjects in the experiment to the nearest increment of 25%. We adjust our predictions such that they indicate which of five possible discrete alternatives (0%, 25%, 50%, 75%, 100%) maximizes the objective function of the subject. Analyses are then carried out using estimators that take the ordinal nature of the reported scales into account. The correlations reported in the rightmost two columns of Table G.1 are calculated as Kendall's Tau. The regressions in Tables G.2 use an ordered logit estimator. In the analyses using predicted insurance demand as the independent variable, we use dummy variables to indicate the predicted value. The second analysis of insurance demand as a discrete measure restricts observations and predictions even more and only considers no insurance (0%) or full insurance (100%) as possible options. The results in Tables G.3 use logit estimators and a dummy variable for 100% coverage to reflect this binary nature of insurance demand.

Table G.1: Correlation between actual and predicted coverage levels

	Continuous		25% bins	0% or 100%
Model	Pearson	Kendall's Tau	Kendall's Tau	Kendall's Tau
EV	0.261	0.201	0.212	0.247
EU^+	0.189	0.123	0.144	0.123
EU^-	0.205	0.142	0.157	0.150
DT^+	0.015	0.011	0.009	0.004
DT^-	−0.002	0.001	−0.007	−0.016
KR	0.053	0.043	0.047	0.050
$RDEU^+$	−0.064	−0.050	−0.059	−0.088
$RDEU^-$	0.010	0.008	0.004	−0.015
CPT^-	0.017	0.013	0.008	−0.008
CPT^{NLIB}	−0.008	−0.014	−0.019	−0.037
EV_{CP}	0.098	0.051	0.029	0.021
DT^+_{CP}	−0.025	−0.004	−0.009	−0.008
DT^-_{CP}	−0.023	−0.006	−0.013	−0.020
EU^+_{CP}	0.050	−0.003	−0.001	0.003
EU^-_{CP}	0.042	−0.005	−0.003	0.009
$RDEU^+_{CP}$	−0.069	−0.036	−0.043	−0.036
$RDEU^-_{CP}$	−0.019	−0.015	−0.019	−0.025

Note: For our sample size of 1,276 subjects for whom we can make parametric predictions, the correlation is statistically significant at the 10% level if it is larger than 0.047, at the 5% level if it is larger than 0.055, and at the 1% level if it is larger than 0.073 (in absolute values).

Table G.2: Ordered logit regressions of coverage level (rounded to nearest 25%) on joint preferences

Nonparam./Param.	Nonparametric		Parametric	
	(1)	(2)	(3)	(4)
$UC^{+}_{std}/\gamma^{+}_{std}$	0.05	0.04	0.12***	0.12**
	(0.03)	(0.03)	(0.04)	(0.04)
$PW^{+}_{std}/\beta^{+}_{std}$	–0.00	0.05	0.08	0.15**
	(0.03)	(0.05)	(0.04)	(0.05)
$CP_{std}/\hat{\kappa}_{std}$	–0.02	–0.02	–0.06	–0.06
	(0.03)	(0.03)	(0.04)	(0.04)
$UC^{-}_{std}/\gamma^{-}_{std}$	0.05	0.05	0.07	0.08
	(0.03)	(0.03)	(0.04)	(0.04)
$PW^{-}_{std}/\beta^{-}_{std}$	0.10***	0.18***	0.06	0.13*
	(0.03)	(0.04)	(0.04)	(0.05)
$LA_{std}/\hat{\lambda}_{std}$	0.10**	0.10**	0.13**	0.13*
	(0.03)	(0.03)	(0.05)	(0.05)
Prob ≥ 40		1.78***		1.90***
		(0.07)		(0.09)
Prob $\geq 40 \times PW^{+}_{std}/\beta^{+}_{std}$		–0.14**		–0.18***
		(0.04)		(0.05)
Prob $\geq 40 \times PW^{-}_{std}/\beta^{-}_{std}$		–0.19***		–0.17***
		(0.04)		(0.05)
FOSD violators	Yes	Yes	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject
Pseudo R^2	0.039	0.041	0.045	0.047
N choices	20,760	20,760	15,312	15,312
N subjects	1,730	1,730	1,276	1,276

Note: Dependent variable is the coverage level selected by subject i, rounded to the nearest 25%. All models contain fixed effects for each of the 12 insurance scenarios. Column 1 contains only the nonparametric preference scales. Column 2 adds an interaction between the PW preferences and a dummy for "high probability" (Prob $\geq 40 = 1$ if the probability of loss is 40% or 70%). Columns 3 and 4 replicate columns 1 and 2 using the parametric preferences. In each column, p-values have been adjusted using the Šidák (1967) method. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table G.3: Ordered logit regressions of coverage level (rounded to 0% or 100%) on joint preferences

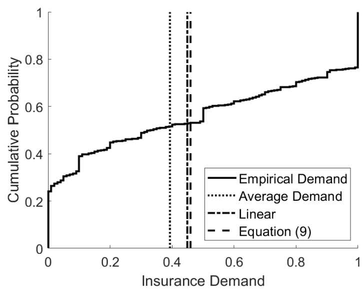
Nonparam./Param.	Nonparametric		Parametric	
	(1)	(2)	(3)	(4)
$UC^{+}_{std}/\gamma^{+}_{std}$	0.04	0.04	0.11**	0.12*
	(0.04)	(0.04)	(0.04)	(0.04)
$PW^{+}_{std}/\beta^{+}_{std}$	0.01	0.06	0.11**	0.15**
	(0.04)	(0.04)	(0.04)	(0.05)
$CP_{std}/\hat{\kappa}_{std}$	−0.02	−0.02	−0.05	−0.05
	(0.04)	(0.04)	(0.04)	(0.04)
$UC^{-}_{std}/\gamma^{-}_{std}$	0.05	0.05	0.09*	0.09
	(0.04)	(0.04)	(0.04)	(0.04)
$PW^{-}_{std}/\beta^{-}_{std}$	0.12***	0.17***	0.06	0.11
	(0.04)	(0.04)	(0.04)	(0.05)
$LA_{std}/\hat{\lambda}_{std}$	0.11**	0.11**	0.13**	0.14**
	(0.04)	(0.04)	(0.05)	(0.05)
Prob ≥ 40		2.26***		2.47***
		(0.08)		(0.10)
Prob $\geq 40 \times PW^{+}_{std}/\beta^{+}_{std}$		−0.18***		−0.14
		(0.05)		(0.06)
Prob $\geq 40 \times PW^{-}_{std}/\beta^{-}_{std}$		−0.16**		−0.20**
		(0.05)		(0.06)
FOSD violators	Yes	Yes	No	No
Fixed effects	Scenario	Scenario	Scenario	Scenario
Clustered SEs	Subject	Subject	Subject	Subject
Pseudo R^2	0.097	0.100	0.113	0.115
N choices	20,760	20,760	15,312	15,312
N subjects	1,730	1,730	1,276	1,276

Note: Dependent variable is coverage level selected by subject i, rounded to the closer of 0% or 100%. All models contain fixed effects for each of the 12 insurance scenarios. Column 1 contains only the nonparametric preference scales. Column 2 adds an interaction between the PW preferences and a dummy for "high probability" (Prob $\geq 40 = 1$ if the probability of loss is 40% or 70%). Columns 3 and 4 replicate columns 1 and 2 using the parametric preferences. In each column, p-values have been adjusted using the Šidák (1967) method. Standard errors clustered by subject are in parentheses. Stars *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

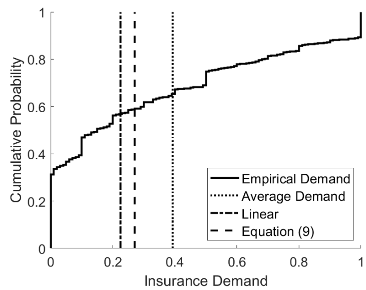
H Additional results on preferences from insurance choices

H.1 CDFs of model predictions

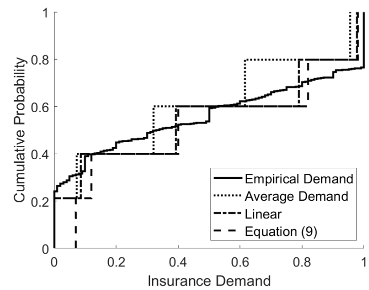
Figure H.1: Cumulative distribution functions of model predictions and empirically observed choices at $p = 10\%$ for $q = 1.00$ and $q = 2.50$ and for the different levels of aggregation



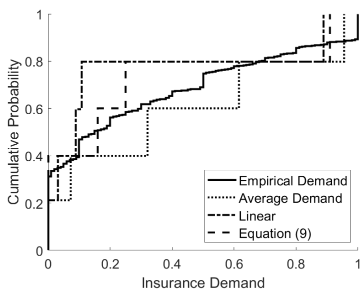
(a) Representative Agent at $q = 1.00$



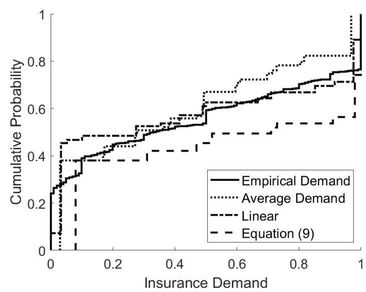
(b) Representative Agent at $q = 2.50$



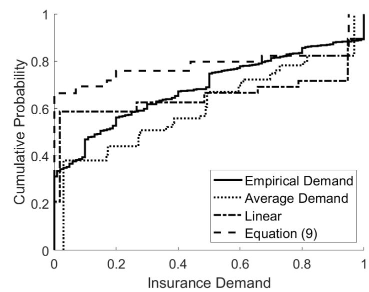
(c) Quintiles at $q = 1.00$



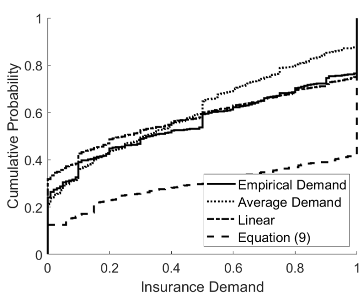
(d) Quintiles at $q = 2.50$



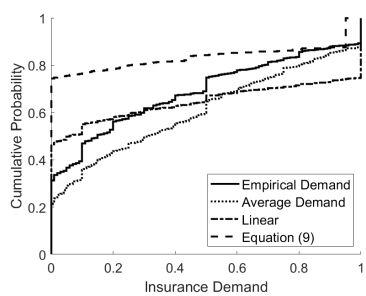
(e) Grid at $q = 1.00$



(f) Grid at $q = 2.50$



(g) Individual at $q = 1.00$

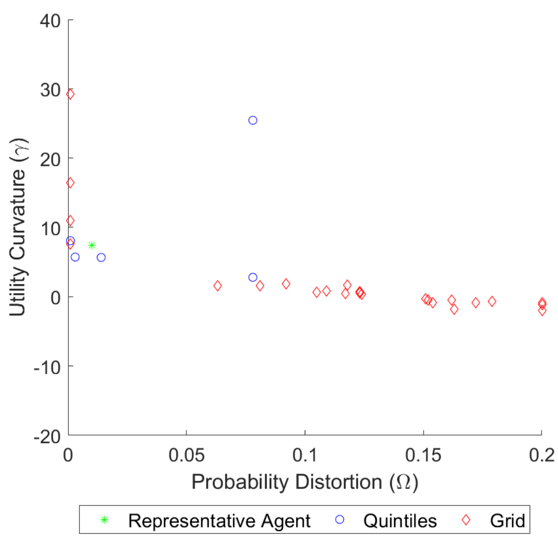


(h) Individual at $q = 2.50$

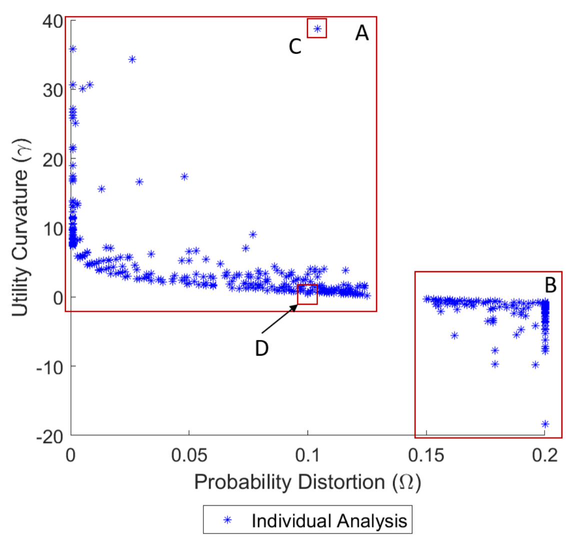
H.2 Elicited preferences and analysis with restricted sample

The preference elicitation from insurance choices makes three assumptions such that all insurance choices can be matched to preference parameters. First, for subjects who choose full insurance at both of the intermediate loads, we code the choice in the $q = 1.25$ scenario as 99% coverage and the choice when $q = 1.50$ as 98% coverage. Second, for subjects who choose higher levels of insurance at the 1.50 load than the 1.25 load, we use the value of Ω which leads to the smallest distance between the two utility curvature parameters implied by the insurance choices. Third, for the corner solution of no insurance coverage at both intermediate loads, we set $\Omega = p$ and utility curvature to the parameter which implies $\alpha^* = 0$ at $q = 1.25$. These three assumptions are not necessary for the aggregation levels of the representative agent or the quintiles. Panel (a) of Figure H.2 shows that all elicited preference parameters for these aggregation levels imply risk aversion and underweighted probabilities. When considering the grid aggregation, there are 10 grid squares where insurance demand is higher for $q = 1.50$ than for $q = 1.25$. The elicitation procedure described in Section 5 leads to risk seeking and probability overweighting preferences for these subjects.

Figure H.2: Scatter plot of elicited preferences according to Equation (9) at the four levels of aggregation



(a) Representative Agent, Quintiles, and Grid



(b) Individual

Note: Each data point is a preference pair elicited from the insurance choices at the respective level of aggregation. Red boxes in panel (b) mark subsets of subjects showing specific preference patterns.

In the individual-level analysis, all three assumptions come into play. Panel (b) of Figure H.2 shows all elicited preference pairs for the 1,730 subjects and categorizes them into four groups. Group A are subjects whose insurance choices do not require any of the three assumptions. Subjects in group B show an increasing demand in the loading of the insurance policy, violating the law of demand. Subjects in group C are those that chose full insurance at both loadings and were set to 99% and 98% coverage for the two loading factors, respectively. Subjects in group D were those which chose 0% insurance coverage for both loading factors and were set to have no probability weighting and only mild risk aversion of $\gamma = 0.41$ such that they exactly maximize expected utility at $\alpha = 0$ for $q = 1.25$.

It is obvious that all three assumptions in the preference elicitation procedure have significant consequences for the implied preferences. To assess the sensitivity of our results in Section 5, we thus repeat the analysis using only subjects from group A in the scatter plot above. That is, we only use subjects who display a strictly lower insurance demand at $q = 1.50$ than at $q = 1.25$. As we can see from Table H.1, results are broadly consistent with the analysis including all subjects.

Table H.1: Goodness of fit analysis at 10% loss probability for structural models calibrated with insurance choices of a restricted sample

	Individual Distance			Population Distance		
Prediction Model	Average	Linear	Eq. (9)	Average	Linear	Eq. (9)
Aggregation Level						
Representative Agent	0.127	0.235	0.282	0.600	0.771	0.796
Quintiles	0.090	0.187	0.179	0.293	0.596	0.500
Grid	0.090	0.158	0.153	0.267	0.475	0.404
Individual	0.087	0.154	0.209	0.219	0.395	0.321

Note: The table reports the results of our calibration analysis in which we use the coverage level decisions in the scenarios with loss probability 10% and loading factors 1.25 and 1.50 to calibrate the decision model in Equation (9) and use it to predict insurance demand in the scenarios with loss probability 10% and loading factors 1.00 and 2.50. The sample of subjects is restricted to those which display $\alpha_{1.50} < \alpha 1.25$. We offer two non-utility models for comparison. The first non-utility model uses the average demand for loading factors 1.25 and 1.50 to predict demand in the other two scenarios. The second non-utility model calibrates an individual linear demand function $\alpha = bq + c$ for predictions. Individual distances are Euclidean distances, population distances are Kolmogorov-Smirnoff distances.

I Experiment supporting materials

Here, we provide screenshots of the full experiment given to the mTurk subjects. In-person subjects completed an identical experiment, without some mTurk-specific questions (e.g., entering the mTurk worker ID). Each box represents a different screen.

The experiment begins with a browser compatibility test and confirmation of the mTurk worker ID. This also prevents bots from continuing the experiment.

Before we begin, we need to make sure your browser is compatible with our study.

Set the slider to 75.

| **1417500** |

0 10 20 30 40 50 60 70 80 90 100

Slider 75

What is the red number that appears between the lines above the slider? If you don't see a number, enter 100.

Please verify that the ID in the field below is your correct Amazon Mechanical Turk ID.

- If it is your ID, please click "Next."
- If it is not your ID, or if no ID is displayed, please enter your ID and click "Next."

Then, subjects are presented with an overview of the experiment.

Overview

Thank you for participating in this study. You will begin this experiment by completing a typing task to earn $5.00. Your final payment at the end of this experiment may be more or less than $5.00, depending partly on your later choices and partly on chance.

After you complete the typing task, we will ask you a series of economic questions. In these questions, you may gain additional money or lose some of your $5.00. Whether you have a gain or a loss is based on the draw of colored balls from a bucket. In different questions you will be asked to make decisions related to these buckets that can affect how much you earn. Each question is designated with a number (Q1, Q2, Q3, etc…). At the end of the experiment, the computer will randomly select a question number. We will apply your choice in that question and the computer will play it out for real money.

Even though only one of your choices will count, you will not know in advance which question will be used to determine your ultimate earnings. Therefore, you should think about each of them carefully before submitting your choice.

There are no correct answers - we are simply interested in your preferences for risky versus safe outcomes.

Following the overall instructions, subjects complete the real-effort task. This involves manually typing a passage correctly into the provided text box. Every character must be correct to pass.[38] The font used in this passage is resistant to optical character recognition. There were five possible passages, and each subject was randomly assigned to complete two of them.

Typing Task

Please type all text from the blue box into the text entry box below, matching capitalization and punctuation. All spaces are single. You do not need to match the line breaks.

For instance, on the planet Earth, man had always assumed that he was more intelligent than dolphins because he had achieved so much (the wheel, New York, wars and so on) whilst all the dolphins had ever done was muck about in the water having a good time. But conversely, the dolphins had always believed that they were far more intelligent than man for precisely the same reasons. (Douglas Adams, 1978)

Subjects are then notified of their payment for the task.

Thank you for completing the typing task. Your compensation for completing this task is $5.00.

Please click the button below to continue to the next stage of the experiment.

[38]If the subject took longer than three minutes for a particular passage, we allowed them to continue to the next passage. This was not disclosed to subjects. In every case, the subject had entered the full text but had made a typo.

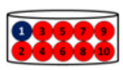
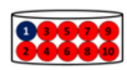
The lottery task begins with a set of instructions and three questions to ensure subjects understood them.

Part 1 Instructions

In this part, you must decide whether you would prefer to draw a ball from Bucket A or Bucket B. Each bucket contains a mixture of colored balls, and the color of the ball you draw will determine how much you gain or lose. We will tell you the mixture of the balls and the dollar value of each colored ball, and you should consider this information in choosing a bucket.

Here is an example of the buckets you will see in this part. Use the buttons in the middle to indicate whether you would prefer to draw from Bucket A or Bucket B.

You currently have $5.00.

	Bucket A			Bucket B
	● Gain $0.50 ● Lose $0.20 Ball mixture: 10% ●, 90% ●			● Gain $5.00 ● Lose $2.00 Ball mixture: 10% ●, 90% ●
Example	 ● Gain $0.50 ● Lose $0.20	○	○	● Gain $5.00 ● Lose $2.00 

Here are a few questions to make sure you understand the instructions.

What would happen if you drew a red ball from Bucket B?

- ○ Gain $0.50
- ○ Lose $0.20
- ○ Gain $5.00
- ◉ Lose $2.00

What is the chance of drawing a blue ball from Bucket A?

- ◉ 10%
- ○ 20%
- ○ 50%
- ○ 90%

If you lost $2.00, what would your total payment be at the end of this experiment?

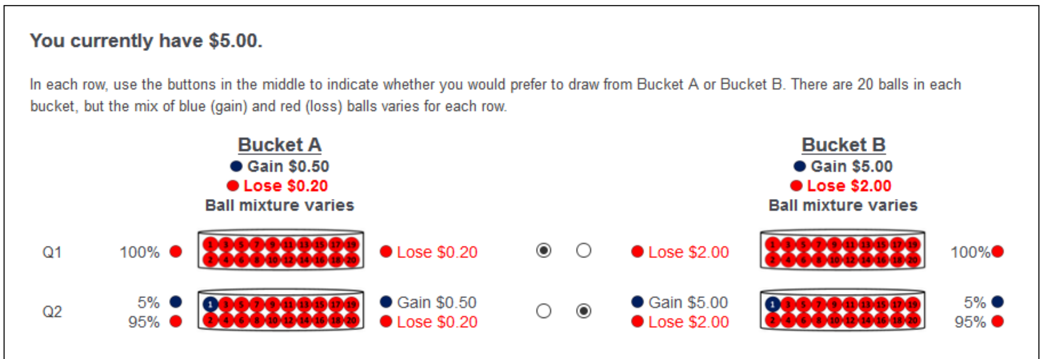
- ○ $0.00
- ○ $2.00
- ◉ $3.00
- ○ $5.00

Subjects who answer the questions correctly may continue to the lottery task. Subjects who answer incorrectly may not continue until they have answered the questions correctly.

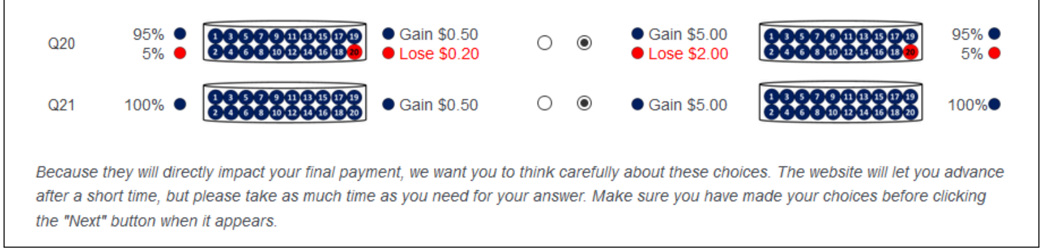
> Yes, that's right. Now we will ask you to make similar choices between two buckets.

Lotteries are presented in random order, and question numbers update automatically. In this example, the LA questions are presented first.

LA



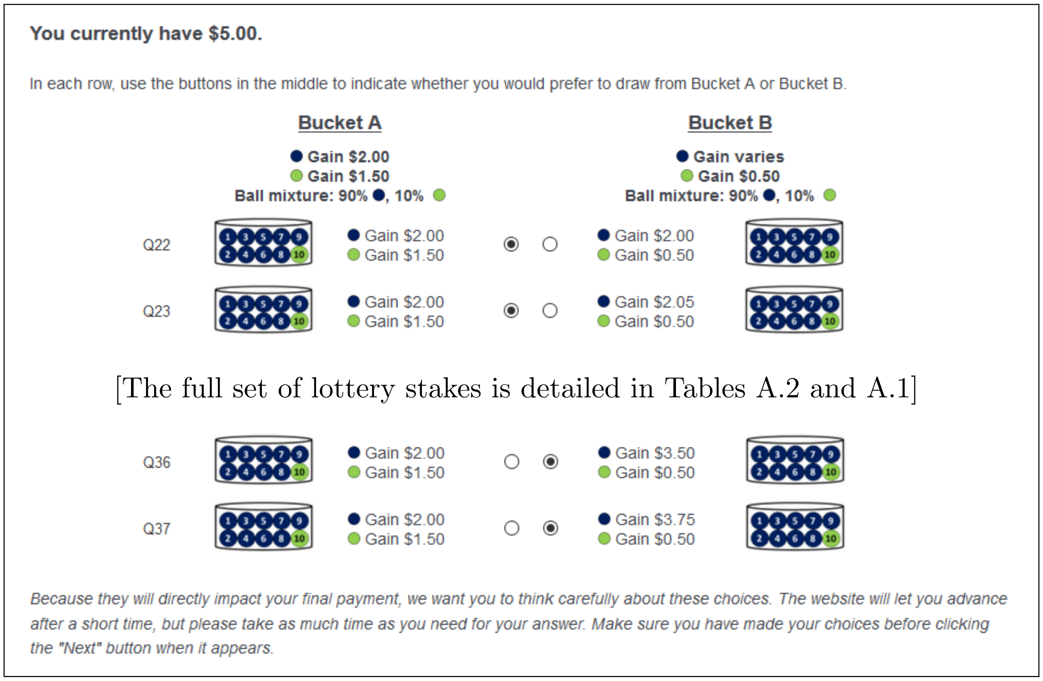
[The full set of lottery stakes is detailed in Tables A.2 and A.1]



To encourage subjects to make careful choices, the “Next” button is hidden for 20 seconds on each lottery page.

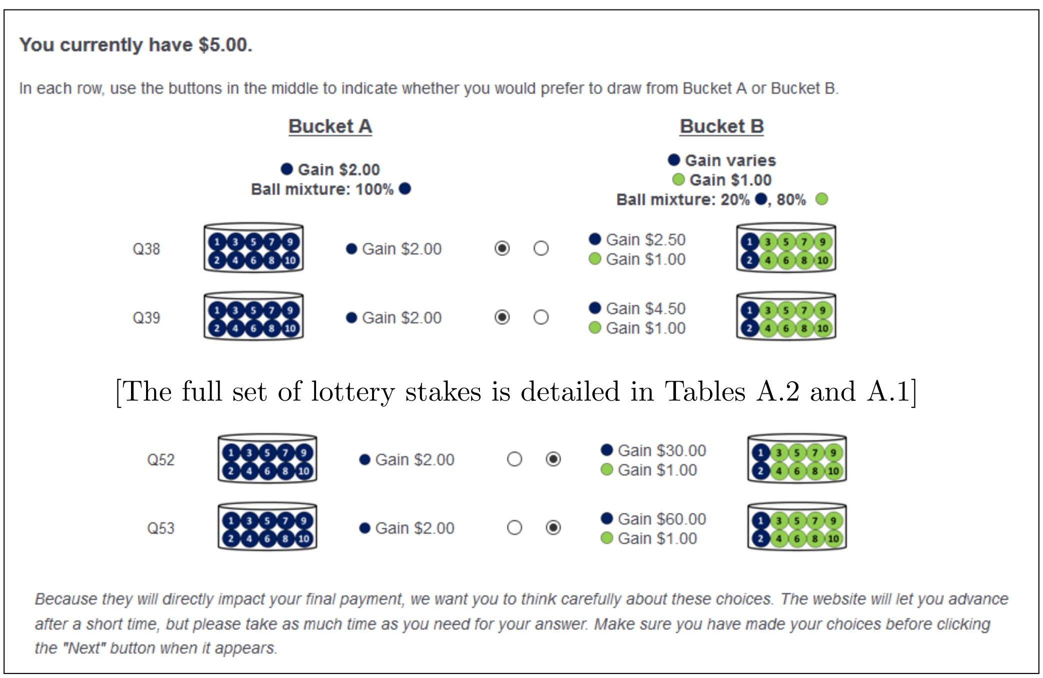
In this example, the GD2 lottery is randomly-selected to appear second.

GD2



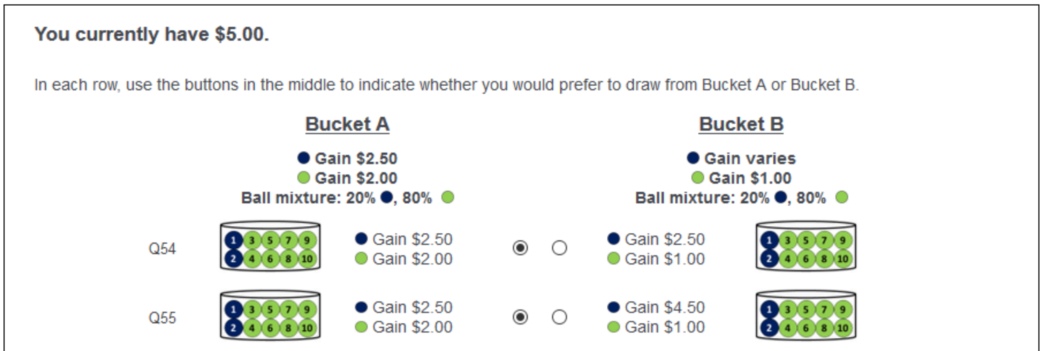
In this example, the CP table is randomly-selected to appear third.

CP

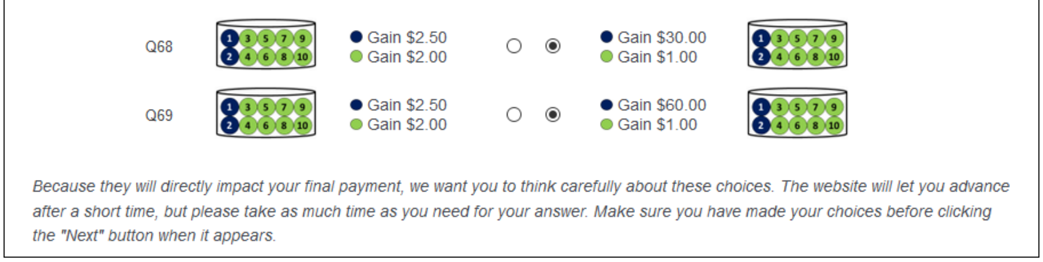


In this example, the GD1 table is randomly-selected to appear fourth.

GD1

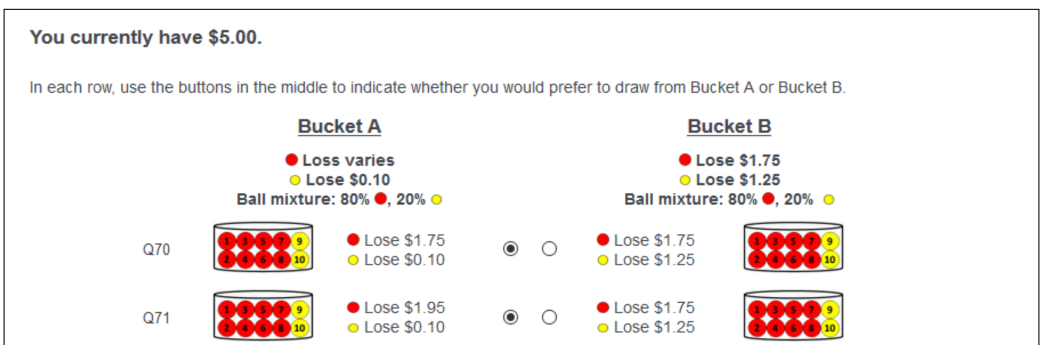


[The full set of lottery stakes is detailed in Tables A.2 and A.1]

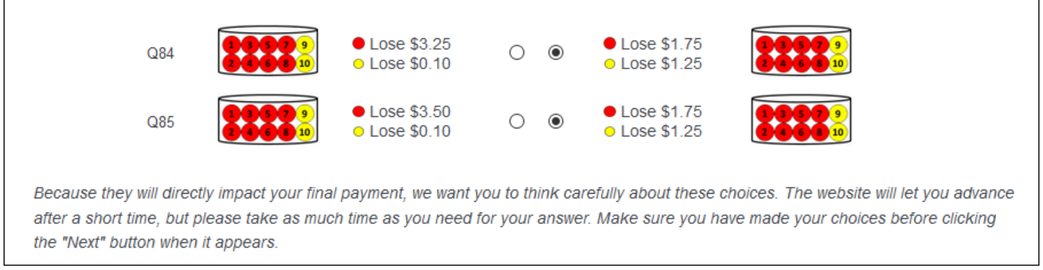


In this example, the LD2 table is randomly-selected to appear fifth.

LD2

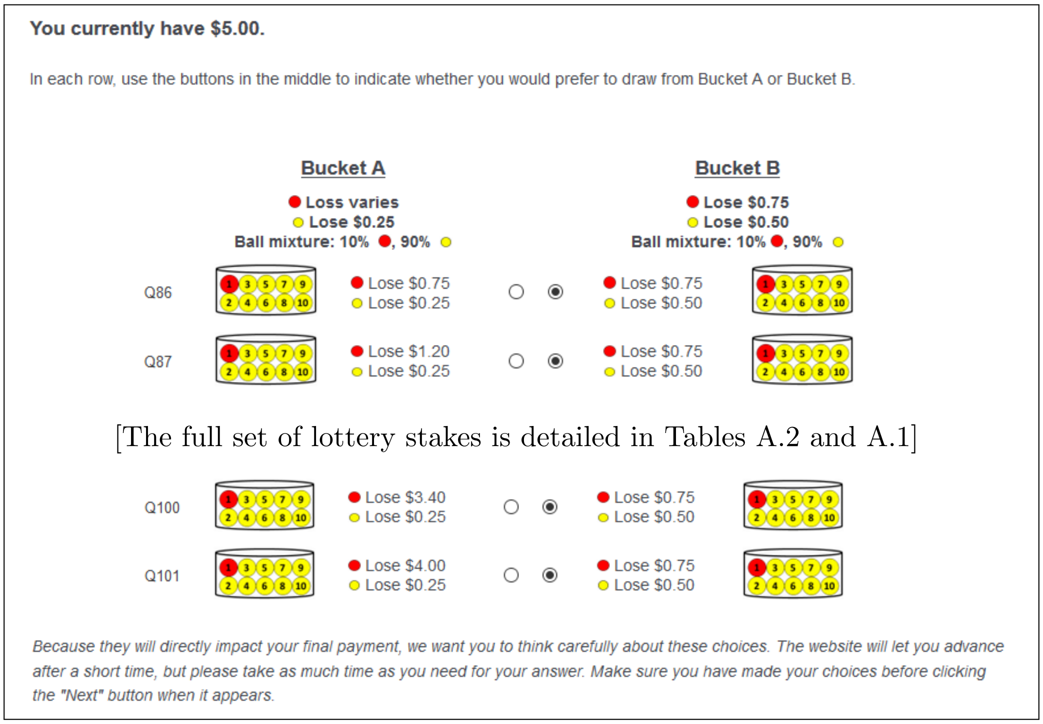


[The full set of lottery stakes is detailed in Tables A.2 and A.1]



Finally, the LD1 table is presented sixth.

LD1



[The full set of lottery stakes is detailed in Tables A.2 and A.1]

The insurance task begins with a set of instructions and two questions to ensure subjects understood them.

Part 2 Instructions

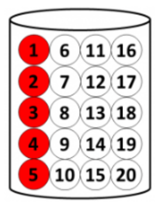
In this part, you will face a number of scenarios in which you may lose $3.00 of your money. Whether you have a loss depends on the draw of one ball from a bucket filled with 20 balls. Drawing a red ball results in a loss of $3.00, while drawing a white ball results in no loss.

You have the option to buy insurance to protect some or all of your money from loss. The price of insurance will be different in every scenario. Scenarios may also have a different chance of loss.

If you want to buy insurance, you must pay for it out of your $5.00 before you draw a ball at the end of the experiment. You may choose to buy varying levels of insurance, from 0% of the potential loss (no insurance) to 100% of the potential loss (full insurance). You may click the slider as many times as you like to see the different options. Your final earnings will depend on the price of the insurance you choose and any uninsured loss you may experience.

Here is an example question so you can see how your choices influence your final payment. Click the slider to practice selecting an insurance amount.

You currently have $5.00.



You have a 25% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 9 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 50%**
- **Before drawing a ball, pay $0.47 for insurance.**

If you draw ●:	If you draw ○:
• $3.00 loss ∘ $1.50 covered by insurance ∘ $1.50 loss to you	• No loss

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 50

Here are a few questions to make sure you understand the instructions:

Select 50% insurance using the slider above. How much would you need to pay for this insurance before drawing a ball?

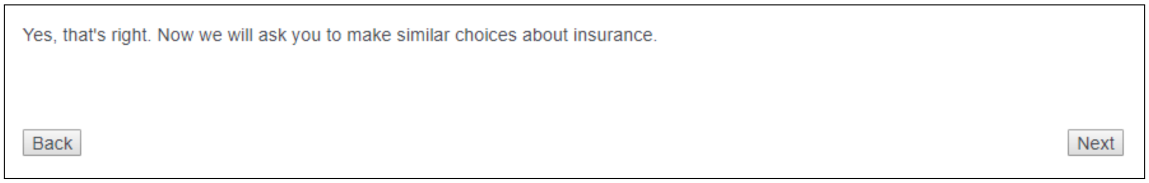
- ○ $0.09
- ○ $0.30
- ◉ $0.47
- ○ $0.94
- ○ $1.50

Select 50% insurance using the slider above. If you had this level of insurance and drew a red ball, how much of the $3.00 loss is covered by insurance?

- ○ $0.25
- ○ $0.47
- ○ $0.94
- ◉ $1.50
- ○ $3.00

Next

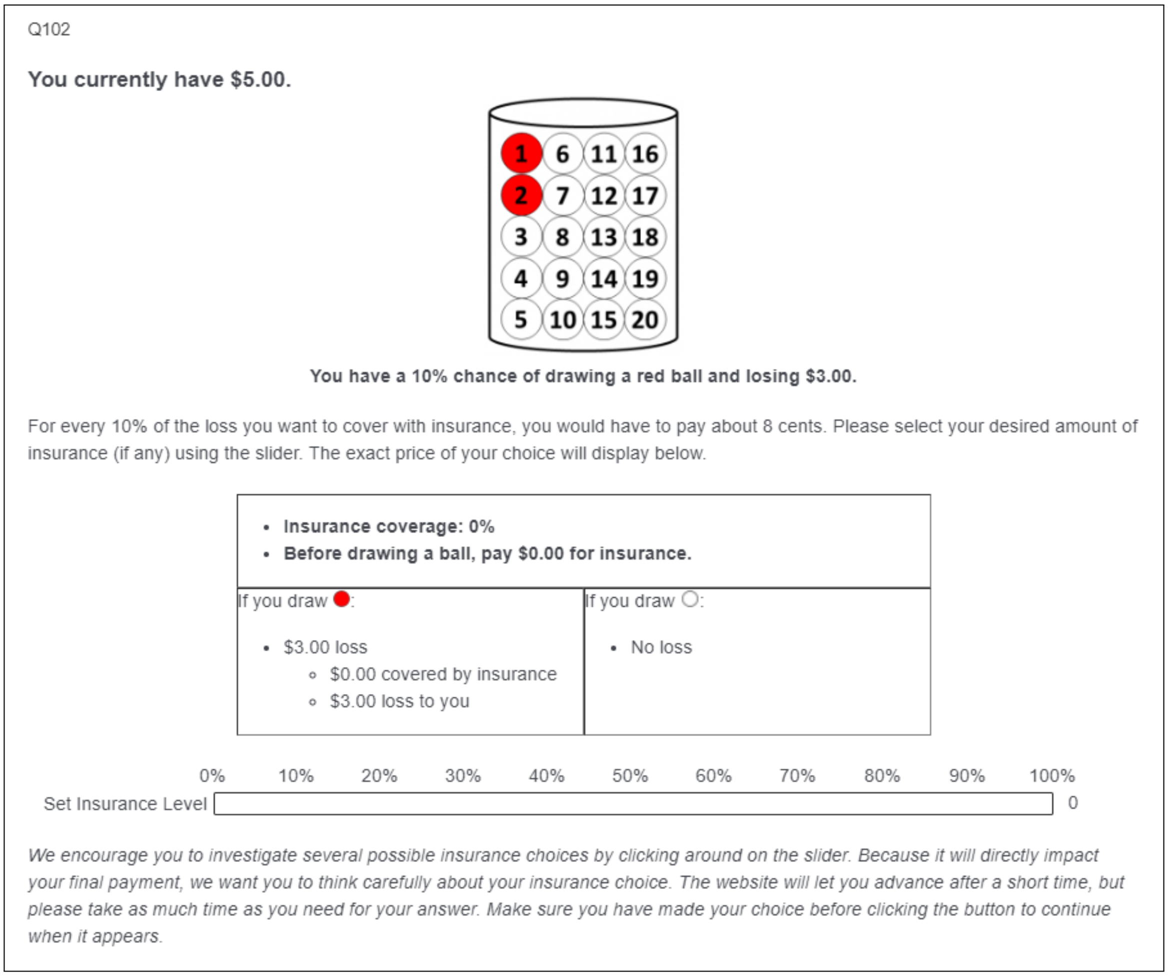
Subjects who answer the questions correctly may continue to the insurance task. Subjects who answer incorrectly may not continue until they have answered the questions correctly.


Yes, that's right. Now we will ask you to make similar choices about insurance.

Back

Next

Insurance scenarios are presented in random order, and question numbers update automatically. In this example, an insurance scenario with a 10% probability of loss is presented first. We have selected 0% coverage here.


Q102

You currently have $5.00.

You have a 10% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 8 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 0%**
- **Before drawing a ball, pay $0.00 for insurance.**

If you draw ●:	If you draw ○:
• $3.00 loss ◦ $0.00 covered by insurance ◦ $3.00 loss to you	• No loss

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 0

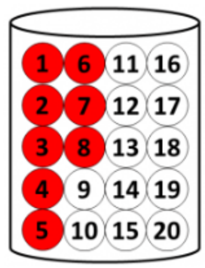
We encourage you to investigate several possible insurance choices by clicking around on the slider. Because it will directly impact your final payment, we want you to think carefully about your insurance choice. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choice before clicking the button to continue when it appears.

To encourage subjects to make careful choices, the "Next" button is hidden for 10 seconds on each insurance page.

The next randomly-selected insurance scenario involves a 40% chance of loss. We have selected 50% coverage here.

Q103

You currently have $5.00.



You have a 40% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 18 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 50%**
- **Before drawing a ball, pay $0.90 for insurance.**

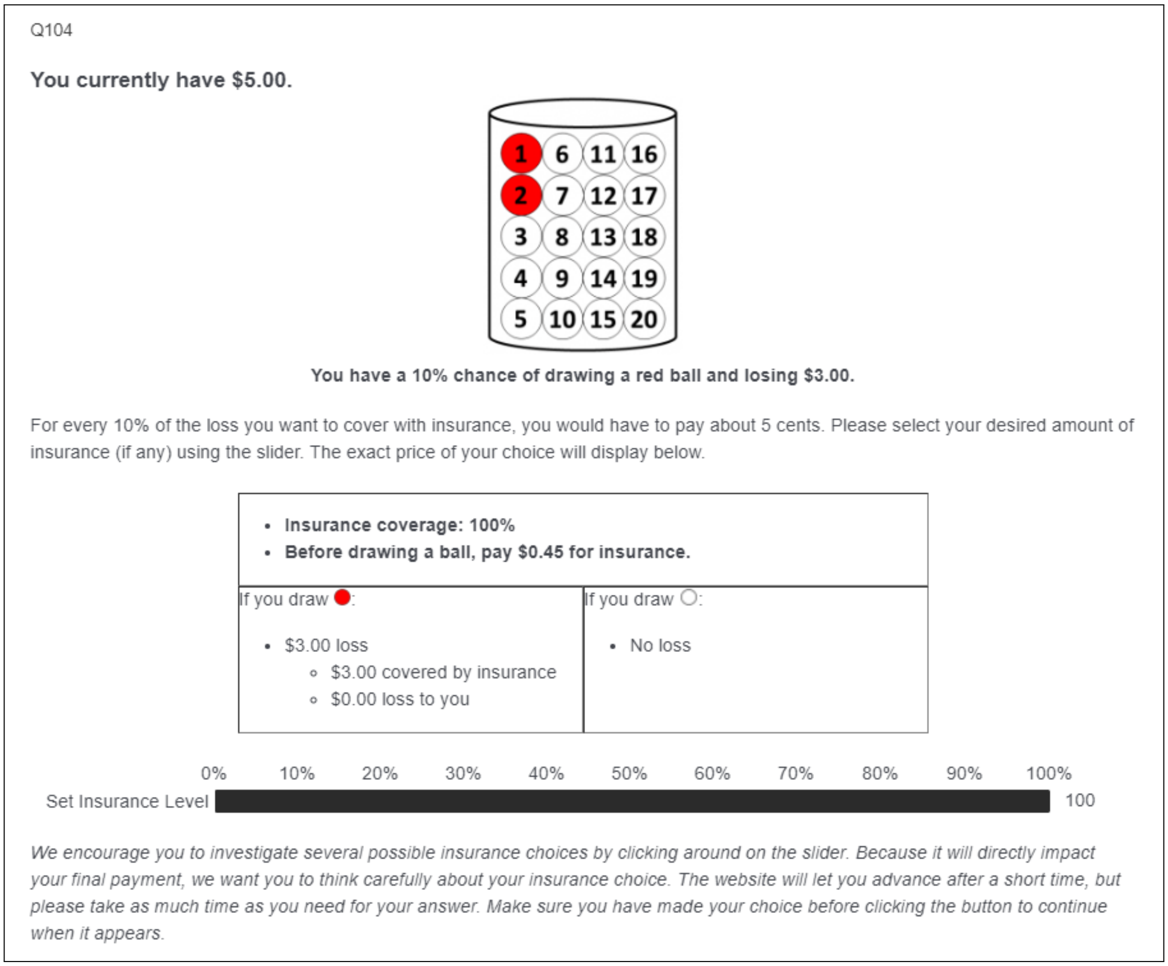
If you draw ●:	If you draw ○:
• $3.00 loss ◦ $1.50 covered by insurance ◦ $1.50 loss to you	• No loss

0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 50

We encourage you to investigate several possible insurance choices by clicking around on the slider. Because it will directly impact your final payment, we want you to think carefully about your insurance choice. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choice before clicking the button to continue when it appears.

The next randomly-selected insurance scenario again involves a 10% chance of loss. We have selected 100% coverage here.


Q104

You currently have $5.00.

You have a 10% chance of drawing a red ball and losing $3.00.

For every 10% of the loss you want to cover with insurance, you would have to pay about 5 cents. Please select your desired amount of insurance (if any) using the slider. The exact price of your choice will display below.

- **Insurance coverage: 100%**
- **Before drawing a ball, pay $0.45 for insurance.**

If you draw ●:	If you draw ○:
• $3.00 loss ∘ $3.00 covered by insurance ∘ $0.00 loss to you	• No loss

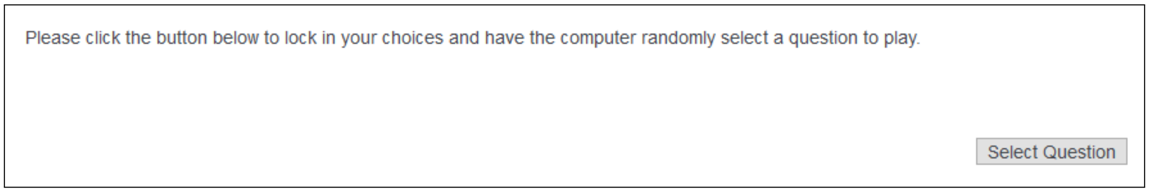
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Set Insurance Level 100

We encourage you to investigate several possible insurance choices by clicking around on the slider. Because it will directly impact your final payment, we want you to think carefully about your insurance choice. The website will let you advance after a short time, but please take as much time as you need for your answer. Make sure you have made your choice before clicking the button to continue when it appears.

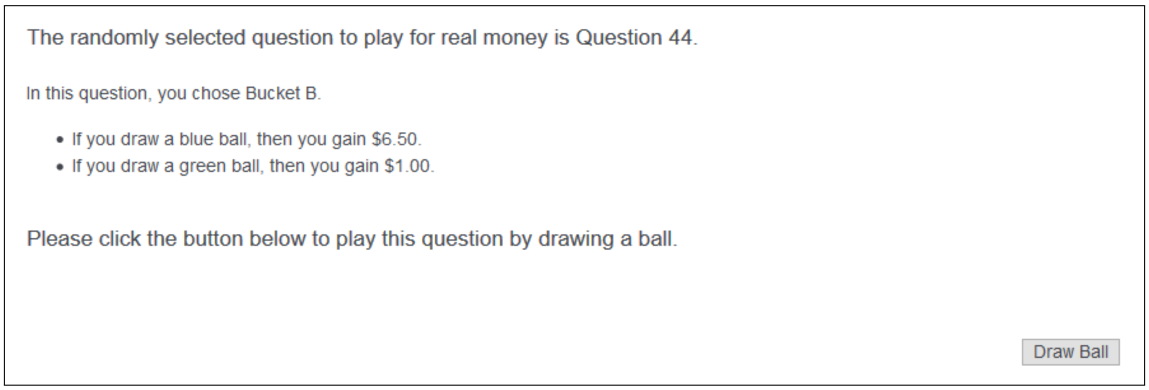
The nine remaining insurance scenarios have identical layouts, so we omit them from this appendix. The last question is numbered Q113.

After all choices are made in the experiment, the computer randomly selects one decision to play out.


Please click the button below to lock in your choices and have the computer randomly select a question to play.

Select Question

In this example, Question 44 is the randomly-selected decision. We confirm to the subject which selection he/she originally made and the possible outcomes. Then, they click the button to draw a "ball."


The randomly selected question to play for real money is Question 44.

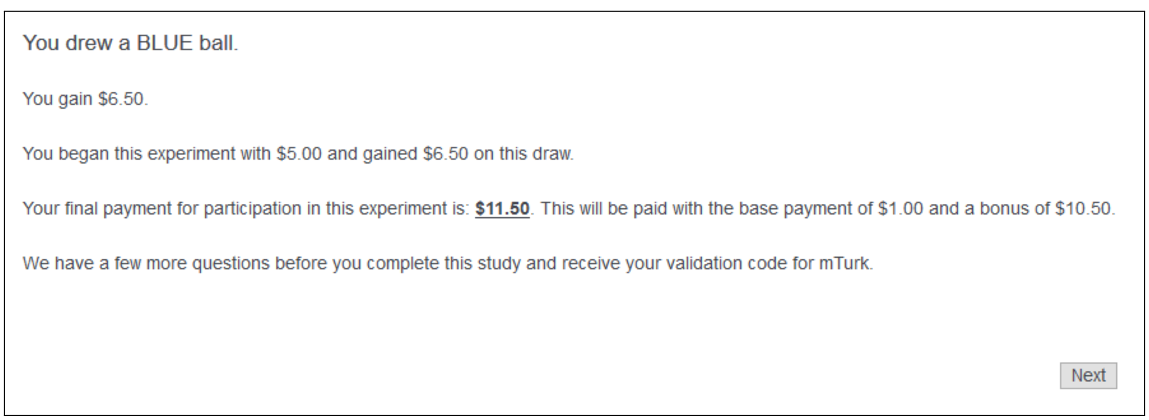
In this question, you chose Bucket B.

- If you draw a blue ball, then you gain $6.50.
- If you draw a green ball, then you gain $1.00.

Please click the button below to play this question by drawing a ball.

Draw Ball

The computer then displays the outcome of the draw and outlines the subject's payment. Amazon mTurk requires variable payments to be paid as a "base" plus a "bonus." We were clear in the mTurk posting that our task involved variable payments paid as bonuses. This appears a common way to compensate subjects, and no subjects expressed confusion about the payments. During our pilot studies, we had built a positive reputation in a number of third-party websites for paying bonuses quickly, so nonpayment risk was a minimal concern. All pilot participants were excluded from our main experiment.


You drew a BLUE ball.

You gain $6.50.

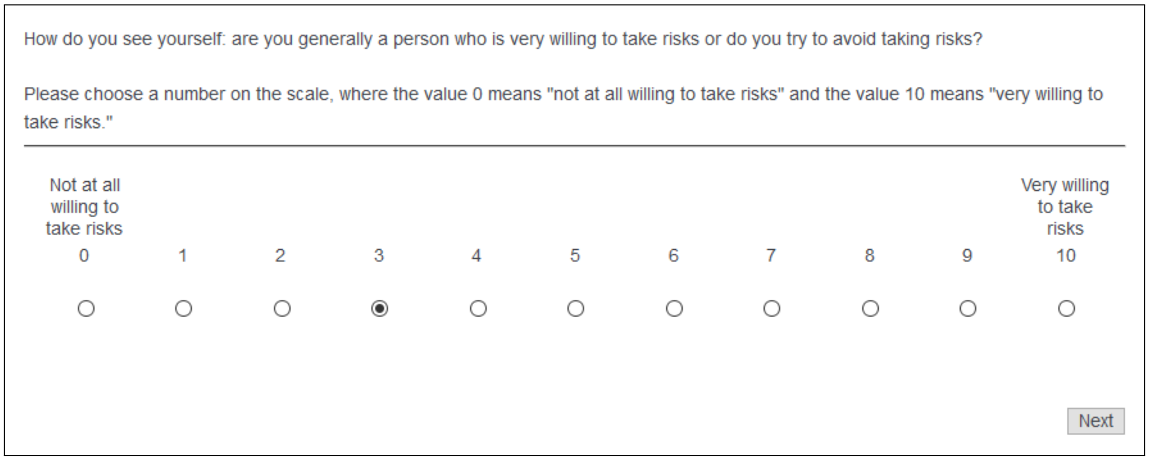
You began this experiment with $5.00 and gained $6.50 on this draw.

Your final payment for participation in this experiment is: **$11.50**. This will be paid with the base payment of $1.00 and a bonus of $10.50.

We have a few more questions before you complete this study and receive your validation code for mTurk.

Next

Immediately after the draw, we ask the GRQ. The direction of the scale (0-10 or 10-0) is randomly assigned.



Finally, we ask the following demographics questions and follow-up questions about the experiment.

What is your year of birth?

1983

What is your gender?

- ◉ Male
- ○ Female
- ○ Transgender male
- ○ Transgender female
- ○ Gender variant/non-conforming
- ○ Other
- ○ Prefer not to answer

In which country do you currently reside?

In which U.S. state do you currently reside?

I do not reside in the United States

What is your race? You may choose all that apply.

- ☐ White or Caucasian
- ☐ Black or African American
- ☐ Hispanic or Latino
- ☐ Asian
- ☐ American Indian or Alaska Native
- ☐ Native Hawaiian or Pacific Islander
- ☐ Other

What was your approximate household income (in U.S. dollars, before taxes) in 2017? If you need to convert your income from another currency, you may calculate it here (opens in a new window).

- ○ Less than $5,000
- ○ $5,000 to $9,999
- ○ $10,000 to $24,999
- ○ $25,000 to $49,999
- ○ $50,000 to $74,999
- ○ $75,000 to $99,999
- ○ $100,000 to $149,999
- ○ $150,000 or greater

What is the highest level of school you have completed or the highest degree you have received?

- ○ Less than high school degree
- ○ High school graduate (high school diploma or equivalent including GED)
- ○ Some college but no degree
- ○ Associate degree in college (2-year)
- ○ Bachelor's degree in college (4-year)
- ○ Master's degree
- ○ Professional degree (JD, MD)
- ○ Doctoral degree

We have some final questions about your experience with this study.

Please rate your feelings on how easy or difficult this study was to UNDERSTAND:

Very easy to understand	Easy to understand	Neither easy nor difficult to understand	Difficult to understand	Very difficult to understand
○	○	○	○	○

If you had any technical difficulties completing this study, please explain below:

What do you think we were trying to find out in this study?

After all questions are answered, we provide a final "Submit" screen to remind subjects about the upcoming validation code.

Thank you for completing this study. Please click the button below to submit your responses. The next page will include a validation code. You must enter this validation code in mTurk so we can connect your final outcome in this survey to your mTurk account.

Submit Responses

For mTurk subjects, the study concludes with a validation code to connect their experiment outcomes to their mTurk account. In-person subjects were provided with a validation code to write down and bring to the experimenter for payment.

Thank you for your responses in this survey! Your validation code is:

7472154

Write this number down. Once you close this window, the validation code will disappear and cannot be recovered.

Please return to Amazon Mechanical Turk to enter the above validation code.