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Italian Economic Journal
https://doi.org/10.1007/s40797-026-00395-0

RESEARCH PAPER

Catastrophic Risk Perception and the Shared Burden Effect: An Experimental Study Using Prospect Theory

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Received: 31 March 2025 / Accepted: 26 May 2026

Abstract
This study examines how individuals perceive and value low-probability, high-impact risks through a Cumulative Prospect Theory (CPT) framework. We focus on two main contributions. First, we introduce and validate an experimental measure of *Catastrophic Risk Perception* (CRP), derived from individual CPT parameters, capturing probability weighting and loss sensitivity. Second, we define and document a *Shared Burden Effect* (SBE): willingness to pay to eliminate a catastrophic loss falls when the same risk is shared collectively rather than borne individually, under identical probabilities and outcomes. We further explore how background characteristics and cognitive mechanisms shape these behaviors, distinguishing between distortions in probability perception and sensitivity to losses. Our findings shed light on how collective framing alters perceived risk severity and help explain public underinvestment in preparedness for extreme events.

Keywords Risk perception · Catastrophic risk · Prospect theory · Experimental economics · Shared burden effect

JEL Classification D81 · C91

1 Introduction

Catastrophic risk refers to low-probability, high-impact events–such as pandemics, nuclear accidents, or large-scale natural disasters. Despite their rarity, these events have captured significant attention, especially in recent years, because of their profound societal and individual relevance. For example, during the COVID-19 pandemic, individuals exhibited significantly different responses to measures such as lockdowns and vaccination campaigns, leading to heterogeneity in compliance and beliefs about

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Published online: 12 June 2026

the restrictions (Cipolletta et al. 2022). Additionally, individual attitudes and trust were significantly affected, with lockdown experiences influencing prosocial behaviors such as fairness and cooperation (Buso et al. 2020). Similarly, public discourse surrounding the war in Ukraine revealed considerable variation in nuclear risk perception, with some individuals dismissing the possibility of nuclear escalation and others exhibiting heightened concerns (Lauriola et al. 2024). The existing literature shows that risk perception is inherently subjective and shaped by a complex interaction of cognitive biases, past experiences, personality, and sociodemographic factors (Slovic 2000). In standard economic theory, decision-making under risk is typically modeled using Expected Utility Theory (EUT), where individuals evaluate uncertain prospects by combining objective probabilities with the utility of outcomes. Under this benchmark, probabilities enter linearly into expected utility calculations and preferences depend only on final outcomes. As a result, extremely low-probability events should have only a limited influence on choices unless the associated losses are sufficiently large.

However, extensive empirical evidence documents systematic deviations from these predictions, particularly for low-probability, high-impact risks (Kahneman and Tversky 1979; Quiggin 1993). In practice, individuals often behave as if rare events receive a much larger weight than their objective probability would imply. For example, people may be strongly concerned about extremely unlikely disasters such as plane crashes or nuclear accidents, despite their very small statistical probability. Conversely, the same probability distortion leads individuals to overestimate the likelihood of highly improbable gains, such as winning large lottery jackpots. In addition, individuals tend to evaluate potential losses more strongly than comparable gains, reacting more intensely to the possibility of losing a given amount than to the prospect of gaining the same amount. These behavioral patterns imply that subjective risk perception may diverge substantially from the predictions of Expected Utility Theory, particularly in the context of catastrophic events. We adopt Cumulative Prospect Theory (CPT) (Tversky and Kahneman 1992) as a more accurate framework to capture these behavioral irregularities. CPT incorporates probability distortion, differential sensitivity to gains and losses, and loss aversion, explaining why individuals misperceive probabilities, exhibit asymmetric risk preferences, and value losses more than equivalent gains. CPT is particularly well-suited for modeling catastrophic risk perception given the definition of risk perception in ISO 31010 Risk Management Guidelines, which conceptualizes risk perception as the severity of outcomes weighted by subjective probability assessments. This paper contributes to the literature on risk perception and decision-making under extreme uncertainty in two main ways. First, we introduce a novel experimental measure of catastrophic risk perception (CRP), derived from individually elicited parameters of Cumulative Prospect Theory. Unlike existing approaches that rely on survey responses or reduced-form indicators, this measure allows catastrophic risk perception to be decomposed into its behavioral primitives, namely probability distortion and loss sensitivity. Second, we introduce and test a novel behavioral mechanism that we term the Shared Burden Effect (SBE), whereby identical catastrophic losses are valued less severely when exposure is collective rather than individual. These contributions provide a behavioral framework for understanding underreaction to rare but severe threats and for interpreting willingness to support mitigation and preparedness policies in domains such as disasters, public health, and other collective risks. Recent studies have increasingly linked risk perception and decision-making under uncertainty to CPT, particularly in the context of rare but high-impact events, and thus our framework aligns with recent attempts to incorporate behavioral distortions into disaster-preparedness modeling (Goda and Hong 2021; Yang et al. 2022; Moon et al. 2018; Asgary and Levy 2009). Empirical applications of CPT in disaster economics confirm that probability distortions significantly influence preparedness behavior. In the domain of earthquake risk, for example, Goda and Hong (2021) show that individuals systematically overweight small probabilities in the context of earthquake risk. Similarly, Chou et al. (2022) find that when individuals are presented with explicit probability information, their risk attitudes deviate systematically from rational Bayesian updating, with probability misperception driving insurance demand and mitigation efforts. A key component of CPT, loss aversion, has been widely documented as a major determinant of risk behavior in extreme contexts (Kahneman et al. 1991). The notion that losses loom larger than gains explains why individuals often display stronger reactions to potential catastrophic losses than predicted by standard economic models (Kunreuther and Michel-Kerjan 2013; Bocquého et al. 2014). Recent research has also shown that loss aversion is not uniform across individuals but varies depending on experience, personality, and social context. Studies indicate that prior exposure to disasters can both amplify or attenuate loss aversion: individuals who have previously suffered catastrophic losses tend to develop greater risk sensitivity, while those repeatedly exposed to near-miss events may become desensitized (Wachinger et al. 2013). Moreover, cultural differences influence the extent to which individuals exhibit loss aversion in risk perception (Wang et al. 2017; Gierlach et al. 2010). A growing body of research is exploring the role of trust, social identity, and local culture in shaping risk perception (Buso et al. 2020; Bodas et al. 2022).

Existing studies on catastrophic and disaster-related risk perception have provided important evidence on heterogeneity in perceived risk and preparedness behavior. This literature typically relies on survey responses, stated beliefs, willingness-to-pay measures, or reduced-form associations with demographic and contextual characteristics. While these approaches document substantial variation in perceived risk, they generally do not identify the behavioral primitives through which such perceptions are formed.

Moreover, these studies typically rely on observational or survey-based measures of risk perception, rather than controlled experimental settings that allow direct elicitation of the underlying preference parameters. To our knowledge, no previous study constructs a laboratory-based measure of catastrophic risk perception derived from individually estimated Cumulative Prospect Theory parameters. The experimental measure introduced in this paper addresses this gap by allowing catastrophic risk perception to be decomposed into its underlying behavioral components.

In addition, while prior work has examined how social and contextual factors influence risk perception, no study has formally identified or experimentally tested the behavioral mechanism that we term the Shared Burden Effect (SBE), whereby identical catastrophic losses are perceived as less severe when exposure is collective rather than individual. Empirical evidence already suggests that when catastrophic risks are framed as collective rather than individual threats, individuals exhibit systematically lower willingness to pay (WTP) for mitigation measures. In the domain of disaster insurance, for instance, people are less willing to purchase earthquake coverage when risks are described as affecting an entire community rather than themselves personally (Chou et al. 2022; Moon et al. 2018). Similarly, research on flood preparedness shows that collective framing reduces perceived urgency to act, as individuals assume that governments or other community members will intervene (Asgary and Levy 2009; Botzen et al. 2015). Recent comparative evidence further confirms that perceptions of both natural and human-made disasters are systematically shaped by cultural and collective frames (Bodas et al. 2022; Böhm and Pfister 2008). Related patterns appear in public-goods and social-dilemma settings, where diffusion of responsibility leads to lower individual contributions to collective risk mitigation (Feldman and Hazlett 2016; Darley and Latané 1968). Such findings reinforce the behavioral basis for our notion of a Shared Burden Effect, whereby collective exposure reduces perceived individual severity.

Yet the behavioral phenomenon captured by the Shared Burden Effect (SBE) extends beyond these social-responsibility contexts. It describes a more general perceptual mechanism by which the subjective severity of extreme risks decreases when potential losses are collectively shared—even in the absence of interpersonal responsibility or coordination. In this sense, SBE generalizes the diffusion-of-responsibility principle from the moral and strategic domains to the perceptual valuation of risk itself, linking social interdependence, emotional appraisal, and probability distortion. To date, no study has systematically tested this broader mechanism within a formal Prospect-Theory framework or quantified its effect on the valuation of catastrophic risks borne collectively rather than individually.

Consistent with these contributions, the empirical analysis proceeds in three steps. First, it introduces and validates an experimental measure of Catastrophic Risk Perception (CRP) derived from individually elicited Cumulative Prospect Theory parameters. Second, it introduces and empirically tests the existence of the Shared Burden Effect (SBE). Third, it employs the CPT-based measure of CRP to explore mechanisms and drivers of catastrophic risk perception, linking experimentally elicited CPT parameters to subjective evaluations. In particular, the analysis explores the distinct cognitive mechanisms through which perceptions of catastrophic risk emerge–namely, the weighting of low probabilities and the asymmetric valuation of losses relative to gains. This framework allows us to examine how subjective and experiential factors, such as prior exposure to severe events or sociodemographic background, translate into systematic differences in the psychological processing of catastrophic risks and, ultimately, into divergent economic valuations of mitigation.

The rest of the paper is structured as follows. Section 2 presents the experimental design; Section 3 describes the empirical methodology; Section 4 reports the results; and Sect. 5 concludes with implications for behavioral policy and risk communication.

2 Experimental Design

The experimental design consists of three phases, each addressing a specific research objective while jointly contributing to the overall analysis of catastrophic risk perception and the shared burden effect.

In the first phase, individual parameters of Cumulative Prospect Theory (CPT)–probability weighting, curvature for gains and losses, and loss aversion–are elicited through the method of Abdellaoui (2008). These parameters are used to construct an individual measure of *Catastrophic Risk Perception* (CRP), which quantifies how each participant integrates outcome severity and subjective probability distortion when evaluating extreme risks. This measure serves not only to meet the first research objective–introducing and estimating a CPT-based index of catastrophic risk perception–but also as a key input for the subsequent analyses of collective framing and individual heterogeneity.

The second phase examines behavioral responses to catastrophic risk framing and directly addresses the second research objective: testing for the existence of the *Shared Burden Effect*. Participants state their willingness to pay (WTP) to reduce a low-probability catastrophic loss, under two otherwise identical conditions that differ only in framing–individual versus collective exposure.

In the third phase, participants complete a short survey on perceived severity and likelihood of real-world catastrophic events, along with measures of cognitive ability, personality traits, and sociodemographic background. These data are used to investigate the determinants of both CRP and SBE, in line with the third research objective.

2.1 Theoretical Framework of CPT

Cumulative Prospect Theory (CPT) posits that decision-making under risk follows a weighted valuation of outcomes, where probabilities are transformed by a probability weighting function $w(p)$, and outcomes are evaluated relative to a reference point using a value function $v(x)$. Empirical applications typically assume zero as the reference point, particularly in experimental settings where gains and losses are explicitly framed (Abdellaoui et al. 2007; Köbberling and Wakker 2005). The two principal components are:

1. Probability Weighting Function: Individuals tend to overweight small probabilities and underweight large probabilities, leading to probability distortion. This is modeled as $w(p)$, where

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

with parameter γ capturing the curvature of the probability weighting function.

2. Value Function: The valuation of outcomes follows a convex shape for gains and a concave shape for losses, reflecting diminishing sensitivity, and incorporates loss aversion λ:

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0 \\ -\lambda(-x)^{\beta}, & x < 0 \end{cases} \tag{2}$$

Table 1 Potential Gains and Losses for CPT Elicitation

Outcome Index i	1	2	3	4	5	6
Gains: x_i (€)	2000	4000	6,000	10,000	10,000	10,000
Gains: y_i (€)	0	0	0	0	6,000	8,000
Losses: x_i (€)	–2000	-4000	–	–10,000	–10,000	–10,000
Losses: y_i (€)	0	0	0	0	–6000	–8000

where α and β control the curvature of the value function and λ measures loss aversion.

2.2 Phase 1: Eliciting CPT Parameters Using Abdellaoui's Method

The first phase aims to elicit individual risk preferences under Cumulative Prospect Theory (CPT) to construct a personalized measure of catastrophic risk perception. This phase adapts the semi-parametric method from Abdellaoui (2008), which employs fixed probabilities and certainty equivalents (CEs) to estimate probability distortion, value function curvature, and loss aversion.

Unlike Abdellaoui (2008)'s original approach, which employs two-outcome lotteries with probabilities p and $1 - p$, with

$$p = 1/3, 1/2$$

the present design fixes the probability at $p = 0.05$ across all tasks. This adjustment aligns the elicitation procedure with the low-probability, high-impact nature of catastrophic risks and ensures consistency with the second experimental phase, where the same probability defines the catastrophic loss scenario. Payoff magnitudes and gain–loss combinations are directly taken from Abdellaoui (2008) to preserve the original parametrization that covers a relevant range of values and maintain comparability with established estimates of value-function curvature and loss aversion. While Abdellaoui's design uses an iterative bisection procedure to identify certainty equivalents (CEs), we adopt a direct elicitation method in which participants state the CE explicitly. This simplification reduces task duration and cognitive load, which is particularly important given the low-probability framing and the broader experimental sequence, without affecting the theoretical identification of CPT parameters.

The method comprises three stages, using stated CEs for two-outcome prospects to derive CPT parameters.

Table 1 lists the potential gains and losses, adapted from Abdellaoui (2008). All lotteries were presented in a neutral monetary frame, without references to specific contexts: keeping the tasks abstract helps isolate risk attitudes from domain-specific perceptions or emotions, which are known to influence decision-making under risk. The above payoffs are used across these stages:

1. **Elicitation in the Gain Domain**
   Participants state CEs for six gain prospects of the form $(x_i, 0.05; y_i)$, where $x_i > y_i \geq 0$ and the probability of x_i is fixed at 5% (thus 95% is the probability

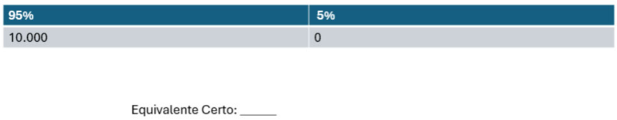

Fig. 1 Example Gain Prospect: Participants state the certain amount G_i equivalent to a 5% chance of €10,000 versus €0

of y_i). Outcomes align with Table 1: x_i ranges from €2000 to €10,000, and y_i from €0 to €8000. For each prospect $(x_i, 0.05; y_i)$, the CE G_i is expressed such that $(G_i, 1; 0) \sim (x_i, 0.05; y_i)$. Here, G_i denotes the certainty equivalent stated by the participant for prospect i, that is, the sure amount that makes the participant indifferent between receiving G_i for certain and facing the lottery $(x_i, 0.05; y_i)$. In the experiment, this was explained to participants as the amount of money that would make them indifferent between the sure payment and the lottery, and respondents were asked to directly state this amount.

An example task is shown in Fig. 1, where participants state the sure amount equivalent to a 5% chance of €10,000 versus €0.

Assuming a power value function $v(x) = x^{\alpha}$ for $x \geq 0$, and given i indifference equations

$$v\left(G_i\right) = w^{+}(0.05)\left[v(x_i) - v(y_i)\right] + v\left(y_i\right) \tag{3}$$

α (curvature for gains) and $w^{+}(0.05)$ (probability weight at 5%) are estimated through non linear least squares.

2. **Elicitation in the Loss Domain**

CEs are elicited for six loss prospects of the form $(x_i, 0.05; y_i)$, where $0 \geq y_i > x_i$, with the probability fixed at 5%. Outcomes mirror Table 1: x_i ranges from -€2000 to -€10,000, and y_i from €0 to -€8000. The CE L_i is determined such that $(L_i, 1; 0) \sim (x_i, 0.05; y_i)$. Analogously, L_i represents the certainty equivalent reported by the participant for loss prospect i. It corresponds to the sure loss that makes the participant indifferent between paying L_i with certainty and facing the lottery $(x_i, 0.05; y_i)$. Participants were instructed to report the certain loss that they considered equivalent to the risky prospect. Figure 2 illustrates an example, asking for the sure amount equivalent to a 5% chance of -€10,000 versus €0.

Assuming $v(x) = -\lambda(-x)^{\beta}$ for $x < 0$, the indifference equations

$$v\left(L_i\right) = w^{-}(0.05)\left[v\left(x_i\right) - v\left(y_i\right)\right] + v(y_i) \tag{4}$$

yields estimates of β (curvature for losses) and $w^{-}(0.05)$ (probability weight at 5%).

3. **Loss Aversion Estimation**

This stage links gains and losses to estimate the loss aversion coefficient λ. A mixed prospect $(G^{*}, 0.05; L^{*})$ is presented, where,$G^{*} > 0 > L^{*}$, and L^{*} chosen by the participant such that $(G^{*}, 0.05; L^{*}) \sim 0$. Then the equation

$$w^{+}(0.05)v\left(G^{*}\right) + w^{-}(0.95)v\left(L^{*}\right) = 0 \tag{5}$$

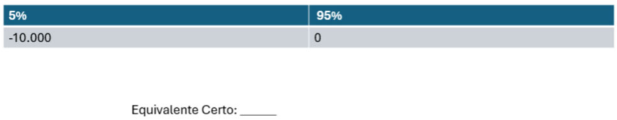

Fig. 2 Example Loss Prospect Task: Participants state the certain amount L_i equivalent to a 5% chance of -€10,000 versus €0

is solved. With $w^+(0.05)$, $w^-(0.05)$, $v(G^*)$, and $v(L^*)$ known, and $w^-(0.95) = 1 - w^-(0.05)$ under CPT, λ is derived as

$$\lambda = -\frac{w^+(0.05)v\,(G^*)}{w^-(0.95)v\,(L^*)}. \tag{6}$$

Approximately 13 elicitations (six per stage + one per loss aversion) are conducted, estimated to take around 20 min. Outcomes represent catastrophic risks (e.g., earnings losses in thousands), ensuring contextual relevance. Incentives are not implemented, consistent with Abdellaoui (2008)'s stance (p. 252, 261) that real incentives are neither necessary nor feasible for losses and mixed prospects. Hypothetical outcomes suffice, supported by evidence showing no systematic incentive effects for such tasks (e.g., Beattie and Loomes 1997; Camerer and Hogarth 1999), and real losses pose ethical and practical challenges, particularly in a laboratory setting.

This method retains the efficiency of Abdellaoui (2008) approach by fixing the probability (here 5%), requiring only one weight per domain, and avoids full assumptions on $w(p)$.

2.3 Phase 2: Testing the Shared Burden Effect

The second phase tests for the Shared Burden Effect (SBE) by measuring participants' willingness to pay (WTP) to eliminate a low-probability adverse event under two framing conditions: an individual risk condition and a collective risk condition. In both cases, the adverse event carries a 5% probability of eliminating all accumulated experimental earnings. All participants received the same fixed €20 amount at the end of Phase 1, independent of their choices in the elicitation tasks, since those tasks involved stated certainty equivalents rather than performance-based payoffs. Together with the €3 show-up fee, this amount constituted almost the entire monetary compensation for participation in the experiment. The 5% probability level mirrors that used in Phase 1 and was deliberately chosen to represent a rare, high-impact risk consistent with the definition of catastrophic events, while maintaining a non-trivial probability that participants could intuitively assess. While the absolute monetary magnitude is modest, it was chosen to ensure a salient loss without exposing participants to excessive financial risk. Importantly, the identification of the Shared Burden Effect does not require the loss to be perceived as catastrophic in absolute terms; rather, it relies on the comparison between identical risks framed as individual versus collective. Together with the €3 show-up fee, this amount constituted the monetary compensation for participation, so that the potential loss constituted almost the entire monetary compensation for participation in the experiment. The 5% probability level mirrors that used in Phase 1 and was deliberately chosen to represent a rare, high-impact risk consistent with the definition of catastrophic events, while maintaining a non-trivial probability that participants could intuitively assess. While the absolute monetary magnitude is modest, it was chosen to ensure a salient loss without exposing participants to excessive financial risk or relying on abstract framing. Importantly, the identification of the Shared Burden Effect does not require the loss to be perceived as catastrophic in absolute terms; rather, it relies on the comparison between identical risks framed as individual versus collective.

The two conditions differ only in the framing of exposure. In the individual risk condition, the 5% probability applies independently to each participant, whereas in the shared risk condition the same random draw determines the outcome for all participants in the session. To avoid order or learning effects, the presentation order of the two conditions was randomized across participants. This within-subject design allows direct comparison of willingness-to-pay (WTP) across identical probabilities and outcomes that differ only in the sharedness of exposure, ensuring that the estimated difference reflects the framing manipulation rather than order or individual heterogeneity.

Importantly, in both conditions participants decide how much of their own earnings they are willing to pay to reduce the risk that directly affects them. In the shared condition, the realization of the adverse event is common to all participants, but each individual's decision concerns the reduction of their own exposure.

- **Individual Risk Condition**
  In this scenario, the realization of the random variable is independent for each participant. Each individual faces a unique draw: with 5% probability, their €20 earnings are lost, and with 95% probability, they are retained. Participants state their maximum WTP to eliminate this risk, ensuring their earnings are preserved regardless of the outcome.
- **Collective Risk Condition**
  In this scenario, the realization of the random variable is identical for all participants. A single draw determines the outcome for the group: with 5% probability, all participants lose their €20 earnings, and with 95% probability, all retain them. Participants state their maximum WTP to eliminate this collective risk, securing their earnings if successful.

Participants provide WTP values for both scenarios in a single session, with one scenario (individual or collective) randomly selected for implementation. A random-cost mechanism ensures incentive compatibility in participants' stated willingness to pay (WTP). Specifically, after participants indicate the maximum amount they are willing to pay to eliminate the risk, a random cost uniformly distributed between €0 and €20 is drawn. If the participant's WTP exceeds this random cost, the risk is eliminated and the participant pays that cost; otherwise, the risk remains, and its realization follows the stated probability. This procedure makes truthful reporting of WTP the optimal strategy.

Two WTP elicitations (one per condition, with order randomized across participants) are conducted, taking approximately 5–10 min. The WTP data enable testing the shared burden effect by comparing differences between the collective and individual conditions with those that will be observed in Phase 3's real-world catastrophic risk assessments, conducted under both individual and collective risk framings. A systematically lower WTP in collective scenarios, mirrored by similar patterns in real-world perceptions, would indicate that shared risks are perceived as less severe across experimental and real-world settings, despite identical probabilities and outcomes.

2.4 Phase 3: Assessing Real-World Risk Perceptions and Individual Characteristics

The third phase assesses perceptions of real-world catastrophic risks and collects data on individual characteristics. These assessments test the predictive relevance of the measure constructed with CPT parameters—as outlined in the next section—and the findings of the shared burden effect from Phases 1 and 2, while individual characteristics (sociodemographics, IQ, personality and past experience) serve as covariates in regression models to explore their relation with risk perception. This survey-based approach examines whether the shared burden effect–lower perceived severity and WTP for collective risks—extends beyond the laboratory to naturalistic settings, while exploring cognitive, psychological, and sociodemographic influences on catastrophic risk attitudes.

Participants complete a structured survey with the following components:

1. **Perceived Risk Severity**
   Participants rate the perceived severity of five catastrophic risks–fatal accident, mortal illness, pandemic, nuclear total war, and natural disaster–on a scale from 1 (minimal risk) to 10 (extreme risk). Each risk is assessed as it naturally occurs: individual for personal events (e.g., fatal accident, mortal illness) and collective for group-wide events (e.g., pandemic, nuclear war, natural disaster), enabling comparison with Phase 2's WTP differences based on inherent scenario characteristics.
2. **Past Experience with Extreme Risks**
   A binary question (yes/no) asks whether participants have experienced an extreme risk event (e.g., natural disaster, severe illness), providing a covariate to assess experiential influences on risk perception.
3. **Willingness to Pay for Risk Mitigation**
   Participants state their WTP to insure against two specific risks–nuclear total war and fatal illness–assuming a €100,000 endowment. Nuclear total war, inherently a collective risk, is assessed as "How much would you pay to eliminate nuclear war risk?" while fatal illness, inherently individual, is assessed as "How much would you pay to eliminate fatal illness risk?" This leverages the natural distinction between these real-life scenarios to compare with Phase 2's lab-based shared burden effect, where individual and collective conditions were experimentally manipulated.
4. **Personality and Cognitive Ability**
   The Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism) are measured using a validated 10-item short-version test. Cognitive ability is assessed with a 10-question short-form IQ test (UNIT test),

providing standardized scores. These measures explore psychological and cognitive drivers of risk perception variability.

5. **Sociodemographic Data**
   Age, gender, and place of origin are collected as covariates to analyze demographic influences on risk attitudes and the shared burden effect.

The survey comprises approximately 35–40 questions: 5 risk severity ratings, 1 past experience question, 2 WTP elicitations, 10 personality items, 10 IQ questions, and 3–5 sociodemographic items. Administered post-Phases 1 and 2, it takes an estimated 20 min. Participants receive a 3 euro show up fee in addition to their earnings at the end of phase 2.

This phase allows to check real world consistency of the shared burden effect by comparing Phase 2's WTP differences (individual vs. collective lab conditions) with Phase 3's real-world assessments, where nuclear war is collective and fatal illness individual. A lower WTP and severity for nuclear war versus fatal illness, be consistent with the observation of the Shared Burden Effect in Phase 2. Phase 3 data, combined with Phase 1's CPT parameters, will be used to check the consistency and the validity of the CRP measure and to explore mechanisms and drivers underlying perceptions of extreme risks.

3 Data and Methodology

3.1 Data

The dataset was collected through an experimental session conducted at the CESARE laboratory at LUISS Guido Carli University, Rome. Participants were recruited primarily among LUISS students using the ORSEE recruitment system. A total of 98 participants took part in the experiment; however, 7 participants were excluded due to incomplete or inconsistent responses, resulting in a final sample of 91.

Table 2 presents descriptive statistics for key variables, including CPT parameters and participant characteristics. The sample was predominantly male (58.24%), with a majority of participants originating from Southern (32.9%) and Central Italy (36.2%), while fewer came from Northern Italy (12.09%) or abroad (18.68%). Participants completed a standardized Big Five personality questionnaire (Rammstedt and John 2007), with scores for each personality item ranging from 1 to 5. Participants scored moderately high on conscientiousness (mean = 3.64, SD = 0.65) and openness (mean = 3.25, SD = 0.75), whereas neuroticism exhibited big variability (mean = 3, SD = 0.94). Approximately 17.5% of the sample reported previous direct experience with catastrophic events (e.g., severe illness).

Key experimental variables included CPT-derived parameters: loss aversion (λ), curvature of the value function for gains (α), curvature for losses (β), and probability weighting for rare losses ($w^{-}(0.05)$). These parameters were estimated using non-linear least squares, as specified in the experimental design and in line with Abdellaoui's method.

Table 2 Summary Statistics of CPT Parameters and Covariates

Variable	Mean	Median	Std. Dev	Min	Max
λ	1.99	2.15	0.87	0.55	3.46
α	0.98	1.00	0.02	0.81	1.01
β	0.98	1.00	0.05	0.75	1.03
$w^{-}(0.05)$	0.16	0.11	0.16	0.02	0.60
Percent Male	58.24%	–	–	–	–
Percent Female	41.76%	–	–	–	–
Percent North	12.09%	–	–	–	–
Percent Center	36.26%	–	–	–	–
Percent South	32.97%	–	–	–	–
Percent Out of Italy	18.68%	–	–	–	–
Big Five: Extraversion	3.15	3.00	0.81	1.00	5.00
Big Five: Agreeableness	2.86	3.00	0.77	1.00	4.50
Big Five: Conscientiousness	3.64	3.50	0.65	2.00	5.00
Big Five: Neuroticism	3.00	3.00	0.94	1.00	5.00
Big Five: Openness	3.19	3.00	0.76	1.00	5.00
Percent with Past Experience	17.58%	–	–	–	–

For interpretation, standard benchmarks in the CPT literature provide useful reference points. A value of $\lambda = 1$ indicates symmetric evaluation of gains and losses, while $\lambda > 1$ reflects loss aversion, meaning that losses are perceived as more severe than equivalent gains. Empirical estimates typically fall between 1.5 and 2.25 (Tversky and Kahneman 1992; Abdellaoui et al. 2007).

As shown in the table, the distributions of these parameters reveal substantial heterogeneity. Loss aversion (λ) ranged from 0.55 to 3.46 with a mean of 1.99, aligning closely with standard estimates in the behavioral economics literature.

The parameters α and β capture the curvature of the value function. Values close to 1 indicate approximately linear valuation of outcomes, while values below 1 reflect diminishing sensitivity, meaning that marginal changes in outcomes have a decreasing psychological impact as their magnitude increases. In our sample, both parameters display relatively low variance around values slightly below 1, suggesting limited heterogeneity in curvature sensitivity for low-probability prospects. While the observed values of β align closely with existing studies, α is not significantly lower as often observed in the literature (Desmoulins-Lebeault et al. 2016), potentially reflecting a context-specific effect where participants perceive gains with reduced diminishing sensitivity, possibly due to the high stakes and structured environment of the experiment.

Probability weighting for rare losses ($w^{-}(0.05)$) captures how individuals transform objective probabilities. Under Expected Utility Theory probabilities enter linearly (i.e., $w(p) = p$), whereas CPT predicts that small probabilities are often overweighted. In our data, the average value of $w^{-}(0.05) = 0.16$ substantially exceeds the objective probability of 0.05, indicating a pronounced overweighting of rare catastrophic losses, consistent with standard findings in prospect theory (Kahneman and Tversky 1979; Gonzalez and George 1999).

To identify potential multicollinearity and interdependencies among CPT parameters, a correlation analysis was conducted. Moderate correlations emerged, notably between loss aversion (λ) and probability distortion ($w^{-}(0.05)$), suggesting that while these are conceptually distinct constructs–emotional aversion versus cognitive distortion–there is a meaningful interdependence, and individuals prone to overweight probabilities might also experience heightened loss sensitivity. The possible interactions and implications will be discussed more deeply in the next sections.

Initial data processing involved exclusion of incomplete responses (7 participants) and standardization of psychological variables (Big Five scores, IQ) to facilitate clear interpretation in subsequent regressions.

3.2 Constructing and Analyzing Catastrophic Risk

The Catastrophic Risk Perception (CRP) measure is newly constructed in this paper to provide a behavioral index of how individuals evaluate rare catastrophic losses within the Cumulative Prospect Theory framework. In this subsection, we show how the CRP index is derived directly from individually elicited CPT parameters. We then assess its predictive validity using real-world risk assessments, examine its determinants, and decompose it into its main behavioral components, namely probability distortion and loss aversion. Finally, we test the presence of the Shared Burden Effect in the laboratory and complement this analysis with willingness-to-pay (WTP) assessments in the survey. Results are presented and discussed in the next section.

The Catastrophic Risk Perception (CRP) measure is constructed based on the cumulative prospect theory (CPT) framework, using the parameters elicited from the participants in Phase 1 of the experiment. Specifically, the CRP measure for each participant is computed as the average of the CPT value function evaluated across all six elicited loss amounts x_i:

$$\mathrm{CRP}_i = \frac{1}{6}\sum_{i=1}^{6} w_i^{-}(0.05)\cdot v_i\left(-x_i\right), \tag{7}$$

where $w_i^{-}(0.05)$ represents the probability weighting function evaluated at the low-probability level ($p = 0.05$), and $v_i(x)$ is the value function under CPT for losses, defined as:

$$v_i(x) = -\lambda_i \cdot (-x)^{\beta_i}, \tag{8}$$

with λ_i capturing individual loss aversion, and β_i representing the curvature of the value function for losses. Evaluating the CRP across multiple elicited amounts rather than at an arbitrary single point ensures robustness and a consistent reflection of participants' catastrophic risk evaluations over a relevant range of loss magnitudes.

3.3 Consistency with Real-World Risk Assessments

To test the predictive consistency of the CRP measure, individual risk scores from Phase 3—specifically participants' ratings (1–10, according to its severity and likelihood, with higher values indicating higher perceived risk) for four separate real-world risks (fatal accident, mortal illness, pandemic, and nuclear war)—are individually regressed on the standardized CRP measure (z-score normalization applied to the measure defined in previous subsection). The choice to use separate ordinary least squares (OLS) regressions for each risk without additional covariates is deliberate, as the objective here is not to establish causality, but rather to verify whether the variation in the CRP measure alone meaningfully explains variation in participants' real-world risk assessments. A significant positive correlation in these regressions would confirm that the constructed CRP measure effectively captures real-world catastrophic risk perception differences among participants. Formally, each regression is specified as:

$$\text{RiskScore}_{r,i} = \alpha_0 + \alpha_1 \text{CRP}i + u_{r,i} \tag{9}$$

where $\text{RiskScore}_{r,i}$ represents participant 's perceived severity (scale 1–10) for risk r. To complement standard parametric tests and ensure robustness without distributional assumptions, we conducted non-parametric permutation tests (10,000 randomizations) on the main contrasts. This approach provides an exact inference framework based on resampling, evaluating how likely the observed test statistic is under random rearrangements of the data (Ernst 2004).

3.4 Exploring Drivers and Mechanisms of Catastrophic Risk Perception

Motivated by the CPT framework, we explore how background characteristics are associated with individual differences in catastrophic risk perception (CRP) and we analyze cognitive channels that mediate this perception. In this context, "cognitive channels" refer to the distinct psychological pathways through which risk perception may arise: distortions in the weighting of small probabilities, or asymmetric sensitivity to losses relative to gains.

We first estimate the following regression specification to identify potential correlates of CRP:

$$\text{CRP}_i = \beta_0 + \beta_1 \text{Gender}_i + \sum_{j=1}^{3} \phi_j \text{Origin}_{j,i} + \sum_{k=1}^{5} \gamma_k \text{Big Five}_{k,i} + \delta \text{IQ}_i + \theta \text{PastExp}_i + \epsilon_i. \tag{10}$$

This full model includes demographic factors (gender and regional background), psychological traits (Big Five personality dimensions; Rammstedt and John 2007), cognitive ability (IQ), and prior exposure to catastrophic events. Given the relatively small sample size (91 participants), we treat this specification as an exploratory benchmark rather than a definitive model, using it to gauge which factors show meaningful associations with CRP.

To discipline the analysis, given power issues that arise with a sample of $n = 91$, we pair the full exploratory specification with a reduced-form model. The reduced model focuses on core demographic and experiential variables (gender, regional background, past exposure). In addition, we report a power analysis for the relevant coefficients of the reduced form, to clarify what effect sizes are realistically detectable with our design. Hence, the full specification is best viewed as descriptive and hypothesis-generating, while the reduced model concentrates power on central predictors.

As discussed in the introduction, the two components of catastrophic risk perception are subjective probability and outcome severity, represented in this framework by probability distortion and loss aversion. Therefore, each covariate could potentially impact risk perception differently in its two components. Past experience, for instance, may shape risk perception through distinct cognitive mechanisms. First, past exposure to catastrophic events may influence the perception of likelihood, leading individuals to distort probability weighting. This occurs when personal experience makes rare events feel more probable than objective statistical frequencies suggest. Second, past experience can alter the perception of loss severity. On one hand, frequent exposure to extreme events may reduce sensitivity to losses, therefore decreasing loss aversion. On the other hand, particularly traumatic past experiences may heighten the psychological weight of losses, increasing loss aversion. These distinct channels require separate analysis to isolate their effects.

We therefore analyze whether the observed correlations in the previous reduced form regression arise from loss aversion or probability distortion:

$$w_i^-(0.05) = \rho_0 + \rho_1 \text{PastExp}_i + \mathbf{X}_i' \boldsymbol{\rho} + \varepsilon_i, \tag{11}$$

$$\lambda_i = \theta_0 + \theta_1 \text{PastExp}_i + \mathbf{X}_i' \boldsymbol{\theta} + \xi_i, \tag{12}$$

where λ_i represents loss aversion, and$w_i^-(0.05)$ probability distortion, and X_i includes covariates correlated with CRP from previous analysis.

3.5 Shared Burden Effect

The Shared Burden Effect (SBE), introduced earlier in this paper, captures the tendency for individuals to perceive catastrophic risks as less severe when exposure is collective rather than individual. This subsection analyzes this behavioral anomaly across both laboratory and the naturalistic settings presented in Phase 2 and Phase 3.

Paired t-tests are performed to analyze WTP disparities across settings. In Phase 2, WTP_{ind} (individual risk) is tested against WTP_{coll} (collective risk) for a 5% chance of losing €20:

$$H_0 : \text{WTP}_{\text{ind}} = \text{WTP}_{\text{coll}}$$
$$H_1 : \text{WTP}_{\text{ind}} > \text{WTP}_{\text{coll}}$$

In Phase 3, $\text{WTP}_{\text{fatal illness}}$ (personal threat) contends with $\text{WTP}_{\text{nuclear war}}$ (collective catastrophe)—extreme events with different framing but both implying same negative

Table 3 Consistency Check: Regressions of Risk Severity Ratings on Standardized CRP

Dependent Variable	CRP_z Coef.	SE	p-value
Fatal Disease Risk	0.574***	0.208	0.007
Nuclear War Risk	0.594***	0.215	0.007
Pandemic Risk	0.323	0.225	0.155
Extreme Accident Risk	0.448**	0.175	0.012

* p < 0.1; ** p < 0.05; *** p < 0.01

consequence (death)—from a €100,000 endowment, probing:

$$H_0 : \text{WTP}_{\text{fatal illness}} = \text{WTP}_{\text{nuclear war}}$$
$$H_1 : \text{WTP}_{\text{fatal illness}} > \text{WTP}_{\text{nuclear war}}$$

To account for potential violations of normality and, to ensure robustness without distributional assumptions, we complement all key paired comparisons and correlation tests with non-parametric permutation analyses (10,000 random resamples), as for the analysis of consistency with real-world scenario risk assessment outlined in previous section.

To explore the potential drivers behind this effect, an OLS regression dissects the Phase 2 WTP gap:

$$\Delta\text{WTP}_i = \phi_0 + \phi_1\lambda_i + \phi_2 w_i^-(0.05) + \phi_3\beta_i + \phi_4(\lambda_i \times \text{Past Experience}_i) + \phi_5\text{Past Experience}_i + \mathbf{Z}_i'\boldsymbol{\phi} + \nu_i$$

where $\Delta\text{WTP}_i = \text{WTP}_{\text{ind,i}} - \text{WTP}_{\text{coll,i}}$, Past Experience$_i$ (1 = experienced fatal illness, 0 = no), and $\mathbf{Z}_i$ includes age, gender, place of origin, Big Five traits, and IQ. Given our small sample, we employ the same procedure as for CRP estimating different reduced-form models, and the results of his exploratory analysis are reported in the appendix. A significant drop in collective WTP across both phases will confirm the shared burden effect's strength, connecting lab results to real-world meaning. This will prove the effect is a solid behavioral trend and shows how CPT explains it, offering a new way to understand collective risk valuation.

4 Results

4.1 Consistency of Catastrophic Risk Perception

To validate the relevance of the experimentally-derived Catastrophic Risk Perception (CRP) measure, four separate linear regressions are estimated–one for each self-reported risk rating collected in the post-experimental survey: fatal disease, nuclear war, pandemic, and extreme accident. Each regression uses the standardized CRP score as the sole predictor, allowing for a clean reduced-form assessment of whether variation in risk perception measured under laboratory conditions explains heterogeneity in real-world risk assessments.

The regression results are reported in Table 3.

Table 4 Permutation test results for CRP–Risk Severity Ratings (10,000 replications)

Risk Type	Correlation (r)	Permutation p-value	N	Replications
Extreme event	0.791	<0.001	91	10,000
Nuclear risk	0.742	<0.001	91	10,000
Disease risk	0.727	<0.001	91	10,000
Pandemic risk	0.724	<0.001	91	10,000

Two-sided nonparametric permutation tests were conducted to assess the robustness of the correlations between CRP scores and subjective severity ratings of catastrophic risks
p-values are based on 10,000 random permutations

For both disease and nuclear risks, the CRP measure significantly and positively predicts the severity ratings, supporting its predictive validity. The relationship is also significant for extreme accidents, though with a slightly smaller coefficient. Positive coefficient but no statistically significant association for pandemic-related risk is found, suggesting a potential context-specific variation in how laboratory risk preferences translate into real-world concerns. This lack of significance for pandemic-related risk may also reflect confounding effects of recent collective experience with COVID-19, which could homogenize responses or interact with unobserved emotional or contextual factors, attenuating the explanatory power of individual-level CRP. To assess the robustness of these associations, we implemented nonparametric permutation tests (10,000 replications) between the Catastrophic Risk Perception (CRP) index and the four real-world risk ratings, providing an assessment of significance suitable for small samples. All correlations remained positive, strong, and highly significant ($|r| = 0.72$–0.79, all $p < 0.001$), confirming the robustness and predictive consistency of the CRP measure across catastrophic domains. Full results are reported in Table 4.

Overall, the results provide empirical support for the CRP measure as a meaningful proxy for catastrophic risk perception.

4.2 Exploring Drivers and Mechanisms of Catastrophic Risk Perception

We explored factors associated with catastrophic risk perception (CRP) through regression analyses using our CRP measure. Initially, a full regression model was estimated, incorporating demographic variables, past experience, personality traits (Big Five), and gender as predictors. Results from the full model are reported in the Appendix. Given sample size limitations, we then estimated a reduced form model excluding psychometric variables and focusing on experiential and sociodemographic variables. A justification for emphasizing sociodemographic variables comes from the correlation analysis and their significant role in loss aversion, as shown in the next subsection, suggesting these factors may be associated with differences in sensitivity to catastrophic losses.

Results from the reduced-form regression model are presented in Table 5.

The origin from Southern Italy and gender differences are above conventional significance threshold and do not reach statistical significance.

Table 5 Regression results: reduced model of CRP determinants

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	−0.385	0.188	−2.046	0.044
Past Experience	0.715***	0.199	3.594	0.001
Gender (Male)	−0.269	0.155	−1.736	0.086
North	0.010	0.271	0.039	0.969
Center	0.161	0.220	0.728	0.468
South	0.405	0.215	1.886	0.063

Overall, the results indicate that catastrophic risk perception (CRP) is primarily associated with experiential factors, and that this relation is well powered, while the evidence for additional correlates weak and/or power-limited, consistent with our choice to treat this section as exploratory and to emphasize the reduced specification.

However, it remains unclear from this analysis whether this differences in perception are primarily due to an exaggerated subjective assessment of event likelihood (probability distortion) or to greater sensitivity to potential negative outcomes (loss aversion), or how these two potential mechanisms interact. To explore that, separate regressions analyze the impact of the relevant characteristics on the two distinct components of cumulative prospect theory: loss aversion (λ) and probability distortion ($w^{-}(0.05)$). Tables 6 and 7 present these results, respectively.

Loss Aversion (λ). Table 6 reports that past catastrophic experience, gender, and regional origin significantly influence loss aversion. Specifically, individuals who experienced catastrophic events seem to exhibit substantially higher loss aversion (estimate $= 0.554$, $p < 0.001$). This finding aligns with the higher CRP observed earlier and is consistent with the possibility that past exposure is associated with greater sensitivity to losses. Gender differences also correlate strongly: male participants exhibit significantly lower loss aversion compared to females (estimate $= -1.157$, $p < 0.001$). Regional variation shows that respondents from Southern Italy have notably higher loss aversion (estimate $= 0.449$, $p = 0.016$), consistent with evidence in the Italian literature on trust and risk attitude (Bigoni et al. 2017, 2018). These patterns suggest that observed differences in CRP may be more closely associated with sensitivity to losses than with probability distortion.

Probability Distortion ($w^{-}(0.05)$). The analysis of probability distortion yields substantially weaker results, with no significant predictors emerging (Table 7).

Overall, the disentangling analysis suggests that past catastrophic experience primarily influences catastrophic risk perception by shaping the psychological sensitivity to outcomes (loss aversion), rather than by altering probability distortion.

4.3 Shared Burden Effect: WTP Comparisons and Regression Analysis

To explore individual heterogeneity in the Shared Burden Effect, we relate the observed reduction in WTP under the shared condition to participants' CPT parameters and background characteristics. This allows us to interpret whether the shared framing

Table 6 Regression results: correlation with loss aversion (λ)

Variable	Estimate	Std. Error	p-value
Intercept	2.471	0.581	< 0.001
Past Experience	0.554***	0.161	< 0.001
Male (Gender)	−1.157***	0.138	< 0.001
North (Region)	−0.642***	0.224	0.005
Center (Region)	−0.015	0.185	0.934
South (Region)	0.449**	0.182	0.016
Observations	91		
Adjusted R-squared	0.625		

Robust standard errors reported

Table 7 Regression results: correlation with probability distortion ($w^{-}(0.05)$)

Variable	Estimate	Std. Error	p-value
Intercept	0.201	0.115	0.083
Past Experience	0.055	0.032	0.086
Male (Gender)	0.033	0.027	0.222
North (Region)	0.002	0.044	0.962
Center (Region)	0.038	0.036	0.303
South (Region)	0.012	0.036	0.737
Observations	91		
Adjusted R-squared	0.071		

Robust standard errors reported

primarily alters how participants perceive the likelihood of loss or how they emotionally evaluate its impact.

As explained in the Methodology section, paired-sample t-tests have been conducted to compare participants' stated willingness to pay (WTP) between individual and collective in Phase 2 (laboratory settings) and Phase 3 (real-life risks scenarios). Phase 2 is particularly relevant for assessing the existence of the shared burden effect since the risk in the two scenarios is exactly the same, with same probability (and in a controlled laboratory environment) and the only difference is that the realization of the random risky event is the same for everyone in the collective risk scenarios (like if it was a common draw for all participants). The analysis in Phase 3 is useful to confirm consistency and robustness. A significant difference is found: WTP under collective risk was significantly lower than WTP in the individual risk scenario (paired t-test, $p < 0.05$; see Table 8). In Phase 3, participants stated their WTP for an insurance against an individual fatal disease versus an insurance against a nuclear accident (representing a collective fatal risk). Here too the difference was significant: WTP for nuclear accident insurance was lower than WTP for fatal disease insurance (paired t-test, $p < 0.01$; Table 8).

As explained in the Methodology section, we conducted a nonparametric permutation test (10,000 replications) to assess the robustness of the Shared Burden Effect (SBE). This test randomly permutes the assignment of the two framing conditions

Table 8 Paired comparisons of willingness to pay (WTP)

Comparison	Mean WTP_1	Mean WTP_2	$t(df)$	p
Phase 2: Individual vs. Collective	2.21	1.92	$t_{90} = 2.787$	0.003
Phase 3: Disease vs. Nuclear	54479.11	41712.09	$t_{90} = 5.11$	0.008

Phase 2: WTP1 = individual frame; WTP2 = collective frame. Phase 3: WTP1 = fatal disease (individual risk); WTP2 = nuclear war (collective risk)

Table 9 Permutation test results for the Shared Burden Effect (ΔWTP, 10,000 replications)

Statistic	Mean Difference	Permutation p-value	N	Replications
$WTP_{ind} - WTP_{coll}$	0.286	0.006	91	10,000

The permutation test randomly reassigns the framing condition (individual vs. collective) within participants to generate the null distribution of ΔWTP under no Shared Burden Effect

The reported p-value corresponds to the proportion of permuted means as or more extreme than the observed mean difference

(individual vs. collective) within each participant, generating a reference distribution for the mean difference $\Delta WTP = WTP_{ind} - WTP_{coll}$. The observed mean difference (ΔWTP = 0.286) lies well above the 99th percentile of the permutation distribution ($p = 0.006$, two-sided), confirming that participants' willingness to pay is systematically lower under collective exposure. The full permutation results are reported in Table 9.

These findings support the existence of the shared burden effect, indicating that individuals perceive risks differently when they affect larger groups rather than themselves only. The lower WTP observed in collective scenarios suggests a psychological discounting effect, where the responsibility and psychological impact of bearing a catastrophic loss are diluted among group members. This result aligns with behavioral economics theories on responsibility diffusion and risk-sharing mechanisms, suggesting that individuals derive some comfort from collective exposure, potentially underestimating their personal vulnerability within a group context.

Moreover, the consistently lower valuation of collective risks across both laboratory and naturalistic settings strengthens robustness and underscores that the shared burden effect persists irrespective of the scale of hypothetical losses involved. This has relevant implications for public policy and risk communication, highlighting the necessity to consider psychological biases in collective risk management and insurance market design, for example in contexts such as disaster preparedness, public health interventions or, as increasingly present in public debate, deterrence of international conflicts.

5 Discussion and Conclusion

This study aimed to advance the understanding of catastrophic risk perception by developing a behavioral framework that captures both its cognitive mechanisms and its social dimensions. We introduced an experimentally derived index of Catastrophic

Risk Perception (CRP), based on parameters from Cumulative Prospect Theory (CPT), and investigated how individual differences in these parameters relate to the newly proposed Shared Burden Effect (SBE)–the systematic tendency to perceive identical risks as less severe when they are collectively shared rather than individually borne.

The empirical findings support three main conclusions. First, the CRP index proved to be internally consistent and a strong predictor of subjective assessments of real-world catastrophic risks, thereby validating its behavioral and practical relevance. Second, we observed evidence of the Shared Burden Effect: participants' willingness to pay (WTP) to eliminate a catastrophic risk was significantly lower under collective exposure than under individual exposure, even when probabilities and outcomes were identical. The robustness of these findings was confirmed by non-parametric permutation analyses. Third, the regression analysis revealed that differences in catastrophic risk perception primarily arise from differences in loss aversion rather than by probability distortion, which was comparatively stable across individuals. Participants who had previously experienced a catastrophic or near-catastrophic event displayed significantly higher loss aversion and higher CRP, consistent with greater sensitivity to potential losses and stronger emotional responses to extreme outcomes. Conversely, the Shared Burden Effect may operate through the same cognitive channel but in the opposite direction: when the potential loss is collectively shared, individuals exhibit a relative reduction in loss aversion, leading to lower willingness to pay for risk mitigation. These results suggest that loss aversion may be a more relevant channel than probability misperception shaping both heightened sensitivity after personal exposure and attenuation of concern under shared exposure. These findings are broadly consistent with existing research on risk perception and decision-making under rare catastrophic events. Previous studies applying Cumulative Prospect Theory to disaster-related contexts have similarly emphasized the role of probability distortion and loss aversion in shaping preparedness behavior and risk attitudes (Goda and Hong 2021; Kunreuther and Michel-Kerjan 2013). Our results complement this literature by providing an experimentally derived measure of catastrophic risk perception that directly links these behavioral primitives to individual risk assessments. Moreover, the evidence of a Shared Burden Effect connects our findings to a broader literature on collective risk perception and diffusion of responsibility (Darley and Latané 1968; Feldman and Hazlett 2016). While previous studies have shown that collective framing can reduce perceived responsibility and individual mitigation efforts, our results suggest that collective exposure may also attenuate the perceived severity of catastrophic risks themselves, even when probabilities and outcomes remain identical. Several limitations should be acknowledged. The experimental sample was relatively small and composed mainly of university students, which may limit the generalizability of the results. The hypothetical nature of the tasks, while justified by ethical and practical considerations in the context of catastrophic losses, may have attenuated the strength of some behavioral responses. More broadly, it is important to recognize the well-known limitations of experimental risk-elicitation methods. As highlighted by Fehr-Duda and Epper (2012) and Crosetto and Filippin (2016), elicited risk parameters can display context dependence and instability across tasks and domains, reflecting sensitivity to framing, incentives, and cognitive load. Our study mitigates these concerns by employing a consistent CPT-based framework across all experimental phases and by aligning the probability and payoff structures of the CRP and SBE tasks. Nonetheless, these methodological challenges remain intrinsic to laboratory measures of risk preferences and should be considered when interpreting the results.

Future research should replicate these findings using larger and more diverse samples, introduce real economic incentives when feasible, and extend the analysis to field and cross-cultural settings. Longitudinal designs could further clarify whether catastrophic risk perception and the Shared Burden Effect evolve following real extreme events.

Beyond its theoretical contribution, the study carries clear economic and policy implications. The CRP framework offers a behavioral tool for understanding why individuals often underreact to low-probability, high-impact threats–a critical issue for the pricing, communication, and management of catastrophic risks. The identification of the Shared Burden Effect (SBE) offers a behavioral explanation for the persistent underinvestment in collective preparedness measures such as public insurance schemes, pandemic prevention, or climate adaptation. When a threat is perceived as shared, individuals tend to downplay their own exposure, interpreting it as a collective problem rather than an immediate personal risk. As a result, they display lower willingness to contribute financially to mitigation efforts and are more prone to free-ride on the expected actions of others. This mechanism helps explain why societies often allocate fewer resources to collective protection than to individually salient domains such as healthcare or personal safety. For instance, while citizens strongly support healthcare spending or disease prevention, they often show weaker support for investments in civil defense, nuclear safety, or global warming mitigation–domains where the consequences are widely shared but psychologically distant. Recognizing this asymmetry can help policymakers craft interventions that re-personalize collective risks. Framing national defense or climate policies as instruments that enhance personal safety, rather than "public security”, may restore their perceived relevance. Similarly, communication campaigns that make the consequences of collective inaction concrete–by linking them to familiar individual outcomes such as economic disruption, health loss, or local environmental damage–can counteract the perceptual discounting generated by shared exposure. Integrating insights from the Shared Burden Effect into risk communication and fiscal policy design could thus help governments align public preferences, contributions, and preparedness with the true scale of catastrophic threats.

In summary, this research provides both a methodological and conceptual contribution to the economics of rare but severe events. The Catastrophic Risk Perception index captures systematic individual differences in the evaluation of low-probability losses, while the Shared Burden Effect reveals how collective framing reshapes these evaluations in socially relevant contexts. Together, they highlight the cognitive and social foundations of decision-making under catastrophic risk and offer a behavioral basis for more effective risk communication and policy design.

6 Appendix

Table 10.

Table 10 Regression results: full model of CRP Determinants

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	0.864	0.870	0.993	0.324
Past Experience	0.704**	0.242	2.912	0.005
Gender (Male)	−0.266	0.207	−1.288	0.202
North	0.125	0.335	0.373	0.710
Center	0.151	0.277	0.544	0.588
South	0.407	0.272	1.493	0.140
Extraversion	−0.097	0.119	−0.816	0.417
Agreeableness	−0.152	0.125	−1.217	0.227
Conscientiousness	−0.065	0.140	−0.463	0.645
Neuroticism	−0.012	0.110	−0.112	0.912
Openness	−0.061	0.122	−0.505	0.615
IQ	−0.005	0.050	−0.098	0.922

As shown in Table 10, among the psychological traits assessed through the Big Five personality framework, none emerged as significantly associated with CRP. Extraversion (estimate $= -0.097$, $p = 0.417$), agreeableness (estimate $= -0.152$, $p = 0.227$), conscientiousness (estimate $= -0.065$, $p = 0.645$), neuroticism (estimate $= -0.012$, $p = 0.912$), and openness (estimate $= -0.061$, $p = 0.615$) displayed non-significant relationships. Similarly, IQ did not show a significant association with CRP (estimate $= -0.005$, $p = 0.922$). The only significant predictor appears to be Past Experience, enhancing perception of risk.

Given these results and the relatively modest sample size, as discussed before, a reduced-form model excluding the psychological traits and IQ was estimated to enhance statistical power, clarity, and interpretability of the results.

To investigate individual differences in the Shared Burden Effect, we analyze the within-subject gap

$$\Delta WTP_i \equiv WTP_i^{individual} - WTP_i^{collective}$$

from Phase 2, where probabilities and payoffs are identical and only the exposure frame differs. We then relate ΔWTP_i to CPT components (loss aversion λ_i and, probability weighting $w_i^-(0.05)$) and to background characteristics (past exposure, sociodemographics, personality, IQ) to assess whether SBE covaries primarily though the likelihood or the severity channel (see Table 11).

The analysis indicates a limited general explanatory power even with different reduced form specifications. Among all predictors, only the probability distortion parameter approached statistical significance (estimate $= -1.678$, $p = 0.053$), with its significance increasing in the reduced forms, suggesting that participants who distort probabilities to a greater extent exhibit a smaller shared burden effect. This finding may suggest that individuals prone to overestimate low probabilities may perceive

Table 11 Regression analysis of drivers of shared burden effect (Δ WTP)

Variable	Estimate	Std. Error	t-statistic	p-value
Intercept	3.680	3.469	1.061	0.292
Past catastrophic experience	0.244	0.323	0.755	0.452
Male gender	0.046	0.360	0.128	0.899
North region	−0.093	0.395	−0.237	0.814
Central region	0.137	0.308	0.444	0.658
South region	−0.267	0.322	−0.828	0.410
Probability distortion ($w^{-}(0.05)$)	−1.678*	0.855	−1.962	0.053
Loss curvature (β)	−1.806	3.035	−0.595	0.554
Loss aversion (λ)	−0.108	0.220	−0.493	0.623
Extraversion	−0.053	0.141	−0.378	0.707
Agreeableness	0.091	0.139	0.656	0.514
Conscientiousness	−0.256	0.159	−1.614	0.111
Neuroticism	−0.014	0.123	−0.111	0.912
Openness	0.026	0.136	0.192	0.848
IQ	−0.069	0.056	−1.216	0.228
Observations	91			
Adjusted R-squared	−0.011			

* $p < 0.1$; robust standard errors reported

catastrophic risks similarly in both individual and collective contexts, thus reducing the discrepancy between their willingness to pay individually versus collectively.

Other predictors, including past catastrophic experiences, socio-demographic factors (gender and region), and psychological traits (Big Five personality dimensions and IQ), did not show any significant relationship with the shared burden effect. Even when replicating the logic employed previously for the CRP determinants by estimating a reduced-form model excluding psychological and cognitive variables, no meaningful additional insights emerged.

Funding Open access funding provided by Luiss University within the CRUI-CARE Agreement.

Data Availability The data that support the findings of this study are openly available in "figshare" at https://doi.org/10.6084/m9.figshare.28697372.v1.

Declarations

Conflict of interest The author reports there are no conflict of interest to declare.

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