LOTTERY-SPECIFIC EFFECTS AND HETEROGENEITY: A UNIFIED FRAMEWORK

JOSE APESTEGUIA[†], MIGUEL A. BALLESTER[‡], AND ÁNGELO GUTIÉRREZ-DAZA[§]

Abstract. We develop a framework for studying lottery-specific deviations from expected utility without imposing a particular behavioral model. Certainty-equivalent valuations arise from a distribution over expected-utility preferences. We characterize two lottery-dependent extensions axiomatically: one allows lottery characteristics to shift the distribution's location, capturing mean risk attitudes, and the other its scale, capturing behavioral noise. Using 197,465 observations from 15 studies, covering 1,299 lotteries, 90 treatments, and 7,362 individuals, we find that complexity-related characteristics primarily affect noise, whereas probability mass tilted toward favorable payoffs and the presence of losses primarily affect mean risk attitudes. The framework organizes empirical regularities usually treated separately.

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1. Introduction

Observed risk attitudes vary systematically with the lotteries used to elicit them; lotteries that differ in their number or range of payoffs, in their probability distributions, or in whether they include prizes equal to zero or are framed as losses can generate very different expected-utility risk-attitude estimates, even for the same underlying population. These patterns are often interpreted through specific behavioral models, such as prospect theory, or by appealing to complexity costs, attention, or salience. At the same time, observed risk attitudes display substantial heterogeneity. These two facts are usually studied separately: behavioral models explain systematic deviations from expected utility, while stochastic or heterogeneity-based models account for dispersion in valuations.

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[†]ICREA, Universitat Pompeu Fabra and Barcelona School of Economics. E-mail: jose.apesteguia@upf.edu.
[‡]IKERBASQUE and Basque Country University. E-mail: miguelangel.ballester@ehu.eus.
[§]Banco de México. E-mail: angelo.gutierrez@banxico.org.mx.

However, it is apparent that these two behavioral facets may share some underlying causes and hence, to properly understand the former, one must necessarily account for the latter. A possible approach is to consider a specific behavioral model and only then to add preference heterogeneity. But as the catalog of behavioral models continues to expand, this approach may result in ad hoc explanations that fail to provide a robust or consensus-based understanding of the underlying data. Instead, we argue that it is best to represent heterogeneity as a probability distribution over expected-utility preferences, and study lottery-specific effects as systematic shifts in that distribution. In this paper, we focus on the two main types of shifts: changes in the location of the distribution, potentially reflecting shifts in average risk attitudes, and changes in the scale of the distribution, or shifts in behavioral noise. We show that this exercise proves useful for studying the interplay between lottery characteristics and observed risk attitudes, uncovering patterns related to mechanisms such as perception, attention, or computational complexity without committing to a particular behavioral functional form.

We develop our theoretical framework for the case of certainty-equivalent valuations. The baseline model represents the certainty-equivalent valuations of any lottery L as resulting from i.i.d. draws from a distribution G over an ordered family of expected-utility preferences $\{U_\alpha\}_{\alpha\in\mathbb{R}}$. We characterize the model axiomatically, analyze how the underlying distribution of risk attitudes can be recovered from data, and discuss parametric versions where the distribution G is determined by a pair of location and scale parameters τ and σ. We then introduce the two above-mentioned extensions in which the distribution of risk attitudes is made lottery-dependent; the first uses a constant location τ but a lottery-dependent scale $\sigma : \mathcal{L} \to \mathbb{R}_{++}$, while the second uses a constant scale σ but a lottery-dependent location $\tau : \mathcal{L} \to \mathbb{R}$. We establish the theoretical predictions of these models, discuss how to recover the lottery-dependent parameters from the data, and provide their axiomatic foundations.

We then estimate these models using 197,465 certainty-equivalent observations from 15 studies, covering 1,299 lotteries, 90 experimental conditions, and 7,362 individuals. For the empirical implementation, we use both CRRA and CARA utility families together with logistic distributions of risk attitudes. The baseline heterogeneous expected-utility model captures the main features of the aggregate distribution of risk attitudes, especially once treatment-level heterogeneity is allowed for. However, it misses systematic lottery-specific patterns. For example, lotteries with a zero prize generate less dispersed risk-attitude estimates than other lotteries. In contrast, lotteries whose probability mass is tilted toward favorable payoffs shift the first moment of the distribution toward greater risk aversion.

Our lottery-specific scale model intuitively addresses the first type of pattern, markedly improving fit. The model allows the scale of the distribution of risk attitudes to vary across lotteries while keeping its location fixed, and the results are intuitively connected to existing ideas of behavioral noise and interpretations based on complexity or attention.

More concretely, the estimates show that characteristics often associated with complexity, such as a larger number of payoffs or more asymmetric probability distributions, increase behavioral noise. Other characteristics, such as larger payoff ranges or irregular probabilities, reduce noise, consistent with greater attention in more consequential or more salient valuation problems.

Our lottery-specific location model intuitively addresses the second type of pattern mentioned above. The model keeps the scale of the distribution fixed while allowing its location to vary across lotteries, and its structure is closely related to classical models involving probability weighting or fanning out. The empirical estimates show that, holding payoffs fixed, risk aversion increases when probability mass shifts toward favorable payoffs and decreases when some of the prizes involve losses. By contrast, we also show that the number of payoffs has little systematic effect on average risk attitudes, despite its substantial effects on behavioral noise.

Taken together, our results illustrate the value of developing, in tandem, an axiomatized and empirically implementable framework for studying lottery-specific deviations from expected utility through changes in the distribution of risk attitudes. Theorem 1 characterizes the baseline case, in which this distribution is common across lotteries, and provides the platform on which Theorems 2 and 3 build two new characterization results establishing exactly how a lottery-dependent scale or location can be recovered from data. This theoretical apparatus is what lets the empirical analysis draw a sharp—rather than merely suggestive—distinction between the two channels. The central empirical lesson is that lottery characteristics do not affect risk attitudes through a single channel. Some characteristics that are often interpreted as changing risk aversion, such as the number of payoffs or the asymmetry of the probability distribution, primarily affect behavioral noise; others, such as the association between probabilities and favorable payoffs or the presence of losses, primarily shift mean risk attitudes. This distinction helps organize several empirical regularities that are usually studied separately—including support size, fanning out, incentives, compound risk, reference dependence, and elicitation procedures—within a single framework.

2. Related Literature

Expected utility as a descriptive theory of risk attitudes has been challenged by many experimental observations documenting lottery-specific effects, such as the certainty and common-ratio effects, failures of the reduction of compound lotteries, and the influence of reference points. Kahneman and Tversky's (1979) prospect theory is perhaps the most prominent behavioral alternative to expected utility, and a broad experimental literature supports prospect-theoretic patterns across experimental designs and countries; see, e.g., Bleichrodt et al. (2007), l'Haridon and Vieider (2019), Ruggeri et al. (2020), and Imai et al. (2025). Despite this empirical success, the framework has also faced recent scrutiny: Bernheim and Sprenger (2020) question the structural validity of probability weighting, while Oprea (2024) argues that some of its building blocks may be the result of cognitive complexity. Our approach contributes to this broad literature by formally introducing heterogeneity into an expected-utility framework, and then using it to study how lottery characteristics affect both behavioral noise and mean risk attitudes. We do not need to specify a particular behavioral model behind the observed deviations; instead, we remain agnostic about the underlying behavioral mechanism and let the data reveal the relevant patterns in light of our framework. Our empirical analysis finds lower mean risk aversion both for lotteries with probability distributions skewed toward bad payoffs and for lotteries involving losses, two well-known patterns associated with prospect theory. Yet, as discussed below, the framework also uncovers patterns often related to other behavioral considerations, such as complexity or attention, thereby providing a more comprehensive view of behavior.

There is also a long tradition in economics studying the role of complexity in risky choice. There is robust evidence that different measures of lottery complexity affect behavior in choices over lotteries. Two early contributions are Wilcox (1993) and Huck and Weizsäcker (1999), who document that subjects tend to prefer less complex lotteries and take longer to decide about more complex menus. Recently, Enke and Shubatt (2026) develop quantitative indices of lottery-choice complexity and use them to study behavioral attenuation, inconsistency, and spurious revealed risk attitudes. Much of this evidence comes from choice tasks, where complexity can arise both from the lotteries themselves and from the comparisons induced by the menu.[1] This distinction is important for our purposes because certainty equivalents isolate the evaluation of a single lottery. In line with this distinction, Oberholzer, Olschewski, and Scheibehenne (2024) show that complexity may affect choice tasks and single-lottery evaluation tasks differently. We therefore focus next on papers that study how specific characteristics of individual lotteries affect their evaluation.

Several papers have studied aversion to particular lottery characteristics. Puri (2025) shows experimentally that increasing the number of payoffs makes a lottery less attractive and proposes a representation based on expected utility with a complexity cost.[2] de Clippel et al. (2025) show that subjects undervalue compound risk. Oprea (2024) shows experimentally that complexity may reflect the difficulty of computing expected values, and that this difficulty can rationalize behavior often attributed to prospect theory. Enke and Graeber (2023) introduce cognitive uncertainty as a measurable proxy for complexity and show it is positively correlated

[1]Some other recent papers in lottery choice study the impact of complexity on procedural decision-making (Nielsen and Rehbeck, 2022; Arrieta and Nielsen, 2024) and attitudes toward complexity under different informational settings (Corgnet and Hernán-González, 2023).

[2]Mononen (2025) proposes an expected-utility model with an additive complexity cost based on Shannon entropy, and Hu (2023) provides a theoretical framework encompassing these notions of complexity.

with response noise. Our contribution to this literature is not to propose another measure of lottery complexity or another model of aversion to a particular lottery characteristic. Rather, we provide an axiomatized framework, grounded in heterogeneous expected-utility risk attitudes, to study how lottery characteristics perturb the distribution of underlying risk attitudes. This allows us to distinguish between lottery-specific shifts in mean risk aversion and lottery-specific changes in behavioral noise. Empirically, this distinction matters: characteristics such as the number of payoffs and the asymmetry of the probability distribution mainly affect the scale of the distribution, while features such as probability distributions skewed toward good payoffs or the presence of losses primarily affect its location.

Our paper is also related to the literature on attention in the study of risk preferences.[3] Attention may be modulated, rationally or not, by incentives or salience considerations. Kachelmeier and Shehata (1992) and Holt and Laury (2002) are early influential papers showing that higher payoffs induce more risk aversion. Smith and Walker (1993) survey evidence documenting that higher incentives reduce the variance of data, suggesting a role for attention or decision noise. Khaw, Li, and Woodford (2022) use an efficient noisy-coding model that accounts for some lottery characteristics, such as incentives. Belzil and Jagelka (2025) propose a method to separate the impact of taste heterogeneity from the effects of rationally inattentive choices. Manzini and Mariotti (2014) and Cattaneo et al. (2020) propose stochastic models of limited attention, and Barseghyan, Molinari and Thirkettle (2021) and Aguiar et al. (2023) empirically study limited attention in risky settings. Bordalo, Gennaioli and Shleifer (2020) model how the salience of lottery characteristics in a menu draws decision-makers' attention and distorts behavior. Our contribution to this literature is, as above, to axiomatically develop a model of lottery evaluations that accounts for heterogeneity while allowing this heterogeneity to depend on the lottery under evaluation. This permits us to uncover behavioral patterns that may be related to attention. For example, we find that behavioral noise is markedly reduced when valuations are more consequential, in the sense that they involve larger payoff ranges, or when they involve less familiar probabilities.

The stochastic choice literature is large and has grown sharply in recent years; see Strzalecki (2025) for a comprehensive synthesis. The baseline model proposed in this paper is aligned with the tradition of heterogeneous preferences, studied by Block and Marschak (1960) in abstract settings, and by Gul and Pesendorfer (2006) in the context of risk preferences. Barseghyan et al. (2018) discuss identification and estimation issues in the empirical study of heterogeneous risk preferences in the field. Closer to the implementation in this paper, Apesteguia, Ballester, and Lu (2017) introduce a framework of ordered random utility models built on one-dimensional heterogeneity, subsequently extended to boundedly rational families of behavior by Filiz-Ozbay and Masatlioglu (2023). Within this same class of ordered random

[3]See the recent survey of Loewenstein and Wojtowicz (2025).

utility models, Apesteguia and Ballester (2026) study which parametric assumptions carry testable content, including ordered-logit specifications. The baseline logic of this tradition is what Theorem 1 below specializes to certainty-equivalent valuations of monetary lotteries. Theorems 2 and 3 depart from this tradition in a different direction altogether: rather than restricting or testing the class of admissible distributions, they let the distribution itself respond to the lottery being evaluated, through its location or its scale, and establish exactly how each object is recovered from data—a question neither paper asks. Overall, this paper contributes to this literature by offering a framework that allows us to study behavioral considerations by tracking their impact on the location and scale of the distribution describing preference heterogeneity. In addition, whereas this literature focuses on stochastic choice data, we study the distribution of certainty-equivalent valuations of individual lotteries.

3. Basic Notation

We consider the space of (monetary) payoffs $X = [\underline{x}, \overline{x}] \subseteq \mathbb{R}_{++}$.[4] A (monetary) lottery $L = [p_1, \ldots, p_{I_L}; x_1, \ldots, x_{I_L}]$ is composed of a finite number I_L of payoffs, $x_i \in X$, arranged to satisfy $x_1 < x_2 < \cdots < x_{I_L}$, and their corresponding probabilities, $p_i \in \mathbb{R}_{++}$, which must satisfy $\sum_{i=1}^{I_L} p_i = 1$. The expected value of L is denoted by $\mu_L = \sum_{i=1}^{I_L} p_i x_i$. The space of all lotteries is denoted by $\mathcal{L}$.

We consider the space $\mathcal{U}$ of monetary utility functions $U : X \to \mathbb{R}$ that are continuous and strictly increasing, and satisfy $U(\underline{x}) = 0$ and $U(\overline{x}) = 1$. Since we work with expected utility and all our results are of an ordinal nature, the normalization chosen is without loss of generality. The expected utility using U is denoted EU. Given these assumptions, we know that certainty equivalents of utility U are always unique. We denote the map from utilities and lotteries to certainty equivalents by CE, i.e., $U(CE(U; L)) = EU(L) = \sum_{i=1}^{I_L} p_i U(x_i)$, or alternatively $CE(U; L) = U^{-1}[\sum_{i=1}^{I_L} p_i U(x_i)]$.

4. A Baseline Model

We begin by considering a baseline model that accounts for preference heterogeneity. The simplest interpretation is one in which data come from a representative agent with heterogeneous expected-utility risk attitudes.[5] In particular, we consider the simplest case in which data are generated by a one-dimensional family of utilities. Formally, consider a generic family of expected utilities based upon monetary utilities $\{U_\alpha\}_{\alpha \in \mathbb{R}}$, with $U_\alpha \in \mathcal{U}$. The family is strictly ordered by increasing risk aversion and varies continuously in α. We assume that

[4]These are final outcomes, strictly positive once background consumption ω is added to the lottery prize y (i.e., $x = y + \omega$); we refer to this decomposition only when it is critical, and Section 4.2 is more explicit about its empirical role.

[5]Our framework can be equivalently interpreted at the population or individual level. The first interpretation represents the case where there is a population of heterogeneous expected-utility individuals, while the second assumes that the agent has internal heterogeneity consistent with a random expected-utility model.

the family of utilities contains risk-neutral behavior, and we always locate this behavior at the origin of the family. That is, we assume that $U_0(x)$ is the normalized affine transformation of the identity function. We also assume, as is common with most parametric families of utilities such as CRRA and CARA, that the degree of convexity (respectively, concavity) is unbounded as $\alpha \to -\infty$ (respectively, as $\alpha \to +\infty$); this makes the certainty equivalent of any lottery L converge to x_{I_L} (respectively, x_1). Now, the risk aversion α used by the representative agent when evaluating any given lottery is drawn i.i.d. from a probability distribution on the reals with cumulative distribution function (CDF) G, which we assume to be continuous and strictly increasing.

Given the monotone relationship between risk aversion levels and certainty equivalents, the predictions of the model for any possible lottery $L \in \mathcal{L}$ can be described by its CDF of certainty equivalents, i.e., the cumulative mass $F_G(ce; L)$ of certainty equivalents of lottery L that are predicted to be smaller than or equal to the value ce.

A remark is useful here. The assumptions on $\{U_\alpha\}_{\alpha \in \mathbb{R}}$ guarantee that (i) whenever the lottery at stake is degenerate, the cumulative distribution must have a unique jump from zero to one at the unique payoff of such a lottery and (ii) whenever the lottery has at least two payoffs, the map $F_G(ce; L)$ is continuous and strictly increasing in $ce \in (x_1, x_{I_L})$, where we must have $\lim_{ce \to x_1} F_G(ce; L) = 0$ and $\lim_{ce \to x_{I_L}} F_G(ce; L) = 1$. Accordingly, in the definitions that follow we avoid the (costly) notational burden of explicitly referring to these trivial pieces of information, and state the definitions with lotteries having at least two payoffs and certainty equivalents in the range (x_1, x_{I_L}) in mind. Under these conditions, given $(ce; L)$, there is a unique value of α for which the certainty equivalent of utility U_α for lottery L is ce. This value can be simply denoted as $\alpha(ce; L) \in \mathbb{R}$.[6] Moreover, any risk parameter above (resp. below) $\alpha(ce; L)$ produces a certainty equivalent below (resp. above) ce. The following proposition summarizes the relationship between the distributions of risk attitudes and certainty equivalents of a given lottery.

Proposition 1. *For every $L \in \mathcal{L}$ and every $ce \in (x_1, x_{I_L})$, the predictions of the baseline model are $F_G(ce; L) = 1 - G(\alpha(ce; L))$.*

Proposition 1 follows immediately from the monotonicity between risk attitudes and certainty equivalents. Indeed, monotonicity makes the comparative statics straightforward: a first-order stochastic increase in G induces a first-order stochastic decrease in F_G, while a median-preserving expansion of G induces a median-preserving expansion of F_G.[7] These comparative statics underlie the interpretation of the empirical findings obtained under the extensions of the baseline model developed later.

[6] Note that the map defined this way is simply the inverse of the map $CE(\cdot; L)$.

[7] G' is a median-preserving expansion of G if they have the same median m, $G'(\alpha) > G(\alpha)$ below m, and $G'(\alpha) < G(\alpha)$ above m.

We now discuss the identification and the axiomatic characterization of the model. As for identification, both components of the model are identified. Using standard arguments in expected utility, each of the utilities is identified up to an affine transformation. Also, standard techniques in econometrics guarantee that distribution G is identified up to the relabelling of the family of utilities (see, e.g., Matzkin, 2003). We discuss after Theorem 1 how to recover both the utilities and the distribution over them.

As for the axiomatic characterization, assume that the analyst observes (cumulative) data $F = \{F(\cdot; L)\}_{L\in\mathcal{L}}$, where $F(ce; L)$ represents the observed mass of certainty equivalents of L equal to or lower than ce. We assume that $F(ce; L)$ is equal to zero whenever $ce \leq x_1$, equal to 1 whenever $ce \geq x_{I_L}$, and is continuous and strictly increasing in (x_1, x_{I_L}).[8] As for our first property, observe that in the present case where lotteries have no specific effects, the mass of risk-averse evaluations must be constant across lotteries:

Constancy (of the Mass of Risk-Averse Evaluations). For every $L, L' \in \mathcal{L}$: $F(\mu_L; L) = F(\mu_{L'}; L')$.

Moreover, each quantile should be a representation of an underlying risk attitude and, given the expected utility assumption, each of them must satisfy the classical independence principle across lotteries. To formalize this, denote by $L\lambda L''$ the lottery resulting from the reduction of the compound lottery assigning probability λ to L and probability $1-\lambda$ to L''. Then:

(Quantile) Independence. For every $L, L', L'' \in \mathcal{L}$ and $q, \lambda \in (0, 1)$:

$$F^{-1}(q; L) \geq F^{-1}(q; L') \Leftrightarrow F^{-1}(q; L\lambda L'') \geq F^{-1}(q; L'\lambda L'').$$

We can now present the following result.

Theorem 1. *Data F satisfy Constancy and Independence if and only if there exists a family of monetary utilities $\{U_\alpha\}_{\alpha\in\mathbb{R}}$ and a distribution G such that $F = F_G$.*

Theorem 1 shows that Constancy and Independence are not only necessary but also sufficient conditions for our model. The sufficiency part of the proof is constructive, and therefore it shows how one can recover from data the family of utilities and the distribution over them. First, with respect to the utility functions, note that the quantile associated with the cumulative probability $q \in (0, 1)$, across all lotteries, must always be generated by the same risk preference, the one associated with quantile $1-q$ in the distribution of risk preferences. Since data come in the form of the certainty equivalents of each lottery, we have

[8] Again, only as long as the lottery has two payoffs, with a jump from zero to one at the unique payoff of a degenerate lottery.

direct access to the risk preference via its certainty equivalent representation. Independence guarantees that this is an expected utility representation. To obtain the underlying monetary utility function, it suffices to use the traditional exercise in the proof of expected utility.[9] We then show that uniform randomization over the expected utilities associated with quantiles rationalizes the data. The only remaining step is to parametrize the utilities into the reals and to transform accordingly the uniform distribution on $(0,1)$ into a distribution over the reals. Constancy guarantees that risk neutrality belongs to the family, and hence we can use any (decreasing) bijection from $(0,1)$ to the reals such that U_0 corresponds to risk neutrality. In the proof, we use the bijection that produces a logistic distribution over risk attitudes.

4.1. **Parametric Assumptions.** The model in the previous section is non-parametric, in the sense that not only does it not assume any particular family of utilities, it also does not assume any particular probability distribution over risk attitudes. We now discuss parametric versions of the model that will be important for the subsequent empirical and theoretical analysis.

First, connected to the discussion of the proof of Theorem 1, we can assume any particular probability distribution without loss of generality. Since the aim later will be to study the impact of lotteries on behavioral noise and mean risk attitudes, we consider two-parameter distributions $G_{\tau,\sigma}$ where $\tau \in \mathbb{R}$ denotes location and $\sigma \in \mathbb{R}_{++}$ denotes scale. We will often use the prominent logistic probability distribution that we denote by $lg(\tau,\sigma)$, allowing us to conveniently write the prediction in Proposition 1 as

$$F_{lg(\tau,\sigma)}(ce;L) = 1 - 1/(1+\exp[-\frac{\alpha(ce;L)-\tau}{\sigma}]). \tag{4.1}$$

The logistic distribution allows us to write the predictions of the baseline model in an alternative way that will prove useful later on. It is well-known that the log-odds of a logistic correspond to the standardized value of the underlying parameter. Hence, it can be shown that whenever data are generated by a logistic with parameters (τ,σ), one has

$$\mathcal{LO}_{lg(\tau,\sigma)}(ce;L) = \log\frac{F_{lg(\tau,\sigma)}(ce;L)}{1-F_{lg(\tau,\sigma)}(ce;L)} = -\frac{\alpha(ce;L)-\tau}{\sigma}. \tag{4.2}$$

Second, we discuss the case of particular families of utilities. The most prevalent families of utilities in empirical work are the CRRA and CARA families of utilities. The CRRA monetary utility is the normalized, affine, transformation of $\frac{(y+\omega)^{1-\alpha}-\omega^{1-\alpha}}{1-\alpha}$ whenever the risk aversion parameter α is any real number different from 1, and of $\log(y+\omega)-\log\omega$ otherwise. The CARA monetary utility is simply the normalized affine transformation of $\frac{-\exp\{-\alpha x\}}{\alpha}$ whenever the risk aversion parameter α is any real number other than 0, and of x, otherwise.

[9] For any lottery L and quantile certainty equivalent equal to ce, one can obtain the unique probability p for which the lottery $[p,1-p;\underline{x},\overline{x}]$ has ce as the same quantile certainty equivalent and write the utility of ce to be $1-p$.

We conclude with two remarks on these parametric versions of the model. First, once a particular parametrization of the utility family is fixed, the parameters of the chosen family of probability distributions can be uniquely identified. E.g., for the logistic distribution, take any lottery L and find the certainty equivalents associated to $\alpha = 0$ (i.e., $CE(U_0, L) = \mu_L$) and $\alpha = 1$ (i.e., $CE(U_1, L)$). Then, it is easy to see that σ is the inverse of $|\mathcal{LO}_{\tau,\sigma}(\mu_L; L) - \mathcal{LO}_{\tau,\sigma}(CE(U_1, L); L)|$. The parameter τ can be retrieved from any lottery L and any payoff x, by solving $\mathcal{LO}_{\tau,\sigma}(x; L) = -\frac{\alpha(x;L)-\tau}{\sigma}$, using the empirical log-odds at x for L, the associated parameter $\alpha(x; L)$, and the learnt value of σ. These techniques will prove useful later in the paper. Second, once a particular parametrization of a family of utilities is fixed, and a probability distribution is assumed, the predictions of the model are further restricted.[10] Note, though, that all these specifications are but special cases of our main model characterized in Theorem 1.

4.2. **Empirical Analysis.** We now ask how useful the baseline model is for understanding empirical regularities in certainty-equivalent data, following the standard practice of parametrically estimating risk attitudes. We have collected data from 15 studies that elicit certainty equivalents in a number of experimental conditions. See Table 1 for some details on these studies. These papers cover, to the best of our knowledge, all studies that elicit certainty-equivalent valuations of lotteries, were published in top-five general-interest journals in the last two decades, and for which data were available publicly or upon request. Because these studies focus on binary lotteries, we complemented the sample with prominent published studies eliciting certainty equivalents for lotteries with three or more payoffs.[11] We searched for such studies based only on whether they elicited individual-level certainty equivalents for more-than-two-payoff lotteries and whether we were able to obtain the underlying data. The resulting sample contains 197,465 observations of certainty equivalents elicited from 1,299 lotteries across 90 distinct experimental conditions involving the decisions of 7,362 individuals.[12] We define a treatment j as a specific experimental condition under which a group of participants makes decisions. As a result, treatments differ in many dimensions such as the nature of subject pools (e.g., country variation, type of subjects such as students, Amazon Mechanical Turk or Prolific workers), the presentation of lotteries, or the elicitation

[10]This is relevant since in the empirical part we will adopt the usual CRRA and CARA families, and will start with the logistic distribution. We discuss in Section 7.3 the explanatory power of other distributions.

[11]We are deeply thankful to all authors who have kindly shared their data with us.

[12]Individuals are distinct persons: a person may participate in more than one experimental condition (for instance, Bruhin, Fehr-Duda and Epper (2010) and Fehr-Duda, Bruhin, Epper and Schubert (2010) share an experimental session), so participant counts at the treatment level add up to more (9,177). Also, these numbers correspond to the post-exclusion sample. A total of 5,336 observations in the initial sample report CEs at or below (above) the minimum (maximum) payoff of the corresponding lottery. These observations represent less than 3% of the original sample, and we exclude them from the analysis.

mechanism. In order to facilitate the comparison of results, we adjust all payoffs by inflation and purchasing power parity, expressing them in 2024 USD.

Each treatment j involves a set of lotteries. For each of these lotteries, data comprise the certainty equivalents elicited from the participants in the treatment. In our analysis, we adopt the parametric approach using, for robustness, both CRRA and CARA. For CRRA, we simply set ω equal to the fixed payments specified in the experiment, which typically include a show-up fee and an initial endowment.[13] Given an elicited certainty equivalent for a particular lottery in a treatment, the critical information for the analysis lies in the uniquely induced CRRA and CARA risk aversion parameters associated with it. This allows us to aggregate the entire dataset using the common language of risk attitudes.

We open with an aggregate picture that ignores not only lottery-specific effects but also treatment effects, i.e., we first take all the induced risk aversion parameters from our dataset as if they were produced by a unique representative agent. For the sole purpose of helping to visualize data, the first column of Figure 1 presents the histograms of the underlying risk attitudes for CRRA and CARA after creating a small number of bins. Regardless of the parametric assumptions about the utility function, the distribution of induced risk aversion coefficients in the interior bins is unimodal, relatively symmetric around risk neutrality, and with high dispersion.

For the empirical analysis, we use the logistic distribution $lg(\tau, \sigma)$. Under this specification, each realization of the risk aversion parameter can be written as $\alpha = \tau + \sigma\varepsilon$, where $\varepsilon \sim lg(0, 1)$. The likelihood of observing ce for lottery L under parameters (τ, σ) corresponds to the standard logistic density of the value $\frac{\alpha(ce;L)-\tau}{\sigma}$. For the whole sample, we obtain maximum-likelihood estimates (MLEs) of $(-0.26, 4.00)$ and $(-0.004, 0.135)$ for CRRA and CARA, respectively, in accordance with the broad picture above (see column (i) of Table 2). The red line in Figure 1 shows the PDF of the logistic distribution implied by the MLE. For readability, the leftmost and rightmost bins of the histogram pool all observations below and above the corresponding cutoffs, so that extreme coefficients appear in a single cell. This aggregation is purely a visualization device: the MLE of the logistic parameters and the PDF (shown in red) are obtained from the full unbinned sample, without any truncation.

We then incorporate into our specification the effects arising from the inclusion of very heterogeneous treatments in our dataset. To do so, we allow the location and scale of the distribution to vary with the treatment. That is, we estimate the logistic parameters (τ_j, σ_j) for each experimental treatment in the sample, which amounts to considering one representative agent per treatment. As an illustration of one of these estimations, the second column of Figure 1 shows the histograms and the MLE of the underlying risk attitudes for a specific experimental condition, the experiment conducted on Prolific by Enke and Graeber

[13]This guarantees that all final payoffs are strictly positive.

(2023). There is considerable variation in the estimates across treatments, as shown in Figure 2, which reports the distributions of estimates across treatments.[14] The inclusion of treatment fixed effects produces a significant improvement in the fit, as can be seen in Table 2 by comparing column (i), which pools all data, with column (iv) that introduces treatment fixed effects: the average log-likelihood rises from -3.59 to -3.21 for CRRA and from -0.20 to 0.58 for CARA, the KS statistic falls from 0.22 to 0.16 for CRRA and from 0.23 to 0.15 for CARA, and the Anderson-Darling statistic falls by 45% for CRRA and by 56% for CARA.[15]

To better visualize the baseline model with treatment effects, we now present in Figure 3 the standardized histograms that aggregate all data through the standardized risk aversion coefficients $\hat{\alpha} = \frac{\alpha - \tau_j}{\sigma_j}$, computed using the location and scale estimated in the corresponding MLE. Under the assumption that the data follow a logistic distribution with location and scale parameters differing only by treatment, the coefficients $\hat{\alpha}$ should follow a standard logistic distribution, whose PDF is shown in orange. Notice that to improve visualization in higher-density regions, the last bin in the histograms collapses all extreme observations into a single cell. For this reason, it is not the best tool for detecting the tension that arises in the tails during the estimation. To better visualize this tension, Figure 4 presents log-log plots of the tails of the empirical distribution against those predicted by the logistic distribution, which are shown in orange.[16] We see that the empirical distribution consistently exhibits heavier tails under both the CARA and CRRA specifications, particularly for very large coefficients of risk aversion. In words, there seems to be a significant fraction of responses that are too extreme, with certainty equivalents close to the minimum and maximum payoffs of the corresponding lottery.[17] To complete this picture, columns (ii) and (iii) in Table 2 report the intermediate specifications that allow only the location or only the log-scale to vary across treatments. These specifications show that most of the improvement in the fit

[14]The online appendix reports the specific treatment estimates.

[15]As a reminder, the average log-likelihood measures the model's ability to predict observed choices, with higher values indicating a better fit. The Kolmogorov-Smirnov (KS) statistic tests whether the probability integral transform of the estimated residuals follows a uniform distribution, as implied by a correctly specified model; lower values indicate a better fit. The Anderson-Darling (AD) statistic serves a similar purpose but places greater weight on deviations in the tails of the distribution, making it particularly useful for detecting misspecification in extreme observations; like the KS statistic, lower values indicate a better fit.

[16]The log-log plots display the empirical complementary cumulative distribution function (CCDF), also known as the survival function, for the estimated risk aversion coefficients. For each tail, we plot the empirical probability $\hat{P}(|X| \geq x)$ against the magnitude x on logarithmic axes. This visualization is standard in the heavy-tails literature: under a power-law distribution, the CCDF appears as a straight line with slope equal to the negative of the tail index α; deviations from linearity indicate departures from power-law behavior, while curves lying above the reference distribution indicate heavier tails. The figures include, in orange, a solid line representing the theoretical CCDF of the standard logistic distribution, $1 - F(x) = 1/(1 + e^x)$, for comparison.

[17]These extreme observations markedly distort traditional measures of centrality and dispersion, such as the mean and standard deviation, which take values of $(-1.59, 19.35)$ and $(-0.014, 0.61)$ for CRRA and CARA, respectively. Section 7.3 uses the Student-t distribution, which is known to better deal with thick tails.

of the specification with treatment fixed effects comes from their impact on the scale of the distribution of risk attitudes, rather than on the location, perhaps due to the fact that the scale parameter allows the model to capture the heavy tails of some treatments better.

We conclude that the proper incorporation of heterogeneity in risk attitudes within the expected utility framework provides a first step in the understanding of empirical risk attitudes. Until now, the analysis has ignored the role of lottery-specific effects and the inability of expected utility to capture them. There is, however, robust evidence in the literature showing the existence of lottery-specific effects. We devote the rest of the paper to discussing them and analyzing versions of our simple model that can accommodate them.

5. Lottery-Specific Noise

To motivate the interest of this section, consider the upper panel in Figure 5. It shows the empirical distribution of the CRRA coefficients in the dataset, standardized using the location and scale parameters estimated for each treatment under the baseline model, after separating observations into two groups: lotteries that include at least one alternative with a zero prize (blue) and lotteries that contain only non-zero prizes (orange). The figure suggests that the presence of a zero prize reduces the noise in the induced risk aversion coefficients, perhaps by facilitating the understanding of these lotteries or the computation of their expected values. In this section, we show that the model presented so far can be conveniently extended to incorporate this type of lottery-specific noise. We do so by working with two-parameter distributions and relaxing the homoscedasticity assumption of risk attitudes across lotteries.

Formally, consider a generic family of monetary utilities $\{U_\alpha\}_{\alpha\in\mathbb{R}}$ and a continuous and strictly increasing two-parameter distribution. In this section, we allow for the scale of the distribution to be lottery dependent, i.e. $\sigma : \mathcal{L} \to \mathbb{R}_{++}$, while the location parameter τ remains constant across lotteries; that is, the distribution $G_{\tau,\sigma(L)}$ governs risk attitudes for lottery L. This may be interpreted as a channel linking the complexity of the lottery, or the attention placed on the lottery, with behavioral noise. We will come back to this and other potential interpretations in our empirical analysis.

For any lottery L, the predictions of the model can be obtained as in Proposition 1, by simply considering the appropriate lottery-dependent scale $\sigma(L)$. Now, it is convenient to recall here that this extended model produces non-standard predictions and, hence, the properties of Constancy and Independence are no longer satisfied. Fortunately, given that the location parameter is assumed to be constant across lotteries, the following weaker version of the first principle remains valid.

N-Constancy. For every $L, L' \in \mathcal{L}$: $F(\mu_L; L) > \frac{1}{2} \Leftrightarrow F(\mu_{L'}; L') > \frac{1}{2}$.

Namely, the empirical mass at the expected value of any lottery must reveal whether the population is risk averse or risk seeking on average. For the second principle, note that a given quantile in the distribution of certainty equivalents is no longer generated by a unique utility function. In order to implement the classical independence property, we should first identify which different quantiles of different lotteries correspond to the same utility. Fortunately, the model is tractable; we simply need to properly learn the scale of each lottery $\sigma(L)$ from data and adjust data accordingly. The exercise is rather trivial after having fixed a particular family of utilities because, in this case, the analyst observes the underlying distribution of risk attitudes and, hence, its scale. Importantly, the exercise can also be performed in the general theoretical version of the model, when utilities are unknown. To see the logic, write the underlying distribution $G_{\tau,\sigma(L)}$ in its standardized form, i.e. as a function of $(\alpha-\tau)/\sigma(L)$. Since the expected value of the lottery corresponds to risk neutrality in all cases, the inverse of the CDF at the expected value gives access to the number of scale units that risk neutrality is away from the location of risk attitudes. As a result, the ratio of the inverse of the CDF at the expected value of two lotteries corresponds to the ratio of the scales between them. To exemplify, Proposition 2 illustrates this argument considering the logistic distribution. In this case, for any lottery L, the inverse of the CDF at its expected value is merely the log-odds of $F_{lg(\tau,\sigma(L))}(\mu_L;L)$.[18] Denoting by L^* any normalizing lottery, we have:

Proposition 2. *For every $L \in \mathcal{L}$:*

$$\sigma(L)=\frac{\mathcal{LO}_{lg(\tau,\sigma(L^*))}(\mu_{L^*};L^*)}{\mathcal{LO}_{lg(\tau,\sigma(L))}(\mu_L;L)}\sigma(L^*).$$

Now, building on the previous result, we can adjust the quantile data as follows. Let $NF(ce;L^*)=F(ce;L^*)$ for the normalizing lottery L^*, and for any other lottery L let $NF(ce;L)$ be the unique value that solves $\log\frac{x}{(1-x)}=\mathcal{LO}(ce;L)\frac{\mathcal{LO}(\mu_{L^*};L^*)}{\mathcal{LO}(\mu_L;L)}$. These adjusted data must satisfy independence:

N-Independence. For every $L, L', L'' \in \mathcal{L}$ and $q,\lambda \in (0,1)$:

$$NF^{-1}(q;L)\geq NF^{-1}(q;L')\Leftrightarrow NF^{-1}(q;L\lambda L'')\geq NF^{-1}(q;L'\lambda L'').$$

The following theorem establishes the axiomatic characterization of the model, this time using the logistic distribution.

Theorem 2. *Data F satisfy N-Constancy and N-Independence if and only if there exists a family of monetary utilities $\{U_\alpha\}_{\alpha\in\mathbb{R}}$ and lottery-dependent logistic distributions with parameters $(\tau,\sigma(\cdot))$ such that $F=F_{lg(\tau,\sigma(\cdot))}$.*

The proof of Theorem 2 relies upon the following. First, notice that N-Constancy, together with the independence principle on corrected data, guarantees that the corrected log-odds at

[18] In this and the next section, to simplify the exposition, we restrict attention to data F such that $F(\mu_L;L)\neq\frac{1}{2}$, or equivalently $\mathcal{LO}(\mu_L;L)\neq 0$, for at least one lottery. Under the respective representations, this amounts to assuming $\tau\neq 0$ in this section and $\tau(L^*)\neq 0$ in the next.

the expected value of any lottery are all equal, and hence, corrected data satisfy Constancy. We can then apply Theorem 1 to the corrected data using the logistic distribution, and the result follows. The particular correction of the data used in N-Independence, in turn, requires us to use the logistic distribution. As discussed above, other distributions would require other corrections of the data along the lines elaborated above, that in turn would give rise to other versions of N-Independence, but the logic of the characterization remains.

Overall, learning $\sigma(L)$—the scale associated with lottery L—is therefore both an empirical object of interest in its own right (how does this lottery affect behavioral noise?) and a preliminary step that restores the model's testable content: once the data are corrected using $\sigma(L)$, they again satisfy Constancy and Independence exactly as in Theorem 1. N-Constancy and N-Independence are, in this sense, the same requirements as Constancy and Independence, applied after this correction rather than before it.

5.1. **Empirical Analysis.** We now turn to the empirical analysis. We build on the main baseline estimations in columns (i) and (iv) of Table 2. Our starting point is a unique representative agent with logistic parameters $(\tau, \sigma(L))$ where, importantly, the scale is now lottery-dependent. Column (i) of Table 3 reports the corresponding goodness-of-fit measures for this specification. When compared with the corresponding baseline specification, the lottery-specific noise model delivers a substantial improvement: the average log-likelihood rises from -3.59 to -3.02 for CRRA and from -0.20 to 0.73 for CARA; the Kolmogorov–Smirnov statistic falls from 0.22 to 0.13 for CRRA and from 0.23 to 0.12 for CARA; and the Anderson–Darling statistic drops by roughly two-thirds in both parametric families. It is also noticeable that the estimated locations move towards risk neutrality once we account for lottery-dependent behavioral noise, a result that is confirmed below in the other specifications.

We then allow for different representative agents across treatments, by allowing for treatment fixed effects on both the location and scale parameters and, in addition, for lottery effects on the scale. The most general specification of this kind, reported in Column (ii) of Table 3, is a saturated one with parameters $(\tau_j, \sigma_j(L))$, i.e., the location varies only with treatment, while the scale parameter is both treatment and lottery-dependent and can be recovered as a treatment$\times$lottery fixed effect on the log of the scale. Allowing for lottery-specific noise also improves the fit obtained by the baseline model with treatment fixed effects: the average log-likelihood rises from -3.21 to -2.79 for CRRA and from 0.58 to 0.94 for CARA; the Kolmogorov–Smirnov statistic falls from 0.16 to 0.10 for CRRA and from 0.15 to 0.09 for CARA; and the Anderson–Darling statistic drops, again, by roughly 60% in both parametric families. Figure 6 reports the standardized distributions of risk attitudes and Figure 7 zooms in on the tails of the distributions. The estimated lottery fixed effects exhibit substantial dispersion beyond the one due only to treatment fixed effects, as can be seen by comparing

Figure 8 with Figure 2. In summary, the former analysis shows that lottery-specific effects on noise play a sizable role in the data.

In order to separate treatment-specific noise from lottery-specific noise, we now report in Column (iii) of Table 3 a model in which the log of the scale is the result of the sum of the treatment effect and the lottery-specific effect. Namely, the logistic parameters are $(\tau_j, \sigma_j \times \sigma(L))$. The results are close to the saturated specification of Column (ii). This model allows us to separate the treatment effects from the lottery-specific effects and compare the lottery-specific noise of any two lotteries, provided they can be connected by a sequence of lotteries in which each pair of consecutive lotteries is tested in at least one common treatment. However, since treatments are very heterogeneous in the lotteries used, this separation, and the subsequent possibility of noise comparison between lotteries, only applies to subsets of lotteries. In order to allow for a complete comparison between lotteries, and in order to facilitate the interpretation of what is driving this dispersion, we next express the lottery-specific effects $\sigma(L)$ as a function of a small set of observable lottery characteristics.

The characteristics that we now propose respond to simple ideas arising from discussions of complexity, attention, salience, expectations, and probability perceptions. They span several dimensions that the literature has often identified as relevant: three are related to the structure of the probability mass (*number of payoffs*, $|dominance|$, and *irregular probabilities indicator*) and three to the magnitude of stakes (*payoff range*, *non-zero prizes indicator*, and *loss (prize) indicator*).

- *number of payoffs*: This is the count of distinct payoffs in the lottery, capturing the discrete size of the state space.
- $|dominance|$: This is a measure of how tilted the probability mass is towards one of the ends of the distribution of payoffs. Formally, this variable is the absolute value of *dominance*, which measures how the probability mass is tilted towards high payoffs, scaled to lie in $[-1, 1]$. Namely, having ordered the payoffs from lowest to highest:

  $$dominance = 1 - 2\sum_{j=1}^{n} p_{(j)} \cdot \frac{n-j}{n-1},$$

  where $p_{(j)}$ is the probability of the j-th lowest payoff.[19]
- *irregular probabilities indicator*: An indicator variable equal to one if the lottery contains at least one probability that is neither a multiple of 0.05 nor equal to the boundary values $\{0.01, 0.99\}$.

[19]Note that for given payoffs, *dominance* is a function that extends the notion of first-order stochastic dominance. To illustrate, for two-payoff lotteries $|dominance| = |1 - 2p_{(1)}| = |p_{(2)} - p_{(1)}|$, for three-payoff ones $|dominance| = |1 - 2p_{(1)} - p_{(2)}| = |p_{(3)} - p_{(1)}|$, while for four-payoff lotteries it is $|dominance| = |1 - 2p_{(1)} - 4p_{(2)}/3 - 2p_{(3)}/3| = |(p_{(4)} - p_{(1)}) + (p_{(3)} - p_{(2)})/3|$.

- *payoff range*: This variable ignores probabilities and represents a measure capturing the spread of payoffs in the lottery. Formally, we consider the logarithm of the range of wealth-adjusted payoffs, $\log \big| \max(x) - \min(x) \big|$.
- *non-zero prizes indicator*: An indicator equal to one if all prizes are strictly non-zero.
- *loss indicator*: An indicator equal to one if any of the prizes is negative.

The above characteristics may affect behavioral noise through different channels. One that is gaining increasing interest in the literature is complexity, for which it is natural to expect that higher complexity may trigger greater behavioral noise. For example, a larger number of payoffs or a tilted distribution of probabilities may involve higher complexity, because more payoffs require tracking and comparing more possibilities, while highly uneven probabilities make the relationships between payoffs less uniform and therefore harder to summarize or reason about. Alternatively, the attention the decision-maker allocates to the lottery may also be relevant, with higher attention leading to less noise. For example, a larger payoff range or more irregular probabilities may call the attention of the decision-maker, potentially reducing noise. Yet another channel has to do with salience or reference-dependent thinking, which may be triggered by the presence of prizes equal to zero, or framed as losses.

To bring all characteristics into the picture jointly, we build on the last specification $(\tau_j, \sigma_j \times \sigma(L))$ by modeling lottery fixed effects as linear-in-characteristics, i.e., $\log \sigma(L) = \beta' Z_L$, where Z_L is the vector of lottery characteristics introduced above. This restricts the lottery effect to a parsimonious functional form, but in return it connects all lotteries in our database and allows us to study the strength of the effect created by each characteristic across the entire sample.[20] Table 4 reports the β estimates. In line with a complexity interpretation, $|dominance|$ loads with a sizable positive coefficient (+0.77 for both CRRA and CARA) and the *number of payoffs* enters positively in both families (+0.15 for CRRA, +0.21 for CARA). The *payoff range* loads strongly negatively (−0.57 for CRRA, −0.93 for CARA), consistent both with a manifestation of complexity in the sense that smaller ranges make it more difficult to be precise, and with an attention interpretation in the sense that the evaluations of lotteries with larger ranges are more consequential, calling for more attention. The *irregular-probabilities indicator* loads moderately negatively (−0.41 for CRRA, −0.18 for CARA), which seems to be associated with attention more than with complexity considerations. The *non-zero prizes indicator* is positive and large under CRRA (+0.49) and small under CARA (+0.12), broadly consistent with a salience effect, while the *loss indicator* is small and negative in both families.

In the empirical analysis of the baseline model in the previous section, we established that treatment effects on the scale of the distribution were significant drivers of behavior. It thus

[20]The conditions that guarantee econometric identification of the parameter vector β match those in standard multiplicative heteroskedasticity models, such as those studied by Harvey (1976).

makes sense to study the strength of the effects created by the above lottery characteristics hand in hand with the strength of the effects created by some treatment features. To do so, we present one more linear-in-characteristics estimation exercise in which the treatment contribution is modeled as linear-in-features, i.e., we set $\log \sigma_j + \log \sigma(L) = \gamma' Z_j + \beta' Z_L$, where Z_j is a vector of the following treatment features: indicators for compound lotteries, more mathematical complexity, MPL elicitation, US samples, incentivized choices, and recruitment via Prolific or Amazon Mechanical Turk. Note that the behavioral impact of the compound-lotteries dummy can be viewed as another relevant lottery characteristic, whose effects are perhaps in line with complexity considerations and can only be studied outside expected utility.[21] Table 6 reports the estimated coefficients for each treatment feature. The signs of the lottery characteristics are broadly preserved relative to the above analysis in Table 4, with magnitudes that remain relevant but are somewhat attenuated since the treatment-level dummies now absorb part of the cross-treatment variation previously soaked up by the free fixed effect. Compound lotteries seem to bring more behavioral noise. On the stricter treatment-feature side, the clearest common patterns are that US samples and treatments classified as more mathematical are associated with less behavioral noise under both CRRA and CARA. Other features have effects that are either not robust across utility families or not significative.

Overall, the analysis confirms the empirical relevance of lottery-specific effects on behavioral noise. Our framework allows us to (i) separate treatment from lottery-specific effects, (ii) understand which lotteries are particularly affected, and (iii) study which characteristics are robustly relevant. The patterns we identify resonate with known behavioral intuitions without requiring a commitment to a specific behavioral model.

6. Lottery-specific (Mean) Risk

The lower panel in Figure 5 shows the conditional distribution of the standardized CRRA coefficients for two groups of lotteries: those with *dominance* less than -0.5 (blue) and those with *dominance* greater than 0.5 (orange). The former (respectively, the latter) are lotteries where most of the probability is concentrated on the worst (resp., best) possible payoffs. We can see that this type of skewness of the lotteries has a nontrivial effect on the distribution of risk aversion: mean risk aversion increases when the probability mass is tilted towards better payoffs. This is a classical behavioral pattern, sometimes discussed in the form of fanning out, probability weighting and reference dependence, and is part of the reasoning underlying prospect theory. Motivated by this type of observation, we proceed to develop an extension of the baseline model in which the location parameter depends on the lottery.

[21] In our framework, in order to simplify notation, we have taken the stance of defining lotteries in their reduced form, and hence a compound version of a lottery is but the same lottery.

Formally, the location of the distribution may be lottery-specific, that is, $\tau : \mathcal{L} \to \mathbb{R}$, while we keep σ as a constant parameter across lotteries.[22] Hence, the distribution $G_{\tau(L),\sigma}$ governs risk attitudes for lottery L. This allows for the case where different lotteries may shift the distribution of preferences towards greater risk aversion or more risk-loving behavior. The predictions of the model follow from those of the baseline model by writing $\tau(L)$ instead of the original τ. Also, again, the mapping $\tau(\cdot)$ can be recovered from data. The following proposition illustrates the case for the logistic distribution, although the argument extends easily to other two-parameter distributions, as discussed in the above case of lottery-specific noise.

Proposition 3. *For every $L \in \mathcal{L}$:*

$$\tau(L) = \frac{\mathcal{LO}_{lg(\tau(L),\sigma)}(\mu_L; L)}{\mathcal{LO}_{lg(\tau(L^*),\sigma)}(\mu_{L^*}; L^*)}\tau(L^*).$$

As in the previous section, the appropriate correction of the data allows us to characterize the present model. Naturally, the correction is no longer multiplicative but additive. For the case of the logistic distribution, we can conveniently correct the log-odds as follows: $\eta(ce; L) := \mathcal{LO}(ce; L) - \mathcal{LO}(\mu_L; L)$. By doing so, we no longer need to impose Constancy because the form of η guarantees that the corrected log-odds at the expected value are all equal (and equal to zero). Consider then the following independence-type property.[23]

η-Independence. For every $L, L', L'' \in \mathcal{L}$, $ce, ce', ce'', ce''' \in \mathbb{R}_{++}$ and $\lambda \in (0, 1)$, $\eta(ce; L) = \eta(ce'; L') = \eta(ce''; L\lambda L'') = \eta(ce'''; L'\lambda L'') \Rightarrow [ce \geq ce' \Leftrightarrow ce'' \geq ce''']$.

We are ready to present our next result.

Theorem 3. *Data F satisfy η-Independence if and only if there exist a family of monetary utilities $\{U_\alpha\}_{\alpha\in\mathbb{R}}$ and lottery-dependent logistic distributions with parameters $(\tau(\cdot), \sigma)$ such that $F = F_{lg(\tau(\cdot),\sigma)}$.*

The logic of the proof of Theorem 3 is analogous to that of Theorem 2.

6.1. **Empirical Analysis.** We follow the steps of the empirical analysis in Section 5.1, but now focusing on lottery-specific effects on the location of the distributions. We begin with

[22]To ease exposition, we sometimes use “location,” “mean risk,” “mean risk attitude,” and “mean risk aversion” interchangeably. Under the logistic specification, the location parameter coincides with the mean. Under other distributional assumptions, this terminology is only shorthand. In particular, under the Student-t specification that we study in Section 7.3, the mean is undefined when the degrees-of-freedom parameter satisfies $\nu \leq 1$. However, the location parameter remains well defined and, by symmetry, coincides with the median. Throughout, the primitive object in the model is the location parameter; all comparative statics and estimation statements refer to this parameter, whether or not the distributional mean exists.

[23]Note that the property uses directly the corrected log-odds of the data rather than the corrected data generating them. One could express the property based on the latter.

the simplest approach involving a unique representative agent, i.e., we consider the lottery-dependent logistic specification with $(\tau(L), \sigma)$. With respect to "Baseline (i)", Column (i) of Table 5 shows that this yields a more modest improvement than its lottery-specific noise counterpart: the average log-likelihood rises from -3.59 to -3.54 for CRRA and from -0.20 to -0.14 for CARA, while the Kolmogorov–Smirnov and Anderson–Darling statistics deteriorate slightly. Column (ii) reports the saturated specification $(\tau_j(L), \sigma_j)$, which again yields smaller improvements with respect to "Baseline (iv)" than its lottery-specific noise counterpart. Figure 9 graphs the distribution of standardized risk attitudes, Figure 10 focuses on the tails of the distributions, and Figure 11 shows that the estimated lottery fixed effects on the location seem to be slightly more dispersed, under both CRRA and CARA, than in "Baseline (iv)".

The results of the separable specification $(\tau_j + \tau(L), \sigma_j)$ are reported in column (iii) and those of the separable specification with a linear-in-characteristics specification $\tau(L) = \beta' Z_L$ are reported in column (iv), both yielding similar results. We use the same six lottery characteristics introduced in Section 5.1, with one exception: we now use signed *dominance* (the underlying $1 - 2\sum_j p_{(j)}(n-j)/(n-1)$) rather than $|$*dominance*$|$, motivated by the prospect-theory channels of probability distortion and reference dependence. The last two columns of Table 4 report the estimates. Two effects stand out by sign, magnitude, and economic interpretability. *dominance* loads strongly positively ($+1.02$ for CRRA and $+0.78$ for CARA, with CARA estimates scaled by 100 for readability), and the *loss indicator* loads strongly negatively (-0.36 for CRRA and -0.48 for CARA). In addition, with a somewhat weaker effect, both *non-zero prizes indicator* and *payoff range* enter negatively. The remaining two characteristics — *number of payoffs* and *irregular-probabilities indicator* — do not have a clear effect. The two leading effects map onto the prospect-theory channels foreshadowed at the start of this subsection: probability mass tilted toward better payoffs raises the location of risk aversion (*dominance*), and the presence of negative prizes or the absence of a zero prize lowers it (*loss indicator* and *non-zero prizes*). Recall that *dominance* is a characteristic linking the characteristics of the lotteries to risk aversion only through the structure of probabilities, rather than monetary payoffs.

Finally, we replicate the joint analysis of lottery characteristics and treatment features of Section 5.1, now for the location. Namely, we consider the model where $\tau_j + \tau(L) = \beta' Z_L + \gamma' Z_j$, with Z_j being the same vector of treatment features of Section 5.1. Table 6 reports the estimates. The two strongest behavioral effects related to the lottery characteristics discussed above survive the exercise. MPL seems to increase risk-averse attitudes and, perhaps surprisingly, compound presentations seem to decrease them. However, in line with the observation that treatment fixed effects on location are less helpful, the other experiment-level features load with mixed signs or modest magnitudes, and do not lend a clean common interpretation across CRRA and CARA.

7. Discussion

We have proposed and studied, both theoretically and empirically, a novel framework that incorporates preference heterogeneity and allows us to examine the behavioral impact of different lotteries on noise and (mean) risk attitudes, with the advantage of not specifying an underlying behavioral model. In the remainder of this section, we first place our main empirical findings in context, then we comment on a cross-validation exercise that asks whether the lottery-specific channels identified in Sections 5.1 and 6.1 carry over to out-of-sample observations, then we report on a robustness exercise using an alternative probability distribution over preferences and, before concluding, we briefly discuss on how to view our framework from the perspective of a structural behavioral exercise.

7.1. **Connections to the Empirical Findings in the Literature.** Having studied how lottery characteristics may affect the moments of the distribution of preferences, we are now in a position to place our findings in context. To begin with, a growing literature shows that increasing the number of possible lottery payoffs can lower valuations or choice probabilities, thereby increasing revealed risk aversion, even when standard features of the lotteries are held fixed (Huck and Weizsäcker (1999), Bernheim and Sprenger (2020), and Puri (2025)). However, the evidence is not uniform: event-splitting and support-size manipulations can also generate weak, null, or opposite effects on revealed risk aversion (Wakker (2023); Enke and Shubatt (2026)). Interestingly, our findings show that, once we appropriately account for preference heterogeneity and work with a large dataset, the number of payoffs strongly increases behavioral noise, but does not have a significant effect on mean risk attitudes.

We next discuss the variables *dominance* and $|$*dominance*$|$, which capture how heavily the probability mass is tilted toward favorable outcomes and the overall intensity of this tilt toward either extreme of the distribution, respectively. We find that $|$*dominance*$|$ strongly increases behavioral noise, whereas signed *dominance* shifts mean risk attitudes toward greater risk aversion. The former effect is consistent with greater difficulty in evaluating lotteries in which probability mass is concentrated on extreme payoffs, while the latter matches the well-known fanning-out pattern. Our framework allows us to separate these two effects by studying separately the different moments of the preference-heterogeneity distribution. In essence, it is possible that both findings fit the following simple behavioral mechanism: when probability mass is concentrated on low or high payoffs, some responses deviate from expected-utility valuations toward more central values within the payoff range. This partial pull toward central values may increase behavioral noise and may shift the mean of the estimated risk-attitude distribution.

Experimental evidence suggests that payoff features and incentives can affect elicited risk attitudes. Our results show that wider payoff ranges strongly reduce behavioral noise. This relates to work on payoff dispersion, which finds that relative variability can be behaviorally salient, although its effect in monetary choices is not uniform (Weber, Shafir, and Blais (2004); Cox and Sadiraj (2010)). A separate literature studies absolute payoff magnitudes: some studies find greater revealed risk aversion at higher stakes, while others qualify this effect by showing that it depends on order effects and probability weighting (Binswanger (1980), Holt and Laury (2005), Harrison et al. (2005), Fehr-Duda et al. (2010)). Motivated by this literature, we also study, as a robustness exercise, the inclusion into our set of lottery characteristics of the lottery's expected value, finding that it increases behavioral noise and reduces mean risk, leaving the remaining effects essentially unchanged. Finally, a related literature studies the impact of incentivized or hypothetical experimental tasks. The evidence is mixed: some studies find stronger risk aversion under real incentives, while others find small or no systematic differences between incentivized and hypothetical elicitations (Beattie and Loomes (1997); Camerer and Hogarth (1999); Holt and Laury (2002); Hackethal et al. (2023)). Our findings are that, under CRRA, incentivizing lottery evaluations increases both behavioral noise and mean risk attitudes, while under CARA neither effect is discernible. One possible interpretation is that hypothetical evaluations induce more focal or central responses, whereas real incentives make subjects' idiosyncratic valuations more salient. This interpretation is speculative and requires further investigation.

Several studies find that the compound presentation of risk affects measured risk attitudes. In many certainty equivalent-based designs, compound lotteries receive lower valuations than actuarially equivalent simple lotteries, implying positive compound risk premia and hence greater revealed risk aversion (Halevy (2007); Abdellaoui, Klibanoff, and Placido (2015); Chew, Miao, and Zhong (2017); Fan, Budescu, and Diecidue (2019); de Clippel et al. (2025); Aydogan, Berger, and Bosetti (2026)). Our results complement this discussion: the point estimates suggest that presenting lotteries as compound generates larger behavioral noise, although these effects are imprecisely estimated; the clearer effect is a shift of the distribution of risk attitudes towards more risk seeking.

A further classical determinant of measured risk attitudes is whether lotteries involve losses or contain a zero prize. Reference-dependent models predict that gains and losses are evaluated differently, and the reflection effect implies lower risk aversion, or even risk seeking, in the loss domain (Kahneman and Tversky (1979)). Related work also studies whether the presence of zero payoffs acts as a reference force in lottery evaluation (Diecidue, Levy, and van de Ven (2015)). Our framework offers a complementary perspective on these effects. We find that losses primarily shift mean risk attitudes downward, whereas the presence or absence of a zero prize is more closely related to behavioral noise. Thus, reference-dependent features appear not only as shifts in average risk attitudes, but also as changes in the dispersion of elicited valuations.

A related methodological literature shows that elicited risk attitudes depend on the elicitation procedure itself. In particular, risk aversion estimates can vary substantially across multiple price lists (MPLs), certainty-equivalent tasks, and pairwise choices, sometimes by more than the variation induced by the assumed structural model (Crosetto and Filippin, 2016; Holzmeister and Stefan, 2021). Consistent with this literature, we find that MPL elicitation tends to increase mean risk attitudes, with no discernible effect on behavioral noise. We show that elicitation procedures can be interpreted as shifting different moments of the distribution of elicited risk attitudes, rather than only changing a single representative-agent estimate.

7.2. **Cross-validation.** The empirical analysis so far has centered on the estimation of the models. This has proved useful in explaining data and in gaining a better understanding of the main drivers. In particular, we have seen that the lottery-specific noise and lottery-specific (mean) risk models both improve our understanding with respect to the baseline model. We now analyze the usefulness of these two generalized models in out-of-sample exercises. We do so by setting the bar high, comparing the performance of the most restrictive specifications—the linear-in-characteristics ones—against the predictions of the already rich baseline model.[24]

Here, we report on the most direct of these out-of-sample exercises, a leave-one-lottery-out (LOLO) exercise that asks whether the estimated model predicts behavior for lotteries the model has never seen.[25] Consider first the baseline model with treatment fixed effects. Holding out one lottery L at a time, we fit the model on the remaining lotteries to obtain estimates $\hat{\tau}_{j,-L}$ and $\hat{\sigma}_{j,-L}$. Then, the predictive density for the held-out lottery L is simply determined by (the parameter estimates of) the treatment to which it belongs. Second, for the two extensions of the baseline model, the estimation without lottery L produces estimates $\hat{\tau}_{j,-L}$, $\hat{\sigma}_{j,-L}$ and $\hat{\beta}'_{-L}$. In these cases, the predictive densities for lottery L are determined not only by (the parameter estimates of) the treatment to which it belongs, but also by the linear prediction resulting from $\hat{\beta}'_{-L} Z_L$. The exercise then involves the comparison of the predictive performance of both the noise and the mean model against the baseline model. We do so by using standard scoring rules.[26] In principle, a specification that overfits the lotteries in our sample should not improve held-out predictions, while one that captures genuine lottery-level structure should.

[24] E.g., one could use less demanding comparisons, such as the separable models against uniformly random evaluations.

[25] Alternative out-of-sample tests, including leave-one-study-out (LOSO) and leave-one-treatment-out (LOTO), are reported in the Online Appendix.

[26] See Section C in the Online Appendix for the details of the scoring rules we use.

Averaged across lotteries, the per-lottery gains are modest but consistently positive, with confidence intervals that exclude zero in every case: under CRRA, average improvements in held-out log-score of +0.133 for the noise model and of +0.057 for the (mean) risk model; under CARA, +0.219 and +0.024, respectively. An asymmetry between the two channels emerges in Figure 12. The improvement of the noise model is larger but less uniform across characteristics than the (mean) risk model.

7.3. **Alternative Probability Distribution.** To assess the robustness of our empirical observations, we now implement our empirical strategy with an alternative probability distribution, which merely requires adopting a standardized distribution ε other than $lg(0,1)$ in the expression $\alpha = \tau + \sigma\varepsilon$. We have opted for a distribution with an extra parameter, the Student-t, which can endogenously better accommodate the heavy tails in the observed distributions of risk preferences. That is, we model $\varepsilon \sim t_\nu$, where ν represents the degrees of freedom of the Student-t distribution. This additional parameter ν will be estimated from data but kept constant across treatments and lotteries.

We reproduce the main empirical exercises reported in the paper. The online appendix contains the corresponding versions of the empirical distributions of risk attitudes against the estimated distributions of Figures 3, 6, and 9, and the log-log plots of the tails of the empirical and predicted distributions of risk attitudes of Figures 4, 7, and 10. It is visually apparent that the additional parameter helps to gain a better fit of the data, and in particular of the tails of the distributions. This is confirmed in the goodness-of-fit analysis reported here in Tables 7 and 8. We do appreciate, again, that the two extensions of the baseline model improve, and in this case, both do so substantially and in comparable terms. The addition of the extra parameter governing the tails allows the two extensions to focus better on the main two variables of interest, the location and the scale of the distribution of preferences. Interestingly, we now observe that the location of the distribution moves slightly towards more risk aversion, suggesting that the left tail of the distribution, the one associated with risk-loving, was more relevant than the other. Also, the estimated new parameter $\hat{\nu}$ is around 1 in all the specifications, showing the relevance of the tails. We also report on the results of the linear-in-characteristics analysis, in Table 9. The results are remarkably consistent with those obtained under the logistic, with all the main effects learned through the logistic distribution being preserved. Finally, the qualitative pattern of the out-of-sample LOLO exercise using the Student-t distribution also matches that of the logistic distribution, as shown in Figure 13.

7.4. **Alternative Behavioral Approach.** We have emphasized throughout the paper that our framework does not specify a particular behavioral model ex-ante; we model and learn the behavioral impact of different lotteries through their implications on revealed preference heterogeneity. We have mentioned that an alternative approach would be to assume lottery-independent variation over a behavioral family of risk attitudes. Interestingly, one could do so in the spirit of the ordered boundedly rational stochastic model of Filiz-Ozbay and Masatlioglu (2023). In such a case, following the logic of our quantile characterization in Theorem 1, each of the quantiles of the empirical distribution would be generated by a specific instance of the boundedly rational model. Thus, an interesting line of research involves the systematic study of the structural properties possessed by the empirical quantiles.

7.5. **Concluding Remarks.** This paper develops an axiomatized and empirically implementable framework for studying lottery-specific deviations from expected utility through the distribution of risk attitudes. Starting from preference heterogeneity allows us to distinguish between two channels through which lotteries may affect observed valuations: shifts in mean risk attitudes and changes in behavioral noise. This distinction is empirically consequential. Characteristics commonly associated with complexity primarily affect noise, whereas probability mass tilted toward favorable payoffs and the presence of losses primarily affect mean risk attitudes. These results are robust to alternative distributional assumptions on preferences and are reflected in out-of-sample predictions. More broadly, the framework provides a common structure for organizing empirical regularities that have often been studied separately and for examining additional lottery-specific phenomena without committing in advance to a particular behavioral model.

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Appendix

Proof of Proposition 1: Consider any lottery $L \in \mathcal{L}$ and any monetary value $ce \in (x_1, x_{I_L})$. Given the assumptions, we know that the equation $ce = CE(U_\alpha; L)$ has a unique solution $\alpha(ce; L)$. Now, any realization of α above $\alpha(ce; L)$ produces a certainty equivalent below ce, and vice versa. Hence, the probability that the certainty equivalent of lottery L lies below ce is equal to the mass of realizations of the parameter α above $\alpha(ce; L)$, and the result follows. ■

Proof of Theorem 1: We start with the necessity of the properties. To prove Constancy, notice that for every $L \in \mathcal{L}$, $F(\mu_L; L)$ corresponds to the mass of utilities that are risk averse (i.e., to the mass of utilities U_α with $\alpha \geq 0$). Since the distribution of α is lottery-independent, this value is the constant $1 - G(0)$ for every lottery, and hence Constancy must follow. We now consider Independence. For each lottery, the quantile q of the data F corresponds to the certainty equivalent determined by expected utility $EU_{G^{-1}(1-q)}$. In particular, the q-quantile across lotteries will be a utility representation of this expected utility. From classical results we know that the (ordinal preference associated to the) utility representation determined by the quantile must satisfy independence, and the claim follows.

We now prove that the properties are also sufficient. Suppose that the data F satisfy Constancy and Independence. For every probability value $q \in (0, 1)$, define the binary relation $\succsim^q$ on $\mathcal{L} \times \mathcal{L}$ on the basis of the quantile information:

$$L \succsim^q L' \Leftrightarrow F^{-1}(q; L) \geq F^{-1}(q; L').$$

This binary relation is trivially complete and transitive. Moreover, Independence implies that $\succsim^q$ satisfies the standard independence property in the treatment of expected utility. Given the continuity assumptions on the data F, $\succsim^q$ also satisfies standard continuity properties in the treatment of expected utility, and classical results guarantee that $\succsim^q$ admits an expected utility representation (with monetary utility denoted by W^q).[27]

We now show that $\{W^q\}_{q \in (0,1)}$ is a family of monetary utilities that is strictly decreasing in risk aversion, and that contains risk-neutrality. To prove the former claim, consider two probability values $0 < q < q' < 1$. For every lottery $L \in \mathcal{L}$, the quantile definition of payoffs $F^{-1}(q; L)$ and $F^{-1}(q'; L)$, together with the strict monotonicity of F, guarantee that $F^{-1}(q; L) < F^{-1}(q'; L)$ holds. By standard arguments, W^q must be strictly more concave than $W^{q'}$, and hence the family is strictly decreasing in risk aversion. To prove the latter claim, notice that Constancy guarantees that the expected value of every lottery has the same

[27]Notice that, since $CE(W^q; [1; x]) = x$ for every degenerate lottery $[1; x]$, the certainty equivalents of W^q must be precisely $\{F^{-1}(q; L)\}_{L \in \mathcal{L}}$ or, equivalently, $EW^{F(ce;L)}$ is the expected utility for which the certainty equivalent of lottery L is ce.

associated cumulative mass, q^*, which makes apparent that W^{q^*} corresponds to risk-neutral behavior.

We now show that i.i.d. uniform randomization over the family of expected utilities $\{EW^q\}_{q\in(0,1)}$ rationalizes the observed data. Since the result is trivial for degenerate lotteries, consider any non-degenerate lottery $L \in \mathcal{L}$. Let $ce \in (x_1, x_{I_L})$ with $F(ce; L) \in (0,1)$. By construction, the certainty equivalent generated by utility $W^{F(ce;L)}$ is equal to ce. Moreover, given the ordered nature of expected utilities, the certainty equivalent of L generated by any utility W^q must lie below ce if and only if $q \leq F(ce; L)$. Given uniform randomization, this event happens with probability $F(ce; L)$ and the claim follows.

Finally, select any non-degenerate lottery $L \in \mathcal{L}$ and consider the (decreasing) bijection $b : (0,1) \to \mathbb{R}$ given by $b(q) = \log \frac{F(\mu_L;L)}{1-F(\mu_L;L)} - \log \frac{q}{1-q}$. Define the family of monetary utilities $\{U_\alpha\}_{\alpha\in\mathbb{R}}$ by setting $U_\alpha = W^{b^{-1}(\alpha)}$. Given the analysis above, the family $\{U_\alpha\}_{\alpha\in\mathbb{R}}$ is strictly increasing in risk aversion and contains risk-neutral behavior. Given the bijection chosen, it is apparent that risk-neutral behavior corresponds to U_0. Given the nature of the transformation, a logistic distribution on $\{U_\alpha\}_{\alpha\in\mathbb{R}}$ with location $\tau = b(\frac{1}{2})$ and scale $\sigma = 1$ must rationalize the data. This concludes the proof. ■

Proof of Proposition 2: Consider any lottery $L \in \mathcal{L}$. From the predictions of the model, we know that $\mathcal{LO}_{lg(\tau,\sigma(L))}(\mu_L; L) = -\frac{\alpha(\mu_L;L)-\tau}{\sigma(L)}$. Given the assumption on risk neutrality, we know that $\alpha(\mu_L; L) = 0$ and hence, $\mathcal{LO}_{lg(\tau,\sigma(L))}(\mu_L; L) = \frac{\tau}{\sigma(L)}$; the claim follows. ■

Proof of Theorem 2: We start by showing the necessity of the properties. To prove N-Constancy, notice that for every $L \in \mathcal{L}$, $F(\mu_L; L)$ is above $\frac{1}{2}$ if and only if $\tau > 0$ and since τ is constant across lotteries, the property holds. We now move to the discussion of N-Independence. Notice that the only difference across lotteries is the scale of the logistic distribution generating them. From Proposition 2, $\frac{\sigma(L)}{\sigma(L^*)} = \frac{\mathcal{LO}_{lg(\tau,\sigma(L^*))}(\mu_{L^*};L^*)}{\mathcal{LO}_{lg(\tau,\sigma(L))}(\mu_L;L)}$, which must be strictly positive thanks to N-Constancy. Hence, the correction of the log-odds produces log-odds that correspond to a logistic distribution with the same location τ and scale equal to $\sigma(L^*)$. From Theorem 1, Independence must be satisfied by the corrected CDFs generating these corrected log-odds.

To see the sufficiency part, suppose that the data F satisfy N-Constancy and N-Independence. Consider the normalizing lottery $L^* \in \mathcal{L}$ and set $\sigma(L^*) = 1$. Given the correction produced, it is immediate that the corrected data are such that the log-odds at the expected value of each lottery have the same absolute value. Given N-Constancy, these log-odds must be all equal and hence, the corrected data satisfy Constancy. By N-Independence, the corrected data satisfy Independence. Hence, we can reproduce the constructive proof of Theorem 1 using the transformed distributions NF and identify a unique logistic distribution (with scale equal to 1) producing these corrected data. The family of logistic distributions with the same location and scale $\sigma(L)$ given by Proposition 2 rationalizes the raw data. ■

Proof of Proposition 3: Consider lottery $L \in \mathcal{L}$. Given that $\alpha(\mu_L; L) = \alpha(\mu_{L^*}; L^*) = 0$ holds, using an analogous reasoning to that of Proposition 1, we know that $\mathcal{LO}_{lg(\tau(L),\sigma)}(\mu_L; L) = \frac{\tau(L)}{\sigma}$ and $\mathcal{LO}_{lg(\tau(L^*),\sigma)}(\mu_{L^*}; L^*) = \frac{\tau(L^*)}{\sigma}$. The claim follows immediately. ■

Proof of Theorem 3: We start by showing the necessity of the property. Denote $\eta_{lg(\tau(L),\sigma)}(\cdot; L) = \mathcal{LO}_{lg(\tau(L),\sigma)}(\cdot; L) - \mathcal{LO}_{lg(\tau(L),\sigma)}(\mu_L; L)$. Consider $L, L', L'' \in \mathcal{L}$, $ce, ce', ce'', ce''' \in \mathbb{R}_{++}$ and $\lambda \in (0,1)$ such that $\eta_{lg(\tau(L),\sigma)}(ce; L) = \eta_{lg(\tau(L'),\sigma)}(ce'; L') = \eta_{lg(\tau(L\lambda L''),\sigma)}(ce''; L\lambda L'') = \eta_{lg(\tau(L'\lambda L''),\sigma)}(ce'''; L'\lambda L'')$. Using the analogous expressions to those in Proposition 1, but in the present case with location variation across lotteries, it must be the case that

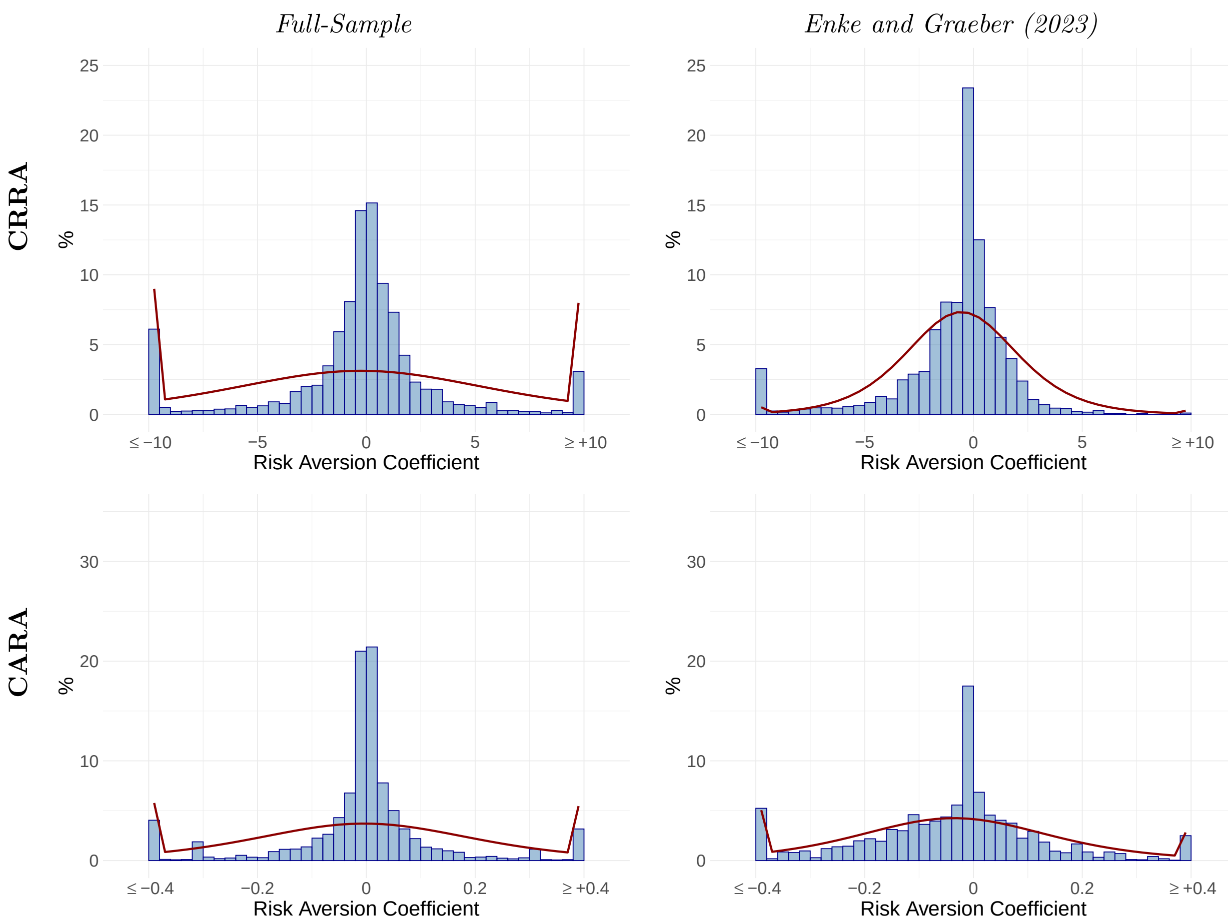
$$\frac{\tau(L) - \alpha(ce; L)}{\sigma} - \frac{\tau(L) - 0}{\sigma} = \cdots = \frac{\tau(L'\lambda L'') - \alpha(ce'''; L'\lambda L'')}{\sigma} - \frac{\tau(L'\lambda L'') - 0}{\sigma}.$$

This implies $\alpha(ce; L) = \cdots = \alpha(ce''', L'\lambda L'')$. As a consequence, these monetary values are generated by the same expected utility and the standard independence property must hold. Necessity follows.

We now show the sufficiency part. Suppose that the data F satisfy η-independence. First, transform all the log-odds of any lottery into their η-version. By construction, these normalized log-odds are all equal at the expected value of the corresponding lotteries (they are all equal to zero). Reproduce the proof of Theorem 1, using the transformed distributions associated to the transformed log-odds, to construct the family of utilities, noting that η-independence guarantees that they are expected utilities.

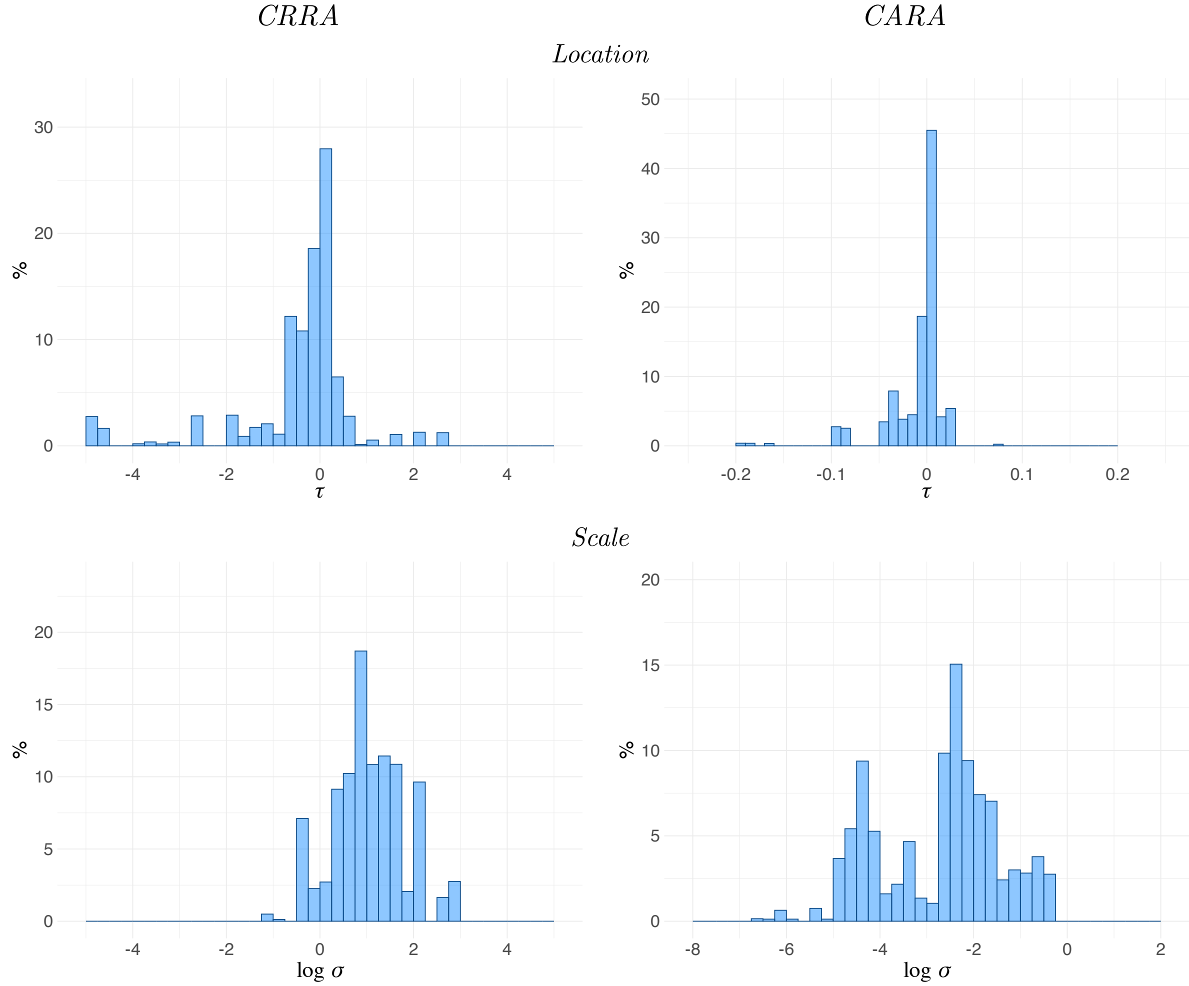
Fix $\sigma = 1$. Select any lottery $L^* \in \mathcal{L}$ for which the log-odds at the expected value are non-zero, and set $\tau(L^*) = \mathcal{LO}(\mu_{L^*}; L^*)$. Following the intuition suggested by Proposition 3, for any other $L \in \mathcal{L}$, define $\tau(L) = \tau(L^*)\frac{\mathcal{LO}(\mu_L;L)}{\mathcal{LO}(\mu_{L^*};L^*)}$, which reduces to $\tau(L) = \mathcal{LO}(\mu_L; L)$. Rationalization of the data follows. ■

FIGURE 1. Baseline: Distribution of Risk Aversion Coefficients



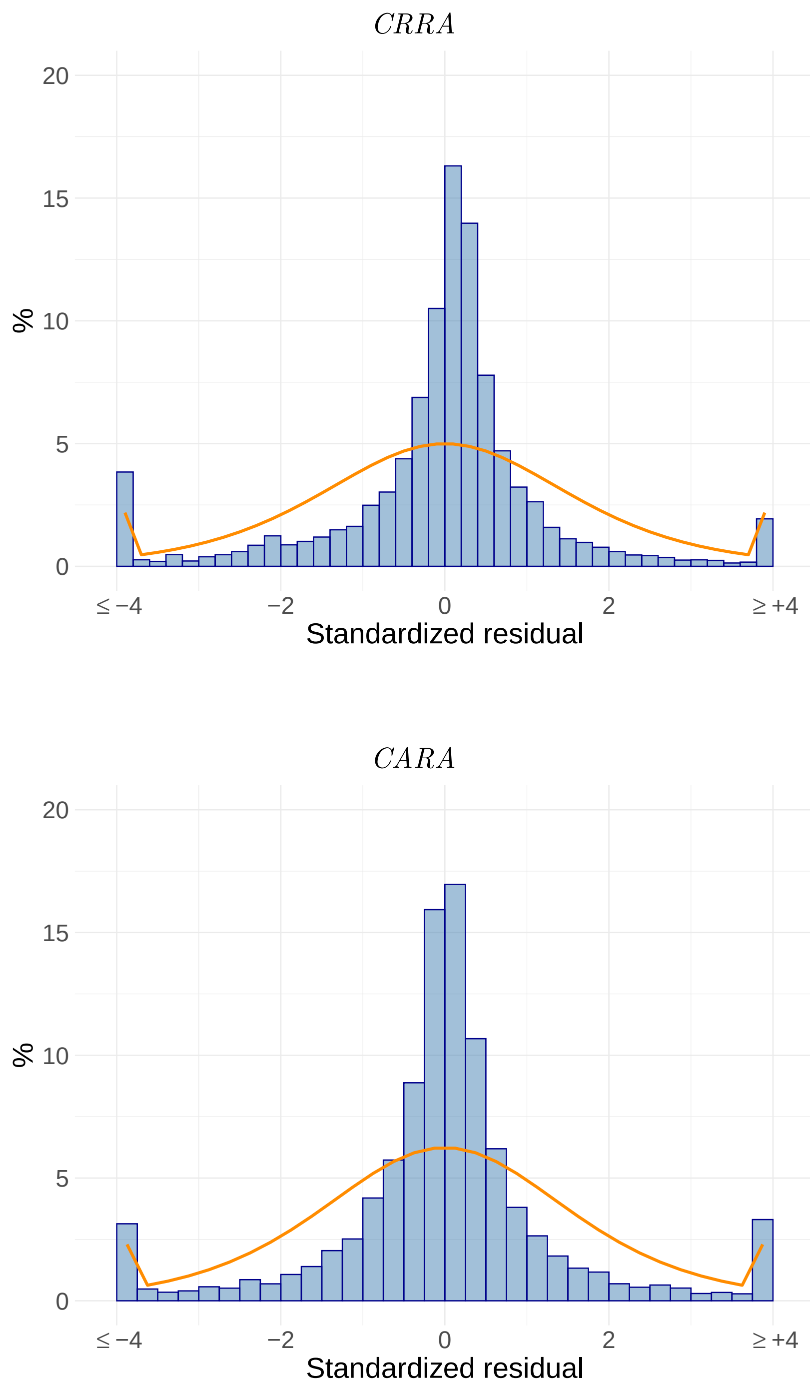
NOTES. The figure shows histograms of the distributions of risk aversion coefficients. The left column reports results for the full sample, while the right column reports results for the Prolific subsample in Enke and Graeber (2023). The top row corresponds to the CRRA utility function, and the bottom row to the CARA utility function. In each panel, the estimated PDF of risk aversion coefficients is shown in red.

Figure 2. Baseline: Distribution of Treatment Estimates



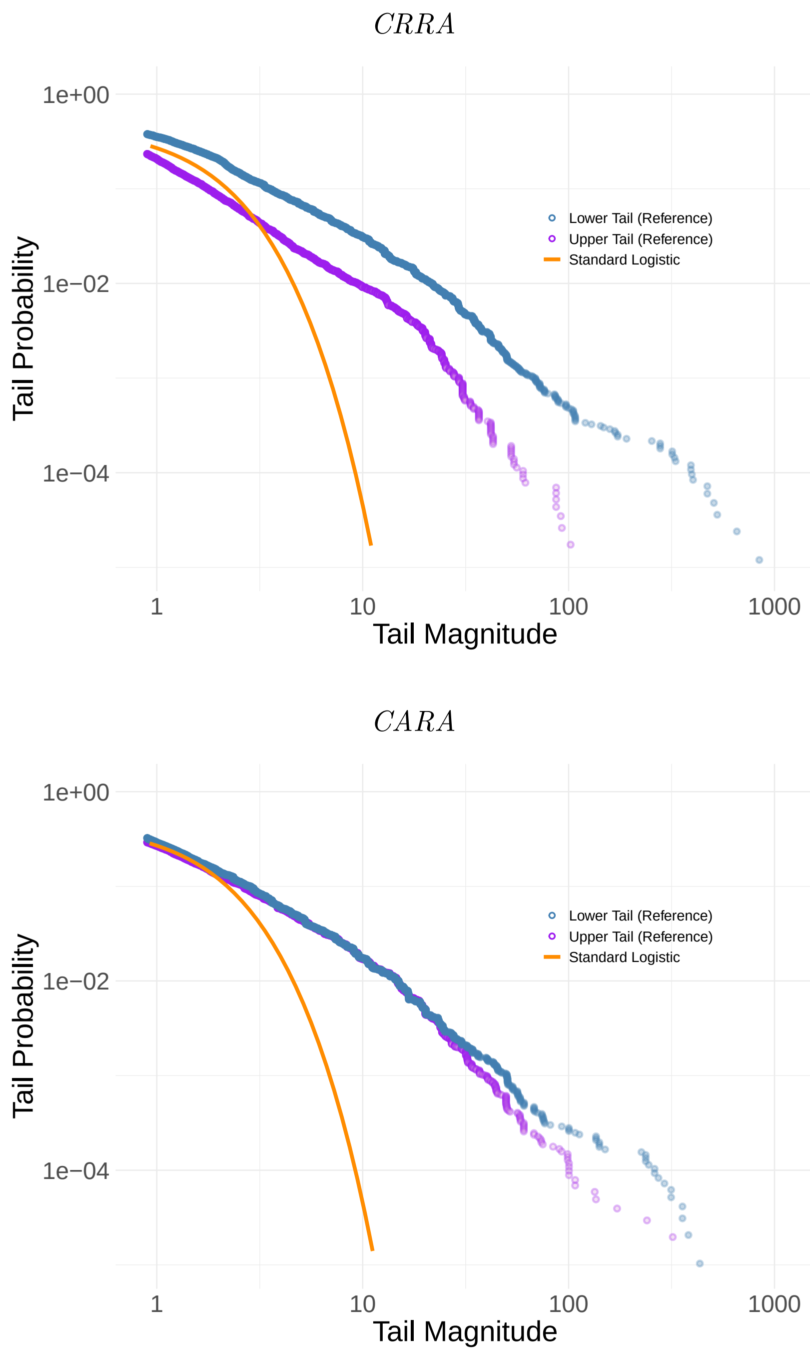
NOTES. The figure shows the distributions of the estimated treatment fixed effects on the location (top row) and scale (bottom row) parameters. The left column reports results for CRRA preferences, while the right column reports results for CARA preferences.

Figure 3. Baseline: Distribution of Standardized Risk Aversion Coefficients



NOTES. The figure shows histograms of the risk aversion coefficients standardized using the estimated location and scale parameters of the corresponding treatment. The top row corresponds to the CRRA utility function, and the bottom row to the CARA utility function. In each panel, the PDF of the standard logistic distribution is shown in orange.

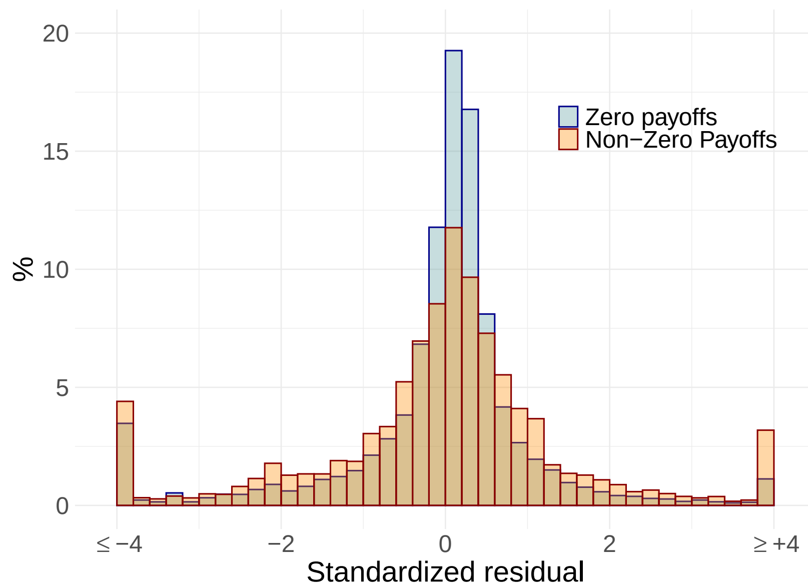
FIGURE 4. Baseline: Log-Log Plots of the Tails of the Empirical Distribution of Standardized Risk Aversion Coefficients



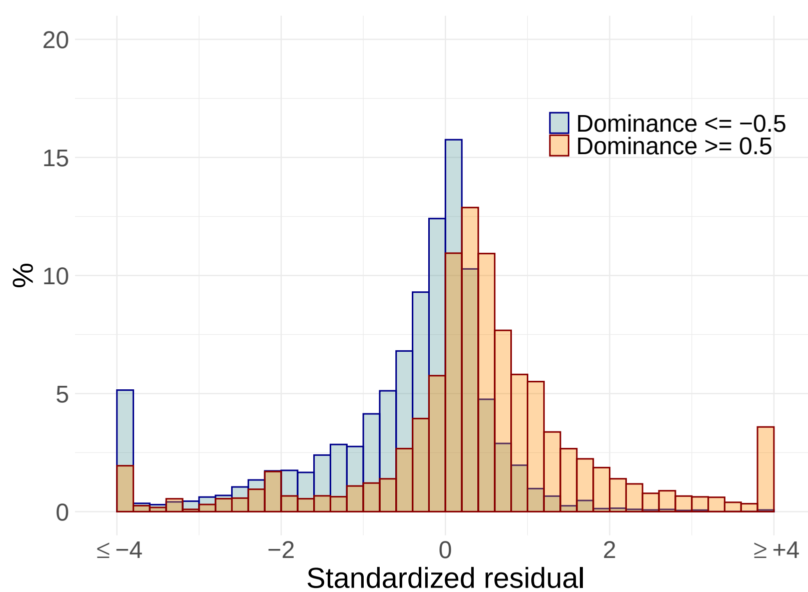
NOTES. The figure shows log-log plots of the tails of the empirical distribution of the risk aversion coefficients standardized using the estimated location and scale parameters of the corresponding treatment. The top row corresponds to the CRRA utility function, and the bottom row to the CARA utility function. In each panel, the tail of the standard logistic PDF is shown in orange.

FIGURE 5. Baseline: Distribution of Standardized CRRA Coefficients for Different Classes of Lotteries

Non-Zero Payoffs

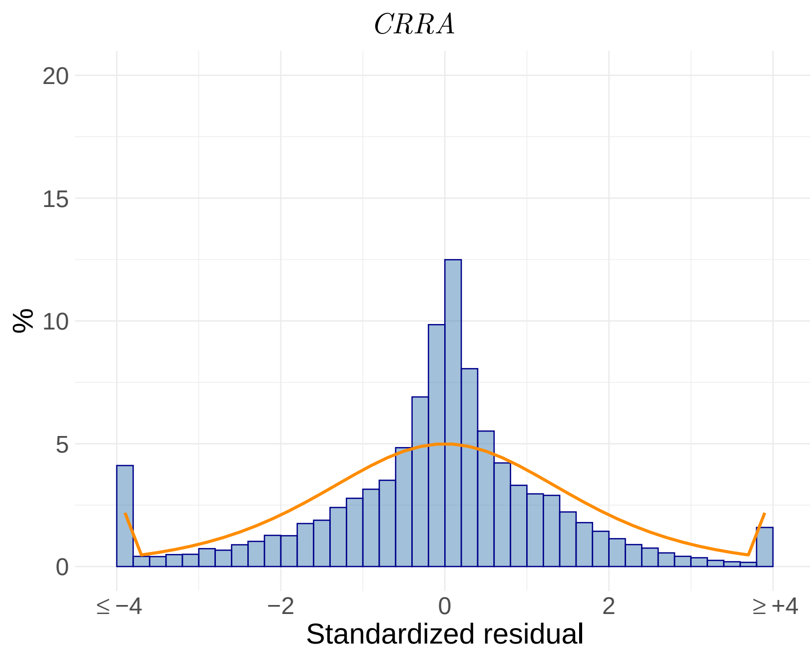


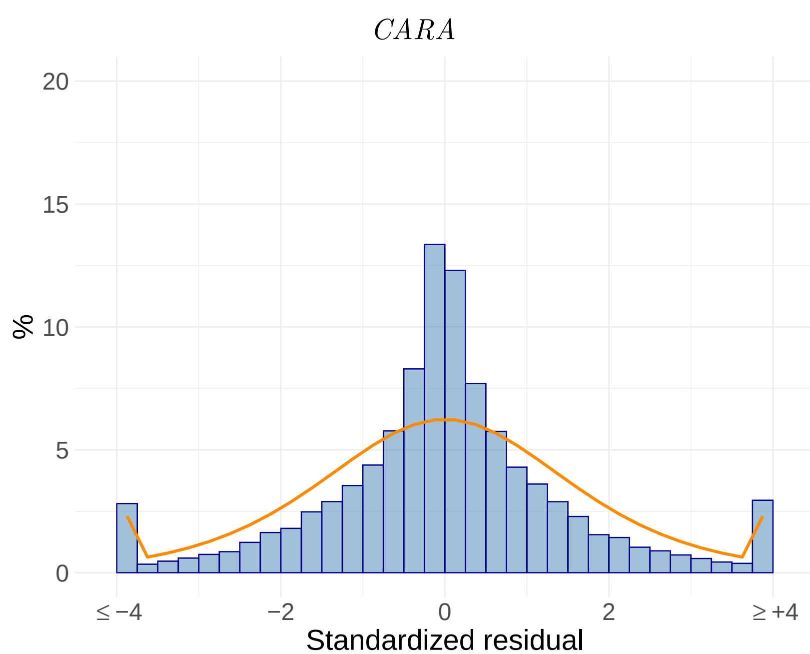
Dominance



NOTES. The figure shows histograms of the standardized CRRA coefficients. The upper panel compares the distributions of coefficients elicited from lotteries with zero payoffs (blue) and non-zero payoffs (orange). The lower panel compares the distributions of coefficients elicited from lotteries with a low degree of dominance (blue) and a high degree of dominance (orange).

Figure 6. Lottery-Specific Noise: Distribution of Standardized Risk Aversion Coefficients

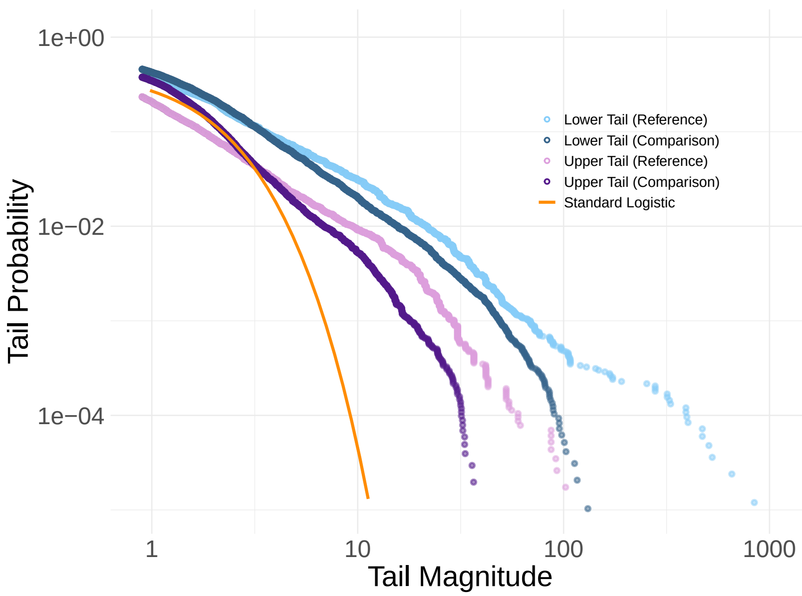




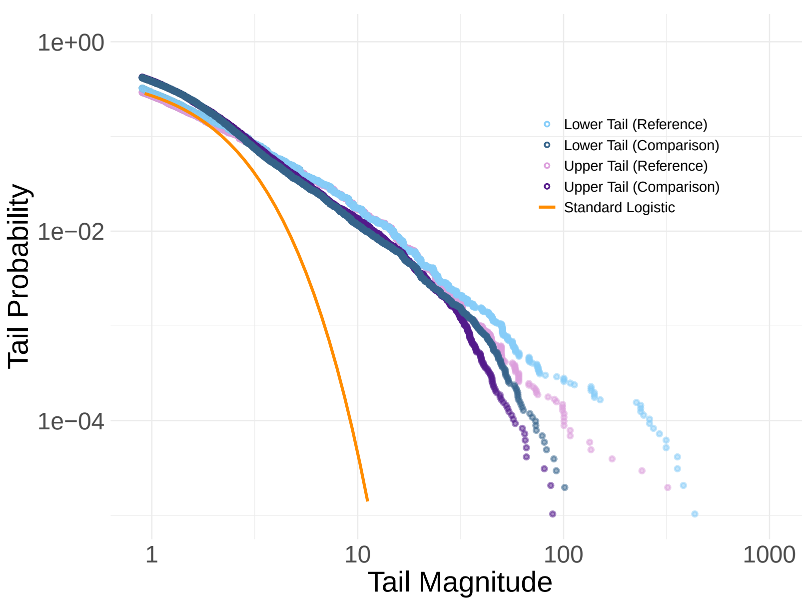
NOTES. The figure shows histograms of the risk aversion coefficients standardized using the estimated location and scale parameters from the saturated specification. The top row corresponds to the CRRA utility function, and the bottom row to the CARA utility function. In each panel, the PDF of the standard logistic distribution is shown in orange.

FIGURE 7. Lottery-Specific Noise vs Baseline: Log-Log Plots of the Tails of the Empirical Distribution of Standardized Risk Aversion Coefficients

CRRA

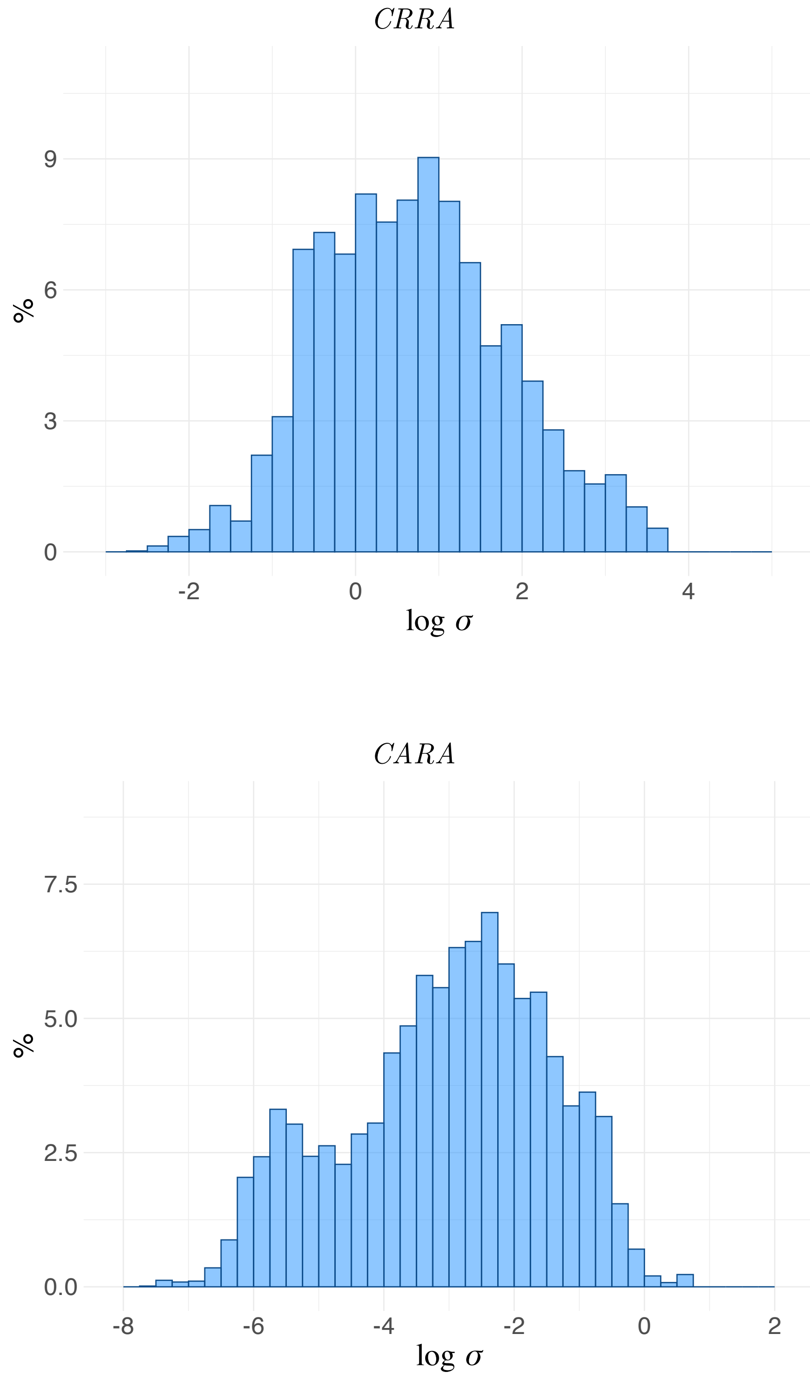


CARA



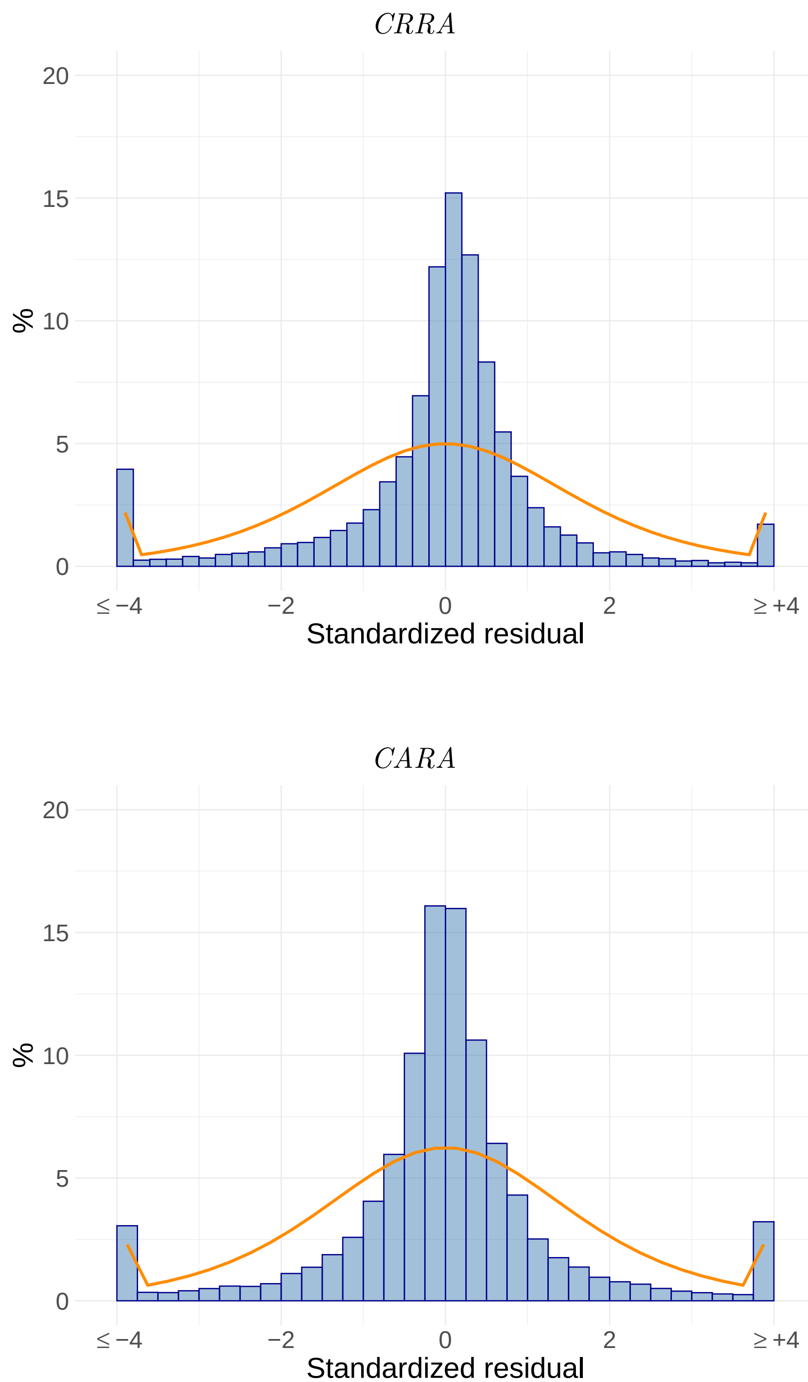
NOTES. The figure shows log-log plots of the tails of the empirical distribution of the risk aversion coefficients standardized using the estimated location and scale parameters from the saturated specification. The top row corresponds to the CRRA utility function, and the bottom row to the CARA utility function. Each panel plots two sets of tails: the series labeled *Reference* in the legend correspond to the Baseline specification (lighter shades), and those labeled *Comparison* to the specification with lottery-specific noise (darker shades). In each panel, the tail of the standard logistic PDF is shown in orange.

Figure 8. Lottery-Specific Noise: Distribution of Log-Scale Estimates



NOTES. The figure shows the distributions of the estimated log-scale parameter from the saturated specification. The upper panel uses CRRA preferences, and the lower panel uses CARA preferences.

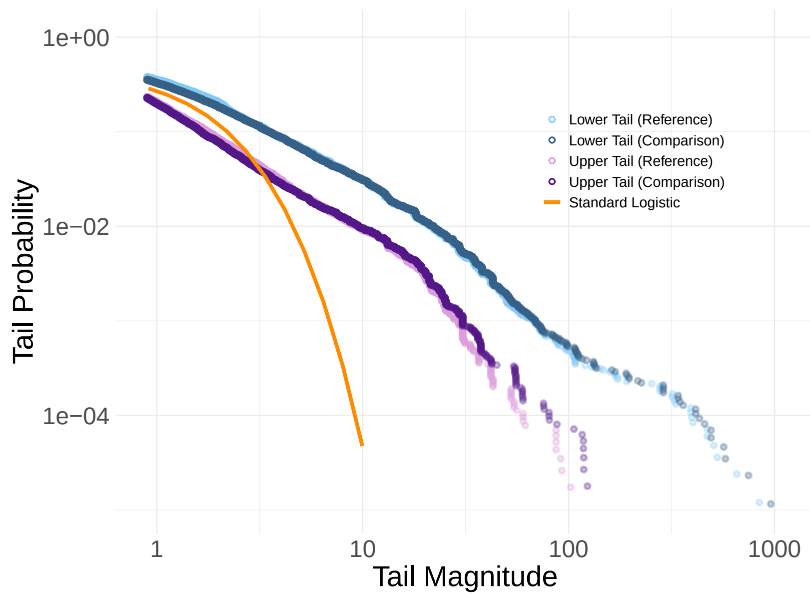
FIGURE 9. Lottery-Specific (Mean) Risk: Distribution of Standardized Risk Aversion Coefficients



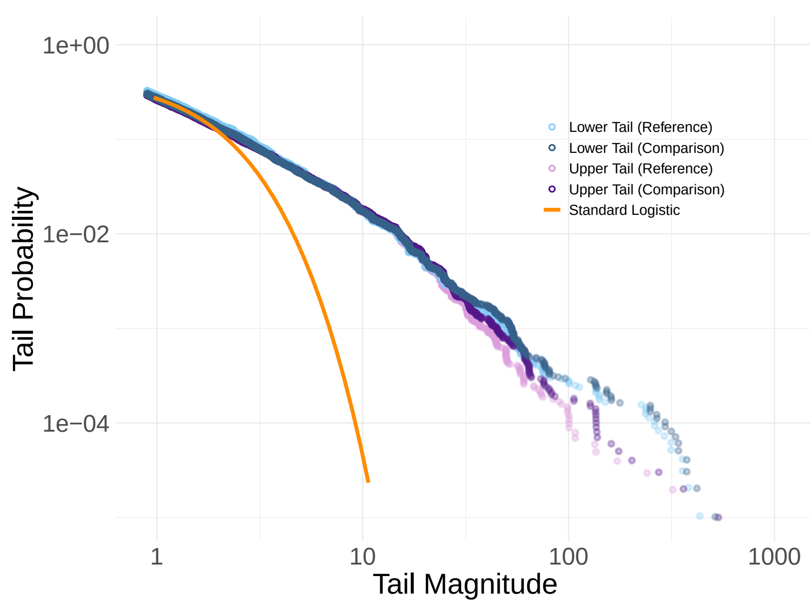
NOTES. The figure shows histograms of the risk aversion coefficients standardized using the estimated location and scale parameters from the saturated specification. The top row corresponds to the CRRA utility function, and the bottom row to the CARA utility function. In each panel, the PDF of the standard logistic distribution is shown in orange.

FIGURE 10. Lottery-Specific (Mean) Risk vs Baseline: Log-Log Plots of the Tails of the Empirical Distribution of Standardized Risk Aversion Coefficients

CRRA

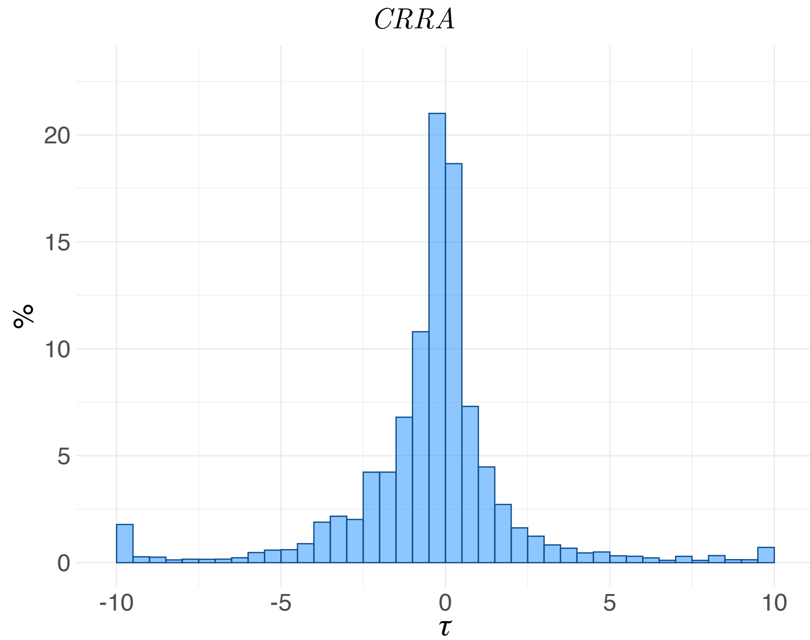


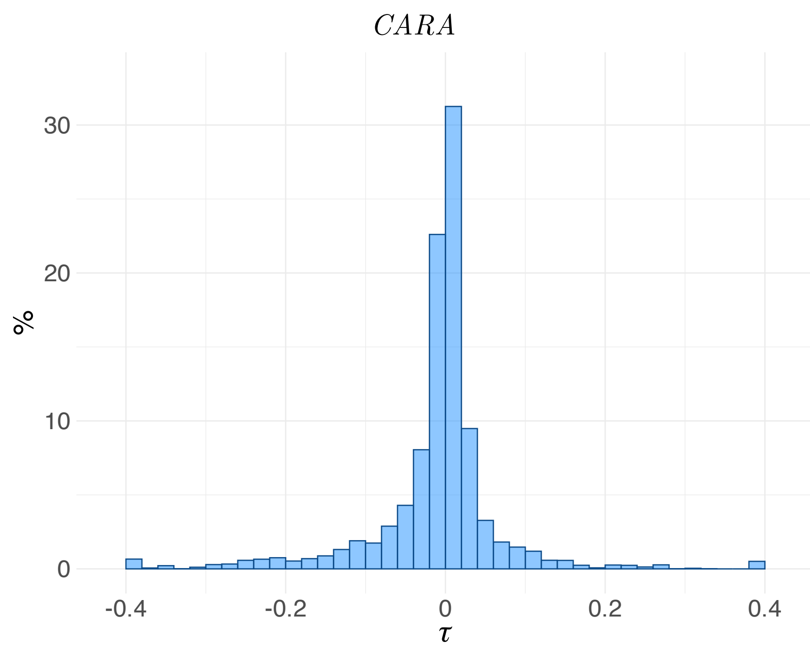
CARA



NOTES. The figure shows log-log plots of the tails of the empirical distribution of the risk aversion coefficients standardized using the estimated location and scale parameters from the saturated specification. The top row corresponds to the CRRA utility function, and the bottom row to the CARA utility function. Each panel plots two sets of tails: the series labeled *Reference* in the legend correspond to the Baseline specification (lighter shades), and those labeled *Comparison* to the specification with lottery-specific (mean) risk (darker shades). In each panel, the tail of the standard logistic PDF is shown in orange.

FIGURE 11. Lottery-Specific (Mean) Risk: Distribution of Location Estimates

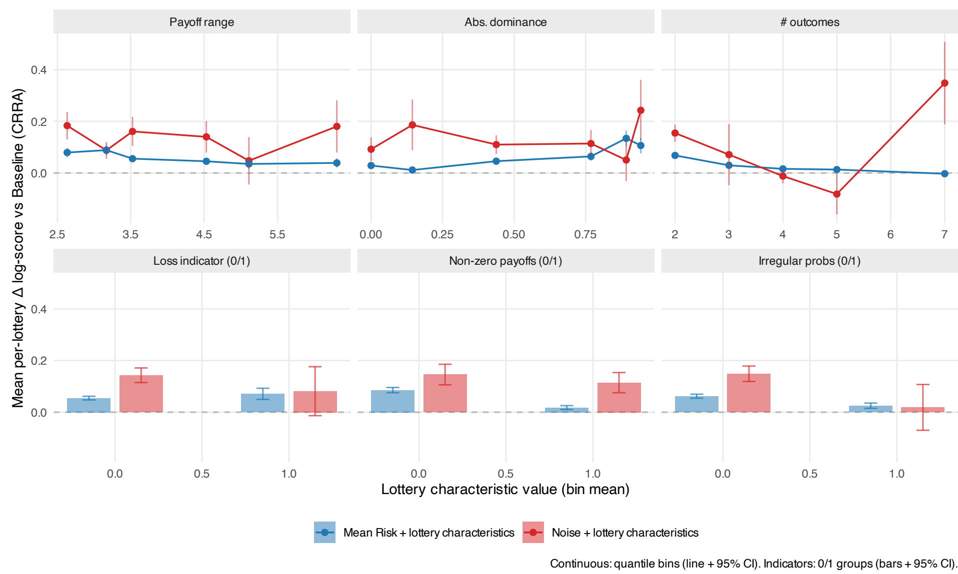




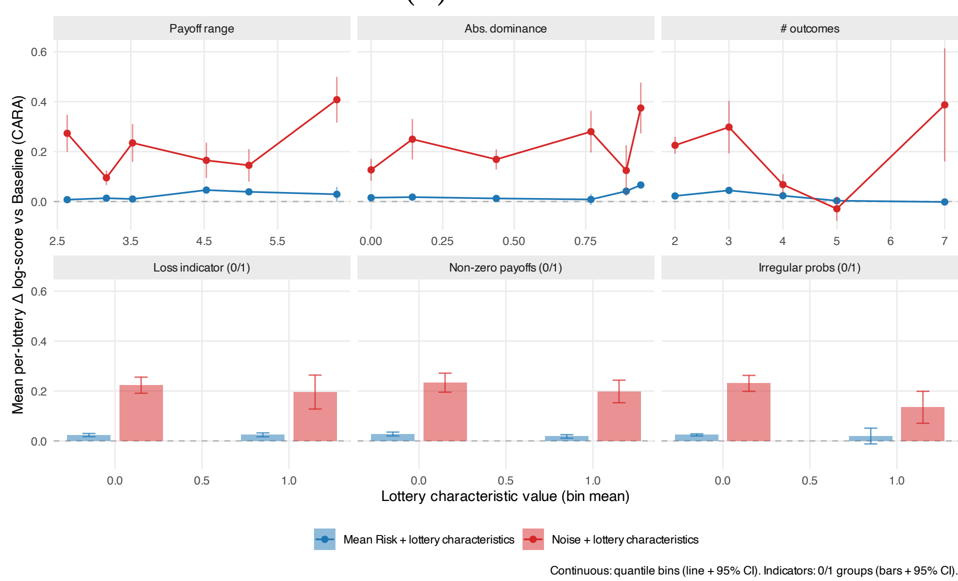
NOTES. The figure shows the distributions of the estimated location parameter from the saturated specification. The upper panel uses CRRA preferences, and the lower panel uses CARA preferences.

Figure 12. Out-of-Sample Predictive Improvement by Lottery Characteristic: Leave-One-Lottery-Out (LOLO)

(a) CRRA



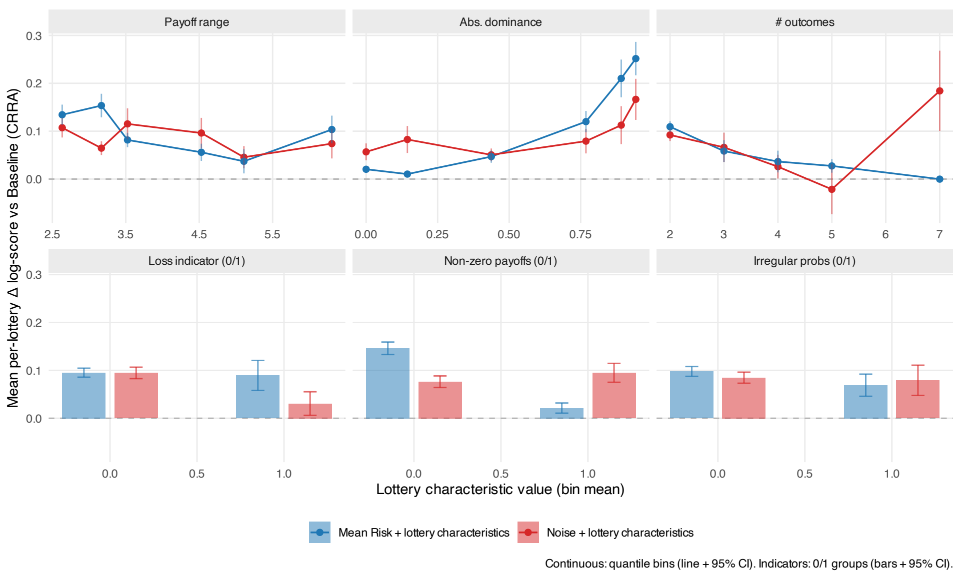
(b) CARA



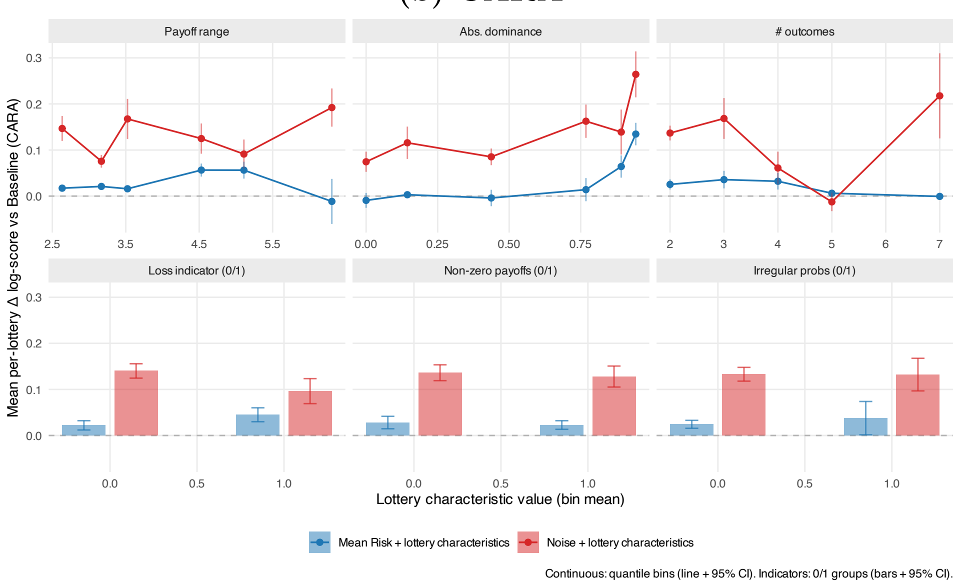
NOTES. Each panel plots the average gain in held-out log score, relative to the Baseline model, delivered by the linear-in-characteristics specifications of the Lottery-Specific Noise and Lottery-Specific (Mean) Risk models. The held-out unit is a single lottery (1,299 folds). Panel (a) uses CRRA preferences, and panel (b) uses CARA preferences. Each panel presents the results from the perspective of each of the six lottery characteristics discussed in the paper.

Figure 13. Out-of-Sample Predictive Improvement by Lottery Characteristic: Leave-One-Lottery-Out (LOLO), Student-t

(a) CRRA



(b) CARA



NOTES. Student-t counterpart to Figure 12. Each panel plots the average gain in held-out log score, relative to the Baseline model, delivered by the linear-in-characteristics specifications of the Lottery-Specific Noise and Lottery-Specific (Mean) Risk models under a Student-t distribution. The held-out unit is a single lottery (1,299 folds). Panel (a) uses CRRA preferences, and panel (b) uses CARA preferences. Each panel presents the results from the perspective of each of the six lottery characteristics discussed in the paper.

Table 1. Experimental Studies in the Dataset

Reference	Years	Subj.	Lot.	Trt.
Abdellaoui et al. (2011)	2006	124	23	3
Beauchamp et al. (2020)	2010	493	112	20
Bleichrodt et al. (2023)	2022	48	10	4
Bruhin et al. (2010)	2003, 2005, 2006	448	88	3
Diecidue et al. (2015)	2009, 2014	137	112	3
Enke and Graeber (2023)	2019, 2022	1488	326	5
Fan et al. (2019)	2015	122	21	5
Fehr-Duda et al. (2010)	2005	153	28	1
Gonzalez and Wu (2022)	1999, 2022	47	201	2
Hajimoladarvish, N. (2018)	2016	33	40	2
l'Haridon and Vieider (2019)	2012	2939	27	30
Kontek and Birnbaum (2019)	2016	185	221	3
Oberholzer et al. (2024)	2019, 2021	369	48	2
Oprea (2024)	2021, 2022, 2023	673	24	5
Vieider et al. (2019)	2011	254	27	2

NOTES. "Subj." denotes the number of distinct individuals in the study; these counts sum to 7,513, slightly exceeding the 7,362 distinct individuals in the pooled sample because 151 persons participated in both Bruhin et al. (2010) and Fehr-Duda et al. (2010) and are therefore counted once in each study. The "Lot." column reports the number of distinct lotteries in each study; these counts sum to 1,308, slightly exceeding the 1,299 distinct lotteries in the pooled sample because 9 lotteries each appear in two studies and are therefore counted once in each study. "Trt." denotes the number of treatments in the study.

Table 2. Baseline: Goodness of Fit across Specifications

	(i)	(ii)	(iii)	(iv)
CRRA				
Avg. Log-Likelihood	-3.5935	-3.5862	-3.2250	-3.2137
Δ Avg. Log-Likelihood	–	+0.0073	+0.3685	+0.3798
Kolmogorov-Smirnov	0.2221	0.2151	0.1721	0.1599
Anderson-Darling	21476	20800	12119	11782
Fitted $\hat{\tau}$	-0.258	-0.287	0.072	-0.452
Fitted $\hat{\sigma}$	3.995	3.969	3.958	3.921
CARA				
Avg. Log-Likelihood	-0.2039	-0.1972	0.5699	0.5793
Δ Avg. Log-Likelihood	–	+0.0067	+0.7738	+0.7832
Kolmogorov-Smirnov	0.2293	0.2273	0.1501	0.1490
Anderson-Darling	22922	22515	10321	10130
Fitted $\hat{\tau}$	-0.004	-0.006	0.001	-0.010
Fitted $\hat{\sigma}$	0.135	0.134	0.129	0.128
Specification				
FE: Location	None	Treatment	None	Treatment
FE: Log-Scale	None	None	Treatment	Treatment

NOTES. This table reports goodness-of-fit measures for the Baseline model under four specifications: (i) constant location and scale; (ii) treatment fixed effects (FE) in location and constant scale; (iii) constant location and treatment FE in log-scale; and (iv) treatment FE in both. Avg. Log-Likelihood measures model fit. Δ Avg. Log-Likelihood reports the improvement relative to specification (i). Fitted $\hat{\tau}$ and $\hat{\sigma}$ report the average estimated parameter values across treatments.

Table 3. Lottery-Specific Noise: Goodness of Fit across Specifications

	Baseline (i)	**Noise (i)**	**Baseline (iv)**	**Noise (ii)**	**Noise (iii)**	**Noise (iv)**
CRRA						
Avg. Log-Likelihood	-3.5935	-3.0160	-3.2137	-2.7921	-2.8509	-3.1082
Δ Avg. Log-Likelihood	–	+0.5775	–	+0.4216	+0.3628	+0.1055
Kolmogorov-Smirnov	0.2221	0.1346	0.1599	0.1036	0.1104	0.1509
Anderson-Darling	21476	7765	11782	4784	5871	10317
Fitted $\hat{\tau}$	-0.258	-0.035	-0.452	-0.031	-0.103	-0.362
Fitted $\hat{\sigma}$	3.995	3.937	3.921	3.877	4.089	3.844
CARA						
Avg. Log-Likelihood	-0.2039	0.7334	0.5793	0.9392	0.8999	0.7291
Δ Avg. Log-Likelihood	–	+0.9373	–	+0.3599	+0.3206	+0.1498
Kolmogorov-Smirnov	0.2293	0.1221	0.1490	0.0919	0.0966	0.1272
Anderson-Darling	22922	6795	10130	3980	4697	7934
Fitted $\hat{\tau}$	-0.004	0.000	-0.010	-0.001	-0.003	-0.006
Fitted $\hat{\sigma}$	0.135	0.128	0.128	0.127	0.131	0.127
Specification						
FE: Location	None	None	Treatment	Treatment	Treatment	Treatment
FE: Log-Scale	None	Lot.	Treatment	Treat. x Lot.	Treat. + Lot.	Treatment
Lottery Characteristics	No	No	No	No	No	Yes

NOTES. This table reports goodness-of-fit measures for the Lottery-Specific Noise model under four specifications, relative to the corresponding Baseline specifications. Noise (i), the representative-agent specification, is compared with Baseline (i). Noise (ii), the saturated specification; Noise (iii), the separable specification; and Noise (iv), the linear-in-characteristics specification, are each compared with Baseline (iv). Avg. Log-Likelihood measures model fit. Δ Avg. Log-Likelihood reports the improvement relative to the corresponding Baseline specification. Fitted $\hat{\tau}$ and $\hat{\sigma}$ report the average estimated parameter values across treatments.

Table 4. Lottery-Specific Noise and Lottery-Specific (Mean) Risk Models with Lottery Characteristics

	Noise (iv)		**Mean (iv)**	
	CRRA	**CARA**	**CRRA**	**CARA**
Dominance	–	–	1.015	0.777
	–	–	(0.023)	(0.029)
|Dominance|	0.773	0.772	–	–
	(0.063)	(0.041)	–	–
Number of Outcomes	0.152	0.214	-0.035	0.023
	(0.016)	(0.017)	(0.026)	(0.036)
Payoff Range	-0.566	-0.925	-0.051	-0.048
	(0.025)	(0.014)	(0.010)	(0.012)
Non-Zero Payoffs Indicator	0.485	0.121	-0.153	-0.127
	(0.044)	(0.028)	(0.018)	(0.021)
Loss Indicator	-0.097	-0.066	-0.359	-0.477
	(0.041)	(0.028)	(0.022)	(0.024)
Irregular Probabilities Indicator	-0.410	-0.183	0.019	0.082
	(0.034)	(0.029)	(0.027)	(0.031)
FE: Location	Treatment	Treatment	Treatment	Treatment
FE: Log-Scale	Treatment	Treatment	Treatment	Treatment
Avg. Log Likelihood	-3.1082	0.7291	-3.1875	0.5928

NOTES. This table reports the estimated effects of the lottery characteristics on the log-scale parameter in the Lottery-Specific Noise model and on the location parameter in the Lottery-Specific (Mean) Risk model under both CRRA and CARA preferences, using the linear-in-characteristics specification. Estimates for the Lottery-Specific (Mean) Risk model under CARA preferences are multiplied by 100 for readability. Robust standard errors, clustered at the subject level, are reported in parentheses.

Table 5. Lottery-Specific (Mean) Risk: Goodness of Fit across Specifications

	Baseline (i)	**Mean (i)**	**Baseline (iv)**	**Mean (ii)**	**Mean (iii)**	**Mean (iv)**
CRRA						
Avg. Log-Likelihood	-3.5935	-3.5351	-3.2137	-3.1180	-3.1234	-3.1875
Δ Avg. Log-Likelihood	–	+0.0584	–	+0.0957	+0.0903	+0.0262
Kolmogorov-Smirnov	0.2221	0.2265	0.1599	0.1627	0.1671	0.1687
Anderson-Darling	21476	22747	11782	12569	12992	12786
Fitted $\hat{\tau}$	-0.258	-0.221	-0.452	-0.443	-0.429	-0.441
Fitted $\hat{\sigma}$	3.995	3.726	3.921	3.652	3.670	3.858
CARA						
Avg. Log-Likelihood	-0.2039	-0.1445	0.5793	0.6820	0.6758	0.5928
Δ Avg. Log-Likelihood	–	+0.0594	–	+0.1027	+0.0965	+0.0135
Kolmogorov-Smirnov	0.2293	0.2324	0.1490	0.1493	0.1515	0.1508
Anderson-Darling	22922	24005	10130	10692	10981	10247
Fitted $\hat{\tau}$	-0.004	-0.006	-0.010	-0.010	-0.010	-0.009
Fitted $\hat{\sigma}$	0.135	0.126	0.128	0.120	0.121	0.128
Specification						
FE: Location	None	Lot.	Treatment	Treat. x Lot.	Treat. + Lot.	Treatment
FE: Log-Scale	None	None	Treatment	Treatment	Treatment	Treatment
Lottery Characteristics	No	No	No	No	No	Yes

NOTES. This table reports goodness-of-fit measures for the Lottery-Specific (Mean) Risk model under four specifications, relative to the corresponding Baseline specifications. Mean (i), the representative-agent specification, is compared with Baseline (i). Mean (ii), the saturated specification; Mean (iii), the separable specification; and Mean (iv), the linear-in-characteristics specification, are each compared with Baseline (iv). Avg. Log-Likelihood measures model fit. Δ Avg. Log-Likelihood reports the improvement relative to the corresponding Baseline specification. Fitted $\hat{\tau}$ and $\hat{\sigma}$ report the average estimated parameter values across treatments.

Table 6. Lottery-Specific Noise and Lottery-Specific (Mean) Risk Models with Lottery Characteristics and Treatment Features

	Noise (v)		Mean (v)	
	CRRA	**CARA**	**CRRA**	**CARA**
Dominance	–	–	1.022	0.781
	–	–	(0.024)	(0.028)
|Dominance|	0.310	0.190	–	–
	(0.043)	(0.038)	–	–
N. Outcomes	0.147	0.165	-0.028	0.025
	(0.039)	(0.029)	(0.030)	(0.034)
Payoff Range	-0.390	-1.092	0.041	-0.096
	(0.042)	(0.032)	(0.013)	(0.015)
Dummy: Non-Zero Payoffs	0.203	-0.206	-0.005	-0.054
	(0.044)	(0.030)	(0.016)	(0.021)
Dummy: Pure Losses	-0.004	-0.025	-0.457	-0.616
	(0.027)	(0.023)	(0.028)	(0.045)
Dummy: Irregular Probs.	0.034	0.345	-0.224	0.011
	(0.050)	(0.032)	(0.029)	(0.025)
Dummy: Compound Lot.	0.355	0.243	-0.223	-5.083
	(0.222)	(0.195)	(0.058)	(0.682)
Dummy: More Math	-0.266	-0.234	-0.007	-0.006
	(0.083)	(0.064)	(0.034)	(0.030)
Dummy: MPL Elicitation	-0.070	-0.036	0.177	0.211
	(0.202)	(0.125)	(0.072)	(0.055)
Dummy: USA Sample	-0.317	-0.507	0.094	0.040
	(0.105)	(0.087)	(0.040)	(0.043)
Dummy: Incentivized	0.314	-0.018	0.219	-0.004
	(0.130)	(0.105)	(0.038)	(0.042)
Dummy: Prolific Pool	-0.089	0.201	-0.387	0.280
	(0.107)	(0.102)	(0.083)	(0.209)
Dummy: AMT Pool	-1.097	-0.075	-0.245	0.454
	(0.119)	(0.113)	(0.045)	(0.255)
FE: Location	Treatment	Treatment	None	None
FE: Log-Scale	None	None	Treatment	Treatment
Avg. Log Likelihood	-3.3892	0.4703	-3.1946	0.5864

NOTES. This table reports the estimated effects of the lottery characteristics and treatment features on the log-scale parameter in the Lottery-Specific Noise model and on the location parameter in the Lottery-Specific (Mean) Risk model under both CRRA and CARA preferences, using the linear specification. The specification includes 13 features in the corresponding parameter. Estimates for the Lottery-Specific (Mean) Risk model under CARA preferences are multiplied by 100 for readability. Robust standard errors, clustered at the subject level, are reported in parentheses.

Table 7. Lottery-Specific Noise with a Student-t Distribution: Goodness of Fit across Specifications

	Baseline (i)	**Noise (i)**	**Baseline (iv)**	**Noise (ii)**	**Noise (iii)**	**Noise (iv)**
CRRA						
Avg. Log-Likelihood	-2.6738	-2.5071	-2.5802	-2.4390	-2.4507	-2.5294
Δ Avg. Log-Likelihood	–	+0.1667	–	+0.1412	+0.1295	+0.0508
Kolmogorov-Smirnov	0.0355	0.0437	0.0345	0.0393	0.0384	0.0305
Anderson-Darling	561	774	760	835	837	794
Fitted $\hat{\tau}$	0.086	0.035	0.105	0.090	0.088	0.115
Fitted $\hat{\sigma}$	0.965	1.775	1.331	2.170	2.036	1.536
Deg. of Freedom ($\hat{\nu}$)	0.8653	1.1940	1.0279	1.3537	1.3192	1.1204
	(0.008)	(0.016)	(0.010)	(0.018)	(0.018)	(0.013)
CARA						
Avg. Log-Likelihood	0.8190	1.1624	1.0926	1.2353	1.2247	1.1768
Δ Avg. Log-Likelihood	–	+0.3434	–	+0.1427	+0.1321	+0.0842
Kolmogorov-Smirnov	0.0384	0.0170	0.0155	0.0105	0.0102	0.0111
Anderson-Darling	436	93	45	50	39	27
Fitted $\hat{\tau}$	0.001	0.000	-0.002	-0.001	-0.001	-0.001
Fitted $\hat{\sigma}$	0.019	0.059	0.050	0.075	0.069	0.060
Deg. of Freedom ($\hat{\nu}$)	0.6588	1.1936	1.0616	1.4272	1.3574	1.2198
	(0.007)	(0.016)	(0.010)	(0.019)	(0.018)	(0.015)
Specification						
FE: Location	None	None	Treatment	Treatment	Treatment	Treatment
FE: Log-Scale	None	Lot.	Treatment	Treat. x Lot.	Treat. + Lot.	Treatment
Lottery Characteristics	No	No	No	No	No	Yes

NOTES. This table reports goodness-of-fit measures for the Lottery-Specific Noise model with a Student-t distribution under four specifications, relative to the corresponding Baseline specifications. Noise (i), the representative-agent specification, is compared with Baseline (i). Noise (ii), the saturated specification; Noise (iii), the separable specification; and Noise (iv), the linear-in-characteristics specification, are each compared with Baseline (iv). Avg. Log-Likelihood measures model fit. Δ Avg. Log-Likelihood reports the improvement relative to the corresponding Baseline specification. Fitted $\hat{\tau}$ and $\hat{\sigma}$ report the average estimated parameter values across treatments, and $\hat{\nu}$ reports the common estimated degrees of freedom of the Student-t distribution.

Table 8. Lottery-Specific (Mean) Risk with a Student-t Distribution: Goodness of Fit across Specifications

	Baseline (i)	Mean (i)	Baseline (iv)	Mean (ii)	Mean (iii)	Mean (iv)
CRRA						
Avg. Log-Likelihood	-2.6738	-2.4838	-2.5802	-2.3973	-2.4142	-2.5260
Δ Avg. Log-Likelihood	–	+0.1900	–	+0.1829	+0.1660	+0.0542
Kolmogorov-Smirnov	0.0355	0.0414	0.0345	0.0443	0.0389	0.0361
Anderson-Darling	561	1114	760	1097	1124	1005
Fitted $\hat{\tau}$	0.086	0.221	0.105	0.177	0.174	0.137
Fitted $\hat{\sigma}$	0.965	0.722	1.331	0.919	1.018	1.229
Deg. of Freedom ($\hat{\nu}$)	0.8653	0.8046	1.0279	0.8805	0.9492	1.0079
	(0.008)	(0.007)	(0.010)	(0.007)	(0.009)	(0.010)
CARA						
Avg. Log-Likelihood	0.8190	0.9893	1.0926	1.2727	1.2516	1.1064
Δ Avg. Log-Likelihood	–	+0.1703	–	+0.1801	+0.1590	+0.0138
Kolmogorov-Smirnov	0.0384	0.0431	0.0155	0.0205	0.0112	0.0241
Anderson-Darling	436	638	45	145	50	115
Fitted $\hat{\tau}$	0.001	-0.007	-0.002	-0.003	-0.002	-0.002
Fitted $\hat{\sigma}$	0.019	0.012	0.050	0.035	0.039	0.053
Deg. of Freedom ($\hat{\nu}$)	0.6588	0.5614	1.0616	0.9029	0.9845	1.1059
	(0.007)	(0.006)	(0.010)	(0.007)	(0.009)	(0.010)
Specification						
FE: Location	None	Lot.	Treatment	Treat. x Lot.	Treat. + Lot.	Treatment
FE: Log-Scale	None	None	Treatment	Treatment	Treatment	Treatment
Lottery Characteristics	No	No	No	No	No	Yes

NOTES. This table reports goodness-of-fit measures for the Lottery-Specific (Mean) Risk model with a Student-t distribution under four specifications, relative to the corresponding Baseline specifications. Mean (i), the representative-agent specification, is compared with Baseline (i). Mean (ii), the saturated specification; Mean (iii), the separable specification; and Mean (iv), the linear-in-characteristics specification, are each compared with Baseline (iv). Avg. Log-Likelihood measures model fit. Δ Avg. Log-Likelihood reports the improvement relative to the corresponding Baseline specification. Fitted $\hat{\tau}$ and $\hat{\sigma}$ report the average estimated parameter values across treatments, and $\hat{\nu}$ reports the common estimated degrees of freedom of the Student-t distribution.

Table 9. Lottery-Specific Noise and Lottery-Specific (Mean) Risk Models with Lottery Characteristics and a Student-t Distribution

	Noise (iv)		**Mean (iv)**	
	CRRA	**CARA**	**CRRA**	**CARA**
Dominance	–	–	0.773	0.589
	–	–	(0.015)	(0.018)
|Dominance|	1.062	1.110	–	–
	(0.020)	(0.020)	–	–
Number of Outcomes	0.212	0.284	0.007	-0.025
	(0.008)	(0.008)	(0.013)	(0.019)
Payoff Range	-0.622	-0.930	0.022	-0.038
	(0.006)	(0.006)	(0.006)	(0.007)
Non-Zero Payoffs Indicator	0.254	-0.045	-0.037	-0.082
	(0.016)	(0.016)	(0.013)	(0.015)
Loss Indicator	-0.048	-0.044	-0.131	-0.381
	(0.013)	(0.014)	(0.013)	(0.016)
Irregular Probabilities Indicator	-0.137	-0.014	0.054	0.045
	(0.014)	(0.014)	(0.010)	(0.018)
Deg. of Freedom ($\hat{\nu}$)	1.120	1.220	1.008	1.106
	(0.013)	(0.015)	(0.010)	(0.010)
FE: Location	Treatment	Treatment	Treatment	Treatment
FE: Log-Scale	Treatment	Treatment	Treatment	Treatment
Avg. Log Likelihood	-2.5294	1.1768	-2.5260	1.1064

NOTES. This table reports the estimated effects of the lottery characteristics on the log-scale parameter in the Lottery-Specific Noise model and on the location parameter in the Lottery-Specific (Mean) Risk model under both CRRA and CARA preferences, using the linear-in-characteristics specification with a Student-t distribution. Estimates for the Lottery-Specific (Mean) Risk model under CARA preferences are multiplied by 100 for readability. Robust standard errors, clustered at the subject level, are reported in parentheses.