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# Cumulative Prospect Theory for Risk and Uncertainty : New Measurement Methods and Applications

Yao Thibaut Kpegli

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Yao Thibaut Kpegli. Cumulative Prospect Theory for Risk and Uncertainty: New Measurement Methods and Applications. Economics and Finance. Université Lumière - Lyon II, 2023. English. NNT : 2023LYO20075 . tel-04467474

**HAL Id: tel-04467474**

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N° d'ordre NNT : 2023LYO20075

# THÈSE de DOCTORAT DE L'UNIVERSITÉ LUMIÈRE LYON 2

**École Doctorale : ED 486**  
**Sciences économiques et de Gestion**

Discipline : Sciences économiques

Soutenue publiquement le 26 juin 2023 par :

**Yao Thibaut KPEGLI**

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## **Cumulative Prospect Theory for Risk and Uncertainty.**

*New Measurement Methods and Applications.*

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UNIVERSITÉ DE LYON – ÉCOLE DOCTORALE DE SCIENCES  
ECONOMIQUE ET GESTION  
UNIVERSITE LUMIERE LYON 2

Groupe d'Analyse et de Théorie Economique

## THÈSE DE DOCTORAT EN SCIENCES ÉCONOMIQUES

Soumise par

**Yao Thibaut Kpegli**

pour une soutenance prévue le 26 juin 2023

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# Cumulative Prospect Theory for Risk and Uncertainty: New Measurement Methods and Applications

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*University Lumière Lyon 2 does not give any approbation or disapprobation about the thoughts expressed in the dissertation. They are only the author's ones and need to be considered as such.*



# Acknowledgments

This thesis would not have been possible without the help and support of many people. First of all, I would like to express my deepest gratitude to my supervisors, Brice Corgnet and Adam Zylbersztejn. They have shared with me their expertise on many of the questions raised in this thesis. Moreover, they have shared with me much more than that and helped me grow as a researcher.

I thank Roberto Hernán-González and Maria Alejandra Erazo Diaz for their contributions as co-authors.

I thank Mohammed Abdellaoui, Olivier L'Haridon, Dorothea Kübler, and Béatrice Rey-Fournier for their involvement in the evaluation of my thesis. I am especially thankful to Mohammed Abdellaoui and Olivier L'Haridon for accepting to be reviewers of the thesis.

I also thank Richard Gonzales and George Wu for sharing the data from their own experiment and from the experiment of Amos Tversky and Daniel Kahneman.

I would like to thank Izabela Jelovac, Béatrice Rey-Fournier, and Corinne Autant-Bernard. To be more specific, they opened the doors of this PhD to me five years ago by accepting my applications to the Msc Program in Economics and Finance and the IDEXLYON scholarship at GATE.

I thank Tai Dao, Yamina Mansouri, and Cindy Arman for facilitating the administrative procedures involved in the PhD program.



I thank all my colleagues at the GATE. A special thanks to the PhD team: Maria Alejandra Erazo Diaz, Sorravich Kingsuwankul, Jona Krutaj, Maxime Le Bihan, Valentin Guigon, Alexandre Angelloznicoud, Sébastien Doustaly, Kamel Ismail, Jocelyn Maillard, Siwar Khelifa, Marie Aurélie Lapierre, Carla Morvan, Kevin Techer, David Lowing, and Adhen Benlahlou. You all have contributed, in your own way, to make my stay at the GATE a memorable one.

I am grateful to all my friends. Those I knew far before my PhD in Benin, Senegal, and Lyon. I thank Henri Mermoz Kouye for the good friendship that we have had since high school. I also thank Bruno Zingan, Marchais Kittika, Louis Magblenou, Kevin Adje, and Kemi Biauou.

Finally, I would like to thank the people who are the most important in the world to me: my family. This thesis is dedicated to my father, Koffi Kpegli, and my mother, Denise Gnanga. My thanks also go to my two older brothers, Raoul Kpegli and Honoré Kpegli.

# Résumé de la thèse

Au cours de leur vie, les gens font des choix en matière d'investissement, d'épargne, d'alimentation, d'éducation, de sport et de carrière professionnelle. Dans la plupart des cas, ces choix ressemblent à des loteries en ce sens qu'ils produisent des résultats stochastiques.

Par exemple, un employeur ne sait pas, au moment où il embauche un salarié, si ce dernier accomplira avec succès les tâches pour lesquelles il est embauché. Le choix de l'employeur peut donc être associé à deux conséquences possibles : (i) l'employé accomplit les tâches avec succès ou (ii) l'employé n'accomplit pas les tâches.

De même, lors d'une séance de tirs au but au football, le capitaine d'une équipe doit choisir l'un des deux côtés (pile ou face) d'une pièce de monnaie équitable. Son choix permet, après que l'arbitre a tiré à pile ou face, de savoir si le premier tir sera effectué par l'équipe du capitaine ou par l'équipe adverse. Dans cet exemple, le choix du capitaine a deux conséquences : (i) le visage qui apparaît après le tirage au sort est le visage choisi par le capitaine et (ii) le visage qui apparaît après le tirage au sort est l'opposé du visage choisi par le capitaine.

Dans de rares cas, les individus disposent d'une mesure objective de la probabilité de chaque conséquence possible de leurs choix. C'est le cas dans l'exemple du capitaine. Il sait que le visage qu'il a choisi a 50% de chances

d'apparaître et 50% de chances de ne pas apparaître à l'issue du jeu de pile ou face.

Cependant, dans la plupart des cas, les individus ne disposent pas d'une mesure objective de la probabilité de chaque conséquence possible de leurs choix. C'est par exemple le cas de l'employeur. Bien qu'il ne dispose pas d'une mesure objective des probabilités associées aux conséquences, l'employeur peut se forger des probabilités subjectives (ou croyances) sur la base des informations (par exemple, le diplôme, l'université, l'expérience professionnelle) qu'il a recueillies au cours du processus de recrutement.

Suivant [Knight \(1921\)](#), en économie, on parle de *risque* lorsque les individus ont des probabilités objectives des conséquences possibles de leurs choix. Les probabilités sont objectives dans le sens où elles sont indépendantes de la personne qui prend la décision. On parle de *incertitude* ou de *ambiguïté*, lorsque les individus ne disposent pas de probabilités objectives des conséquences possibles de leurs choix et que les individus doivent au contraire se forger des probabilités (ou croyances) subjectives. Les probabilités sont subjectives dans le sens où elles dépendent de la personne qui prend la décision.

Les probabilités associées aux conséquences, qu'elles soient objectives ou subjectives, influencent le choix des individus entre plusieurs alternatives. Par exemple, le choix d'un individu de frauder le fisc est fortement déterminé par son appréhension (objective ou subjective) de la probabilité d'être pris par le fisc. De même, le choix d'un individu d'utiliser frauduleusement des services de transport payants est fortement déterminé par son appréhension (objective ou subjective) de la probabilité d'être pris par les contrôleurs.

Mais au-delà des probabilités, il existe d'autres caractéristiques propres aux individus qui déterminent leur choix entre plusieurs alternatives. Une première caractéristique est la valeur subjective (représentant le plaisir ou le bonheur)

que les individus retirent de la réalisation de chaque conséquence. En économie, cette valeur subjective est appelée utilité.

La théorie de l'utilité espérée et la théorie de l'utilité subjective espérée traitent respectivement de la prise de décision en situation de risque (les probabilités objectives des conséquences sont connues) et en situation d'incertitude (les probabilités objectives des conséquences sont inconnues). Ces deux théories standard considèrent que les choix des individus entre plusieurs alternatives sont entièrement et uniquement déterminés par les probabilités et les utilités que les individus associent aux conséquences des différentes alternatives. Ces théories associent à chaque alternative la somme pondérée de l'utilité des conséquences, les poids étant les probabilités (objectives ou subjectives). Ces théories postulent qu'un individu choisira l'alternative qui maximise sa somme pondérée.

Cependant, les théories standard se heurtent à des difficultés empiriques qui suggèrent que les probabilités et l'utilité ne sont pas les seuls déterminants des choix des individus. Une difficulté empirique importante des théories standard est le paradoxe de [Ellsberg \(1961\)](#). Selon ces théories, les sujets devraient être indifférents entre une urne connue contenant 50 boules rouges et 50 boules noires et une urne inconnue comprenant 100 boules rouges et noires dans une proportion inconnue, quelle que soit la couleur gagnante. Or, contrairement à cette indifférence, les sujets ont tendance à préférer l'urne connue à l'urne inconnue, quelle que soit la couleur gagnante. Dans le cadre de ces théories standard, le fait que les sujets tendent à préférer l'urne connue à l'urne inconnue (quelle que soit la couleur gagnante), implique que la somme des croyances d'avoir une boule rouge et d'avoir une boule noire dans l'urne inconnue est inférieure à un.

Les difficultés empiriques des théories standard ont justifié le développement de théories de l'utilité non attendue dans des conditions de risque et

d'incertitude qui intègrent de nouvelles caractéristiques individuelles en tant que déterminants des choix. L'utilité dépendante du rang (RDU ; voir [Quiggin, 1982](#); [Schmeidler, 1989a](#)) et la théorie cumulative des perspectives (CPT ; voir [Tversky and Kahneman, 1992a](#), désormais TK92) sont apparues comme les deux principales alternatives aux théories traditionnelles. Elles expliquent les violations empiriques en introduisant des distorsions de probabilité ([Bleichrodt and Pinto, 2000](#)) et l'aversion aux pertes ([Wakker, 2010a](#)).

Cette thèse contribue à la littérature d'économie comportementale et expérimentale sur le risque et l'incertitude. En particulier, cette thèse (*i*) propose de nouvelles méthodes pour mesurer la fonction d'utilité, la fonction de pondération, l'aversion aux pertes et les croyances et (*ii*) dérive de nouvelles idées théoriques dans le domaine de la définition des incitations ainsi que le développement d'un nouveau paradigme expérimental.

Le chapitre 1 établit une méthode semi-paramétrique complète qui satisfait aux quatre propriétés souhaitables des méthodes paramétriques : traçabilité, efficacité des données, robustesse des erreurs et facilité. Le chapitre 2 propose une version non paramétrique de la méthode semi-paramétrique du chapitre 1 avec une approximation de la fonction d'utilité par une spline de lissage. Les applications des chapitres 1 et 2 à des données existantes concernant le risque confirme les écarts par rapport à la théorie de l'utilité espérée en mettant en évidence la fonction de pondération des probabilités et l'aversion pour les pertes.

Le chapitre 3 étend la méthode semi-paramétrique du chapitre 1 pour mesurer les croyances et les attitudes d'ambiguïté à l'égard de sources discrètes d'incertitude. Les sujets prennent des décisions dans ce type de situations incertaines au quotidien. Dans diverses applications, la méthode passe avec succès les tests de validité et fournit des résultats intéressants dans le cas des jeux de confiance et de coordination. Ce chapitre constate des déviations par rapport

à la théorie de l'utilité attendue subjective grâce à des preuves d'attitudes ambiguës. Il souligne que les gens sont plus insensibles à la probabilité en présence d'événements asymétriques qu'en présence d'événements symétriques, ce qui suggère que la formation des croyances est cognitivement exigeante. À sources d'incertitude égales, les individus présentent *l'aversion à la dépendance des gains* et *la recherche d'une variété de gains*. *Aversion à la dépendance des gains* signifie que les gens n'aiment pas que leurs propres gains dépendent des préférences des autres. Ce comportement est représenté par une fonction d'utilité plus concave. *Recherche de la variété des gains* signifie que les sujets préfèrent un plus grand nombre de gains possibles lorsque ces gains dépendent des préférences des autres. Ce comportement se traduit par un plus grand optimisme.

Le chapitre 4 étudie l'existence du compromis risque-incitations (RIT) en fonction de l'utilité dépendante du rang (RDU) et de la moyenne-variance-squeness (MVS). Les analyses théoriques montrent que le RIT est remarquablement robuste sous RDU mais pas sous MVS. Avec des données basées sur un nouveau modèle expérimental qui élimine les facteurs de confusion, le chapitre 4 fournit des preuves de l'existence de la RIT même dans le cas d'agents qui recherchent le risque, ce qui est une prédiction distincte de la RDU. Les résultats confirment l'existence de l'IRT et suggèrent qu'elle s'applique à un large éventail de situations, y compris les cas où les agents recherchent le risque (par exemple, la rémunération des dirigeants).



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# General introduction

Over their lifetime, people make choices about investments, savings, food, education, sports and professional careers. In most cases, these choices resemble lotteries in that they produce stochastic outcomes.

For example, an employer does not know at the time he hires an employee whether the employee will successfully perform the tasks for which he is hired. The employer's choice can therefore be associated with two possible consequences: *(i)* the employee successfully completes the tasks or *(ii)* the employee fails to complete the tasks.

Also, during a penalty shoot-out in football, a team captain must choose one of the two sides (heads or tails) of a fair coin. His choice allows, after the referee has tossed the coin, to know if the first shot will be taken by the captain's team or the opposing team. In this example, the captain's choice has two consequences: *(i)* the face that appears after the coin toss is the face chosen by the captain and *(ii)* the face that appears after the coin toss is the opposite of the face chosen by the captain.

In rare cases, individuals have an objective measure of the probability of each possible consequence of their choices. This is the case in the captain's example. He knows that the face he has chosen has a 50% chance of appearing and a 50% chance of not appearing at the end of the toss of the fair coin.

However, in most cases, individuals do not have an objective measure of the probability of each possible consequence of their choices. This is for example the case of the employer. Although he does not have an objective measure of the probabilities associated with the consequences, the employer can form subjective probabilities (or beliefs) based on the information (e.g. diploma, university, professional experience) that he has collected during the recruitment process.

Following [Knight \(1921\)](#), in economics, we speak of *risk* when the individuals have objective probabilities of the possible consequences of their choices. The probabilities are objective in the sense that they are independent of the person who makes the decision. One speaks about *uncertainty* or *ambiguity*, when the individuals do not have objective probabilities of the possible consequences of their choices and that individuals must on the contrary form subjective probabilities (or beliefs). The probabilities are subjective in the sense that they depend on the person who makes the decision.

The probabilities associated with the consequences, whether objective or subjective, influence the choice of individuals between several alternatives. For example, an individual's choice of whether to evade taxes is strongly determined by his or her apprehension (objective or subjective) of the probability of being caught by the tax department ([Dhami, 2016](#)). Similarly, an individual's choice of whether to use fare-paying transport services fraudulently is strongly determined by his or her apprehension (objective or subjective) of the probability of being caught by ticket inspectors.

But, beyond probabilities, there are other characteristics specific to individuals that determine their choice between several alternatives. A first characteristic is the subjective value (representing pleasure or happiness) that individuals get from the realization of each consequence. In economics, this subjective value is called utility.



Expected utility theory and subjective expected utility theory deal respectively with decision-making under risk (objective probabilities of consequences are known) and under uncertainty (objective probabilities of consequences are unknown). These two standard theories consider that the choices of individuals between several alternatives are entirely and solely determined by the probabilities and utilities that individuals associate with the consequences of the different alternatives. These theories associate with each alternative the weighted sum of the utility of the consequences, the weights being the probabilities (objective or subjective). These theories posit that an individual will choose the alternative that maximizes his weighted sum.

However, standard theories face empirical difficulties that suggest that probabilities and utility are not the only determinants of individuals' choices. An important empirical difficulty of standard theories is the paradox of [Ellsberg \(1961\)](#). According to these theories, subjects should be indifferent between a known urn containing 50 red and 50 black balls and an unknown urn that comprises 100 red and black balls in an unknown proportion, irrespective of the winning color. However, contrary to this indifference, subjects tend to prefer the known urn to the unknown urn, irrespective of the winning color. Under these standard theories, the fact that subjects tend to prefer the known urn to the unknown urn (irrespective of the winning color), implies that the sum of the beliefs of having a red ball and having a black ball in the unknown urn is less than one.

Empirical difficulties of standard theories (see [Starmer, 2000](#), for a review) justified the development of non-expected utility theories under risk and uncertainty that incorporate new individual characteristics as determinants of choices. Rank Dependent Utility (RDU; see [Quiggin, 1982](#); [Schmeidler, 1989](#)) and Cumulative Prospect Theory (CPT; see [Tversky and Kahneman, 1992](#), henceforth TK92)

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emerged as two main alternatives to the traditional theories. They explain empirical violations by introducing probability distortions (Bleichrodt and Pinto, 2000) and loss aversion (Wakker, 2010).

All chapters of the thesis are related to decision-making under risk and uncertainty. Three chapters provide measurement methods of decision models under risk and uncertainty. The final chapter derives new theoretical insights in the realm of incentive setting along with the development of a new experimental paradigm.

Measuring risk and uncertainty attitudes is of great value in many economic applications. For example, measures of attitudes toward risk and uncertainty can help explain behaviors in finance (e.g. Baillon et al., 2018b), incentive setting (e.g. Corgnet and Hernan-Gonzalez, 2019), health choices (e.g. Attema et al., 2018), human behaviors in face of uncertainty generated by other humans or strategic uncertainty (e.g. Li et al., 2018), the behaviors of sport professionals (e.g. Bleichrodt et al., 2018), tax evasion (e.g. Dhimi and Hajimoladarvish, 2020), election or vote (e.g. Kemel and Mun, 2020).

I present in section 0.1 the prevalent theories that are widely used to model decisions under risk and uncertainty. Section 0.2 reviews measurement methods for risk attitudes. Finally, section 0.3 outlines the main goals of this thesis.

## 0.1 Decision theories under risk and uncertainty

Three prevailing theories are widely used to model decisions under risk and uncertainty: (subjective) expected utility theory, rank dependent utility and cumulative prospect theory. Before presenting them, we lay out the following notations.

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### 0.1.1 Notations

Assume that consequences or outcomes are monetary, with  $\mathbb{R}$  denoting the outcome set. Let denote under risk a lottery that gives outcome  $x_i$  with known probability  $p_i$  as follows:

$$L = (x_1, p_1; x_2, p_2; \dots, x_n, p_n) \quad (1)$$

Denote by  $S$  a source of uncertainty, i.e. a group of events generated by a common mechanism of uncertainty. Denote by  $L$  a lottery that gives outcome  $x_i$  if event  $E_i \subset S$  occurs as follows:

$$L = (x_1, E_1; x_2, E_2; \dots, x_n, E_n) \quad (2)$$

where the objective probabilities of  $E_i$  ( $i = 1, 2, \dots, n$ ) are unknown. For notational convenience, we assume that outcomes are ordered:  $x_1 < x_2 < \dots < x_n$ .

### 0.1.2 Traditional models

The traditional theory to model decisions under risk is expected utility theory ([Von Neumann and Morgenstern, 1947](#), EU henceforth). This theory postulates that decision maker values the lottery specified in (1) in term of expected utility:

$$EU(L) = \sum_{i=1}^n p_i u(x_i) \quad (3)$$

with  $u(\cdot)$  the utility function over outcomes.

For uncertainty, the traditional theory is the Subjective Expected Utility (SEU) of [Savage \(1954\)](#). Because objective probabilities of events are not available, the decision maker forms subjective probabilities on events:  $P(E_i)$ ,  $i = 1, 2, \dots, n$ .

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The value of the prospect specified in (2) under uncertainty is given by the sum of the utility of each of the outcomes weighted by its subjective probabilities:

$$SEU(L) = \sum_{i=1}^n P(E_i)u(x_i) \quad (4)$$

A distinctive feature of EU and SEU, is that objective and subjective probabilities are used linearly in the valuation of prospects. The paradox of [Allais \(1953\)](#) under risk and the paradox of [Ellsberg \(1961\)](#) under uncertainty challenged this feature. Rank Dependent Utility (RDU) and Cumulative Prospect Theory (CPT) emerged as two main alternatives to the traditional models.

### 0.1.3 Rank Dependent Utility (RDU)

[Quiggin \(1982\)](#) proposes a rank dependent utility theory to evaluate the risky lottery specified in (1). The value of the prospect is given by the sum of the utility of each of the outcomes weighted by a non-additive transformation of probabilities:

$$RDU(L) = \sum_{i=1}^n \left[ w\left(\sum_{j=i}^n p_j\right) - w\left(\sum_{j=i+1}^n p_j\right) \right] u(x_i) \quad (5)$$

with  $w(\cdot)$  the probability weighting function which is strictly increasing, transforms probability from  $[0, 1]$  to  $[0, 1]$  and satisfies  $w(0) = 1 - w(1) = 0$ .

[Schmeidler \(1989\)](#) provides a rank dependent utility theory to evaluate under uncertainty the lottery specified in (2) as follows:

$$RDU(L) = \sum_{i=1}^n \left[ W\left(\bigcup_{j=i}^n E_j\right) - W\left(\bigcup_{j=i+1}^n E_j\right) \right] u(x_i) \quad (6)$$

with the event weighting function that satisfies:

1. if  $E \subset F$ , then  $W(E) < W(F)$

---


$$2. W(\emptyset) = 1 - W(S) = 0$$

[Abdellaoui et al. \(2011a\)](#) show that event weighting function  $W(\cdot)$  can be decomposed in terms of a source function  $w_S(\cdot)$  and belief  $P(\cdot)$ :

$$W(E) = w_S(P(E)) \quad (7)$$

The source function  $w_S(\cdot)$  is strictly increasing, transforms subjective probability (belief) from  $[0, 1]$  to  $[0, 1]$  and satisfies  $w_S(0) = 1 - w_S(1) = 0$ .

#### 0.1.4 Cumulative Prospect Theory (CPT)

[Tversky and Kahneman \(1992\)](#) considers that a person evaluate outcomes  $x_i$  ( $i = 1, 2, \dots, n$ ) of the lotteries specified in (1) and (2) in deviation to a reference point, say  $R$ :

$$x_i - R \quad (8)$$

The outcome  $x_i$  is considered as gain (loss) if  $x_i \geq R$  ( $x_i < R$ ). Denote by  $m \geq 0$  (resp.  $t \geq 0$ ) the number of loss (resp. gain) outcomes:

$$\underbrace{y_{-m} < y_{-m+1} < \dots < y_{-1}}_{\text{Losses}} < y_0 = 0 < \underbrace{y_1 < y_2 < \dots < y_t}_{\text{Gains}}$$

The risky prospect specified in (1) becomes under CPT:

$$L = (y_{-m}, p_{-m}; y_{-m+1}, p_{-m+1}; \dots; y_{-1}, p_{-1}; y_0, p_0; y_1, p_1; \dots; y_t, p_t) \quad (9)$$

with  $y_{-m} = x_1 - R$ ,  $y_{-m+1} = x_2 - R$ , ...,  $y_t = x_n - R$ ; and  $p_1 = p_{-m}, p_2 = p_{-m+1}, \dots, p_n = p_t$ . The valuation of (9) is given by

---


$$\begin{aligned}
CPT(L) = & \sum_{i=-m}^0 \left[ w^- \left( \sum_{j=-m}^i p_j \right) - w^- \left( \sum_{j=-m}^{i-1} p_j \right) \right] v(y_i) + \\
& \sum_{i=1}^t \left[ w^+ \left( \sum_{j=i}^t p_j \right) - w^+ \left( \sum_{j=i+1}^t p_j \right) \right] v(y_i)
\end{aligned} \tag{10}$$

with  $v(\cdot)$  the *value function*,  $w^+(\cdot)$  the weighting function in the gain domain and  $w^-(\cdot)$  the probability weighting function in the loss domain. The value function  $v(\cdot)$  is continuous, strictly increasing and satisfies  $v(0) = 0$ . The probability weighting functions are strictly increasing, transform probability from  $[0, 1]$  to  $[0, 1]$  and satisfy:  $w^-(0) = 1 - w^-(1) = 0$  and  $w^+(0) = 1 - w^+(1) = 0$ .

Similarly, the prospect (2) under uncertainty becomes:

$$L = (y_{-m}, E_{-m}; y_{-m+1}, E_{-m+1}; \dots; y_{-1}, E_{-1}; y_0, p_0; y_1, p_1; \dots; y_t, p_t) \tag{11}$$

with  $E_1 = E_{-m}, E_2 = E_{-m+1}, \dots, E_n = E_t$

The valuation of (11) is given by

$$\begin{aligned}
CPT(L) = & \sum_{i=-m}^0 \left[ W^- \left( \bigcup_{j=-m}^i E_j \right) - W^- \left( \bigcup_{j=-m}^{i-1} E_j \right) \right] v(y_i) + \\
& \bigcup_{i=1}^t \left[ W^+ \left( \bigcup_{j=i}^t E_j \right) - W^+ \left( \sum_{j=i+1}^t E_j \right) \right] v(y_i)
\end{aligned} \tag{12}$$

with  $v(\cdot)$  the *value function*,  $W^+(\cdot)$  the event weighting function in the gain domain and  $W^-(\cdot)$  the event weighting function in the loss domain. The value function  $v(\cdot)$  is continuous, strictly increasing and satisfies  $v(0) = 0$ . The event weighting functions satisfy:

- 
1. if  $E \subset F$ , then  $W^+(E) < W^+(F)$  and  $W^-(E) < W^-(F)$
  2.  $W^+(\emptyset) = 1 - W^+(S) = 0$  and  $W^-(\emptyset) = 1 - W^-(S) = 0$

Following the seminal study by TK92, as well as the subsequent developments in [Köbberling and Wakker \(2005\)](#) and [Abdellaoui et al. \(2008\)](#), the value function  $v(\cdot)$  is composed of the loss aversion index  $\lambda > 0$  which reflects the exchange rate between gain and loss utility units, and the utility function  $u(\cdot)$  that reflects the intrinsic value of outcomes:

$$v(x) = \begin{cases} u(x) & \text{if } x \geq 0 \\ \lambda u(x) & \text{if } x < 0 \end{cases} \quad (13)$$

Similarly to RDU, the event weighting functions  $W^+(\cdot)$  and  $W^-(\cdot)$  can be decomposed in terms of source functions  $w_S^+(\cdot)$  and  $w_S^-(\cdot)$ , and belief function  $P(\cdot)$  (e.g. [Attema et al., 2018](#)).

## 0.2 Measurement methods

This section provides a literature review of the main methods to elicit utility functions, weighting functions, loss aversion and beliefs. The methods use binary lotteries of the form  $L = (x, y; p, 1 - p)$  that gives outcome  $x$  with probability  $p$  and outcome  $y$  with probability  $1 - p$ . This notation corresponds to decision under risk. In decision under uncertainty, we just replace  $p$  and  $1 - p$  by  $E$  and  $E^c$  respectively.  $E$  denotes an event of state space  $S$  and  $E^c$  denotes the complement of  $E$  in  $S$ . For notational convenience, we assume that all prospects  $L = (x, y; p, 1 - p)$  are rank-ordered. If a non-mixed prospect involves only gains (resp. losses), we assume that  $x \geq y \geq 0$  (resp.  $x \leq y \leq 0$ ). For mixed prospect we assume  $y \leq 0 \leq x$ .

---

Three types of approach—parametric, semi-parametric and nonparametric—in decisions situation under risk and uncertainty are used.

### 0.2.1 Parametric approach

The parametric approach assumes parametric forms for utility and weighting functions. This approach is followed for example by [Fehr-Duda et al. \(2006\)](#) and [Tversky and Kahneman \(1992\)](#) and is not applicable for decisions under uncertainty.

In this approach, the authors start by collecting certainty equivalents  $ce_g^i$  for  $N$  non-mixed binary lotteries  $L_g = (x_g, y_g; p_g, 1 - p_g)$  that involves different probabilities and outcomes ( $x_g$  and  $y_g$ ) and probabilities  $p_g$ , with  $g = 1, 2, \dots, N$ . Under cumulative prospect theory (10), these certainty equivalents satisfy

$$ce_g^i = u^{-1} \left( w^i(p_g)u(x_g) + (1 - w^i(p_g))u(y_g) \right) \quad (14)$$

Second, the parametric forms of the utility and weighting functions are specified. For example, one can assume a power utility function and the [Prelec \(1998\)](#) two-parameters weighting function:

$$u(x) = \begin{cases} x^\alpha & \text{if } x \geq 0 \\ -\lambda(-x)^\beta & \text{if } x < 0 \end{cases} \quad (15)$$

$$w^i(p) = \exp \left( -\delta^i (-\ln(p))^{\gamma^i} \right) \quad (16)$$



---

With these parametric forms, the equation (1.16) becomes in gain and loss domains

$$ce_g^+ = \left[ \exp\left(-\delta^+(-\ln(p_g))^{\gamma^+}\right) (x_g^\alpha - y_g^\alpha) + y_g^\alpha \right]^{1/\alpha} \quad (17)$$

$$ce_g^- = - \left[ \exp\left(-\delta^-(-\ln(p_g))^{\gamma^-}\right) \left( (-x_g)^\beta - (-y_g)^\beta \right) + (-y_g)^\beta \right]^{1/\beta} \quad (18)$$

The parameters  $\alpha$ ,  $\beta$ ,  $\delta^i$  and  $\gamma^i$  can then be estimated in the equations (17) and (18) by nonlinear least squares or maximum likelihood. Also, Bayesian estimation can be used by making prior assumptions about parameters.

The link between the utility functions of the two domains (gain and loss) is required to elicit the loss aversion index (Abdellaoui et al., 2007b). Abdellaoui et al. (2008) makes this link with one indifference. The indifference consists in using a gain  $ce_g^+$  elicited in the first step and in determining the loss  $X_g$  that satisfies  $(0.5, ce_g^+; X_g) \sim 0$ . This implies in CPT framework that  $X_g$  and the loss aversion index  $\lambda$  satisfy:

$$\eta^+ v(ce_g^+) + \eta^- \lambda v(X_g) = u(0) = 0 \quad (19)$$

For the power utility function, this relation becomes:

$$\eta^+ (ce_g^+)^\alpha - \eta^- \lambda (-X_g)^\beta = u(0) = 0 \quad (20)$$

or equivalently

$$\lambda = \frac{\eta^+ (ce_g^+)^\alpha}{\eta^- (-X_g)^\beta} \quad (21)$$

Application of this method can be done under uncertainty (Gutierrez and Kemel, 2021; Kemel and Mun, 2020; Baillon et al., 2018a). In this context,

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subjective probabilities (beliefs) need to be estimated too.

This approach has four desirable properties: *tractability*, *data-efficiency*, *easiness*, *error-robustness*. We define these properties below.

**Tractable:** the method allows for estimating risk attitudes with standard tools, like OLS or NLS (Abdellaoui et al., 2007a, 2008).

**Error-robust:** the method accounts for the fact that subjects make response errors when answering questions (Abdellaoui et al., 2008).

**Easy (not cognitively demanding):** the method relies on *simple choices* involving the lowest possible number of outcomes, that is 3 (Abdellaoui et al., 2008). A useful benchmark comes from TK92 who ask their subjects to make *simple choices* between a sure outcome and a binary lottery.

**Data-efficient:** the method requires few measurements (observations) to estimate the parameters of the utility function and the probability weights. As a rule of thumb, we take TK92 (with 28 measurements for 9 probability weights and one utility parameter per domain) as benchmark, and consider a method data-efficient if it requires no more than three measurements per estimate of a probability weight.<sup>1</sup>

In addition to these four desirable properties, the parametric methods are also **Comprehensive** in the sense that they allow for estimating utility function, loss aversion and weighting function under risk as well as under uncertainty.

Nevertheless, this approach has several drawbacks. First, empirical estimates are sensitive to the specification of the utility and probability weighting functions

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<sup>1</sup>(Abdellaoui et al., 2008) use the term “efficient” instead. Since this property only relates to the physical resources (such as time and money) used for data collection, we coin the term *data-efficiency* to avoid confusion with the (unrelated) statistical notion of the efficiency of an estimator.

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(Abdellaoui, 2000). Second, parametric methods only provide an overall measure of the goodness of fit of the model, rather than separate measures for each of its components – one for the utility function and one for the probability weighting function (see Gonzalez and Wu, 1999).

## 0.2.2 Semi-parametric approach

The semi-parametric approach assumes parametric forms for the utility function without imposing any parametric restriction on the probability weight. Methods that use this approach can be found Abdellaoui et al. (2008) and Abdellaoui et al. (2011b).

The semi-parametric method of Abdellaoui et al. (2008) entails three steps. It resembles the previous parametric method that we had presented with two important differences. First, the probabilities  $p$  in the binary lotteries is kept fixed so that the decision weight  $w^i(p)$  can be estimated directly as parameter alongside those of the utility function. Second, an additional step is introduced to estimate the loss aversion parameter  $\lambda$ . More precisely, the three steps are as follows.

### **First step: Utility and probability (or event) weight elicitation in the gain domain**

The step starts by two choices from the researcher. First, the researcher has to choose a probability  $\bar{p}$  that will be kept fixed throughout the elicitation of the utility function on the gain domain. Second, the authors have to choose a parametric form for the utility function.

---

To elicit the probability (or event) weight and parameters related that define the selected utility function, the researcher collects certainty equivalents  $ce_g^+$  for  $N$  non-mixed binaries lotteries  $L_g = (x_g, y_g; \bar{p}, 1 - \bar{p})$  that involves different outcomes ( $x_g$  and  $y_g$ ) and the fixed probability  $\bar{p}$ , with  $g = 1, 2, \dots, N$ . Under cumulative prospect theory, these certainty equivalents satisfy:

$$ce_g^+ = u^{-1} \left( \eta^+ u(x_g) + (1 - \eta^+) u(y_g) \right) \quad (22)$$

with  $\eta^+ = w^+(\bar{p})$ . If for example, the authors choose  $\bar{p} = 0.5$  and the power utility function 15, the equation (22) becomes:

$$ce_g^+ = \left[ \eta^+ \left( x_g^\alpha - y_g^\alpha \right) + y_g^\alpha \right]^{1/\alpha} \quad (23)$$

with  $\eta^+ = w^+(0.5)$ . The parameter  $\alpha$  and  $\eta^+ = w^+(0.5)$  in the relation 23 can be estimated by nonlinear least squares.

### **Second Step: Utility and probability (or event) elicitation in the loss domain**

This step is similar to the previous one. The probability  $\underline{p}$  in the series of lottery  $L_g = (x_g, y_g; \underline{p}, 1 - \underline{p})$  indexes  $g = 1, 2, \dots, N$  that will be kept fixed throughout the elicitation of the utility function on the loss domain is such that  $\underline{p} = 1 - \bar{p}$ . This condition is necessary in the third step that elicits the loss aversion parameter. Second, the authors have to choose a parametric form for the utility function. Under prospect theory functional, the certainty equivalents of  $L_g = (x_g, y_g; \underline{p}, 1 - \underline{p})$  satisfy:

$$ce_g^- = u^{-1} \left( \eta^- u(x_g) + (1 - \eta^-) u(y_g) \right) \quad (24)$$

---

If authors have selected  $\bar{p} = 0.5$  in the first step and power utility function (15), the equation (24) becomes

$$ce_g^- = - \left[ \eta^- \left( (-x_g)^\beta - (-y_g)^\beta \right) + (-y_g)^\beta \right]^{1/\beta} \quad (25)$$

with  $\eta^- = w^-(0.5)$ . The parameter  $\beta$  and  $\eta^- = w^-(0.5)$  in the equation (25) can be estimated by nonlinear least squares.

### Third Step: Loss aversion elicitation

The elicitation of the loss aversion follows the same procedure as in the previous parametric methods.

This method has been applied by [Attema et al. \(2013\)](#) with an exponential utility function.

We can point out several limitations of this semi-parametric approach. First, the estimation results—namely the estimations of the loss aversion index and of the probability weight—depend on the choice of the utility function. Second, it allows us to know only one probability weight in each domain (gain and loss) so that the shape of the probability weighting function is not estimated.

[Abdellaoui et al. \(2011b\)](#) extends the method to the elicit a broader range of points of the probability weighting function. [Abdellaoui et al. \(2011b\)](#) start by eliciting the utility function and one probability weight as in [Abdellaoui et al. \(2008\)](#). Having the estimation of the utility function, they elicit the certainty equivalents  $ce_k$  for all desired probabilities  $p_k$ ,  $k = 1, 2, \dots, K$  as follows:

$$ce_k \sim (x_*, 0; p_k, 1 - p_k) \text{ for } k = 1, 2, \dots, K \quad (26)$$

---

with  $x_*$  a fixed outcome that belongs to the elicited utility domain. The probability weights can then be estimated as:

$$w^i(p_k) = \frac{u(ce_k)}{u(x_*)} \text{ for } k = 1, 2, \dots, K \quad (27)$$

The semi-parametric approach can be applied to uncertainty (e.g. [Baillon et al., 2018a](#); [Abdellaoui et al., 2011a](#)). The semi-parametric method of [Abdellaoui et al. \(2008\)](#) keeps all appealing properties of parametric methods. Nevertheless, when extending it as in [Abdellaoui et al. \(2011b\)](#) to estimate probability weighting function, the method is no longer error-robust (e.g. [Etchart-Vincent, 2004](#)).

### 0.2.3 Non-parametric approach

The non-parametric approach does not make any parametric assumption about the utility and the weighting functions. Several methods are proposed in this approach.

#### 0.2.3.1 The gamble-tradeoff method

The first nonparametric method that offers the possibility to elicit utility function in CPT frameworks is the *tradeoff* method proposed by [Wakker and Deneffe \(1996\)](#). The utility elicitation using the tradeoff method is applicable in uncertainty and risky contexts. [Abdellaoui \(2000\)](#), [Bleichrodt and Pinto \(2000\)](#) and [Etchart-Vincent \(2009a\)](#) have extended this tradeoff method to be able to estimate probability and/or event weights.

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**First step: The utility function**

The method consists in eliciting equally-spaced outcomes in terms of utility. To do this, two outcomes  $R$  and  $r$  that have the same sign are fixed. In addition, a probability  $p \in (0, 1)$  and initial outcome  $x_0$  are chosen. Once these values are chosen, the outcome  $x_1$  is elicited from the following indifference:

$$(x_0, R; p, 1 - p) \sim (x_1, r; p, 1 - p)$$

In the gain (resp. loss) domain the outcomes have to be chosen such that  $0 \leq r \leq R \leq x_0 \leq x_1$  (reps.  $0 \geq r \geq R \geq x_0 \geq x_1$ ). This indifference implies:

$$w^i(p) (u(x_1) - u(x_0)) = (1 - w^i(p)) (u(R) - u(r)) \quad (28)$$

After eliciting  $x_1$ , the outcome  $x_2$  is elicited from the following indifference:

$$(x_1, R; p, 1 - p) \sim (x_2, r; p, 1 - p)$$

This indifference implies in the gain domain:

$$w^i(p) (u(x_2) - u(x_1)) = (1 - w^i(p)) (u(R) - u(r)) \quad (29)$$

From equations 28 and 29, we have the following equality:

$$u(x_2) - u(x_1) = u(x_1) - u(x_0) \quad (30)$$

---

From equation 30,  $x_1$  is the midpoint of  $x_0$  and  $x_2$  in terms of utility<sup>2</sup>. The previous procedure is repeated to have the sequence of outcomes  $x_0, x_1, \dots, x_n$  with the following indifferences

$$(x_{j-1}, R; p, 1-p) \sim (x_j, r; p, 1-p) \quad , \quad j = 1, 2, \dots, n$$

By setting  $u(x_0) = 0$ ,  $u(x_n) = 1$  in the gain domain, the valuations of elicited outcomes in this domain are given by

$$u(x_j) = \frac{j}{n} \quad , \quad j = 1, 2, \dots, n \quad (31)$$

Proceeding similar thing in the loss domain by setting  $u(x_n) = -1$  leads to

$$u(x_j) = -\frac{j}{n} \quad , \quad j = 1, 2, \dots, n \quad (32)$$

## Second step: the weighting function

The gamble-tradeoff method does not specify how to estimate the weighting function. Authors like [Abdellaoui \(2000\)](#), [Bleichrodt and Pinto \(2000\)](#) and [Etchart-Vincent \(2009a\)](#) have extended the tradeoff-method to be able to estimate the weighting function.

After determining the sequence  $x_0, x_1, \dots, x_n$  from the tradeoff method, [Abdellaoui \(2000\)](#) proposed to elicit the sequence of probabilities  $p_1, p_2, \dots, p_{n-1}$  from the following indifferences

$$(x_n, x_0; p_j, 1-p_j) \sim x_j$$

---

<sup>2</sup>Indeed, we remark that  $u(x_1) = \frac{u(x_0) + u(x_2)}{2}$



---

From these indifferences, the weighting function is given by

$$w^i(p_j) = \frac{u(x_j) - u(x_0)}{u(x_n) - u(x_0)} = \frac{j}{n} \quad , \quad j = 1, 2, \dots, n - 1 \quad (33)$$

Also, [Bleichrodt and Pinto \(2000\)](#) proposed another way to elicit the weighting function after determining the sequence  $x_0, x_1, \dots, x_n$  from the tradeoff method. The authors proposed to determine probability weights with two types of questions. For any low probability  $p \in (0, 1)$ , the probability weight  $w^i(p)$  is elicited by asking for outcome  $\underline{z}$  such that:

$$(x_i, x_j; p, 1 - p) \sim (x_k, \underline{z}; p, 1 - p)$$

with  $x_k \geq x_i \geq x_j$  in the gain domain,  $x_k \leq x_i \leq x_j$  in the loss domain and  $x_k, x_i$  and  $x_j$  are elements of the sequence elicited in the tradeoff part. From the above indifference, the probability weight is given by

$$w^i(p) = \frac{u(x_j) - u(\underline{z})}{[u(x_j) - u(\underline{z})] + [u(x_k) - u(x_i)]} \quad (34)$$

Similarly, for any higher probability  $p \in (0, 1)$ , the probability weight  $w^i(p)$  is elicited by asking for outcome  $\bar{z}$  in the following indifference:

$$(x_m, x_n; p, 1 - p) \sim (x_q, \bar{z}; p, 1 - p)$$

with  $x_m \geq x_n \geq x_q$  in the gain domain,  $x_m \leq x_n \leq x_q$  in the loss domain and  $x_m, x_n$  and  $x_q$  elements of the sequence elicited in the tradeoff part. The above indifference implies that the probability weight is given by

$$w^i(p) = \frac{u(x_n) - u(x_q)}{[u(\bar{z}) - u(x_m)] + [u(x_n) - u(x_q)]} \quad (35)$$

---

The elicited outcomes  $\bar{z}$  and  $\underline{z}$  do not necessary belong to the sequence of outcomes elicited in the tradeoff part. In this case their utilities are estimated from the utilities of elements of the sequence obtained in the tradeoff part. More precisely, a linear approximation is performed or parametric assumptions are made on utility function to obtain utilities of  $\bar{z}$  and  $\underline{z}$  when these outcomes do not belong to the sequence of outcomes. Doing so, this probability weighting function elicitation is semi-parametric<sup>3</sup> as that of [Etchart-Vincent \(2009a\)](#).

The method of [Etchart-Vincent \(2009a\)](#) consists in determining  $CE_j$  for any fixed probability  $p_j$  with the following indifference

$$CE_j \sim (x_k, x_i; p_j, 1 - p_j) \quad (36)$$

with  $x_i \leq CE_j \leq x_k$  in the gain domain,  $x_k \leq CE_j \leq x_i$  in the loss domain and  $x_k, x_i$  are elements of the standard sequence elicited in the tradeoff part. This indifference implies:

$$w^i(p_j) = \frac{u(CE_j) - u(x_i)}{u(x_k) - u(x_i)} \quad (37)$$

so that

$$w^-(p_j) = \frac{n u(CE_j) + i}{i - k} \quad (38)$$

$$w^+(p_j) = \frac{n u(CE_j) - i}{k - i} \quad (39)$$

---

<sup>3</sup>The methods of [Bleichrodt and Pinto \(2000\)](#) and [Etchart-Vincent \(2009a\)](#) start by eliciting nonparametrically utility points using the tradeoff method. To elicit probability weights, they make use of parametric fits or linear interpolation to the nonparametric utility points obtained from the tradeoff method. The use of parametric fit (resp. linear interpolation) to find utility value to compute a probability weight make the probability weight dependent on the non linear utility function (resp. linear utility function over small interval) used to fit data. Doing so these methods are semi-parametric even though [Bleichrodt and Pinto \(2000\)](#) qualify their method to be parameter-free.

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When choosing  $x_k = x_n$  and  $x_i = x_0$  as in [Etchart-Vincent \(2004\)](#), then  $w^-(p_j) = -u(CE_j)$  and  $w^+(p_j) = u(CE_j)$ . As in the case of [Bleichrodt and Pinto \(2000\)](#), the  $CE_j$  is unlikely to be an element of the previously elicited sequence. Hence,  $u(CE_j)$  is estimated from parametric fitting of utility points obtained from elements of the sequence (in the tradeoff part).

These methods are neither error-robust nor easy. Furthermore, it is worth to mention that the utility function in the gain domain (31) and that in the loss domain (32) are not linked since they are elicited separately. This is due to the fact that two values on the utility function (in addition to the utility of the reference point) — *i.e.*  $u(x_n) = 1$  in the gain domain and  $u(x_n) = -1$  in the loss domain— are chosen. To link between the utility in the gain domain to the utility in the loss domain, only one value on the utility function has to be chosen and so that all the other values only depend on this choice. Consequently, these methods do not allow for the elicitation of *loss aversion*.

### 0.2.3.2 Method of mirror image applicable only in a risky context

[Abdellaoui et al. \(2007b\)](#) provided the first non-parametric method to elicit the utility functions in the gain and loss domains that are linked so that they allow for the estimation of loss aversion. This method is applicable only in decision under risk. The method elicits the probability that has one-half as weight and utility function in the full domain (loss and gain simultaneously) in four steps. The summary of the method is given in table 1.

**First step:** Elicitation of  $p_g$  and  $p_\ell$  with  $w^+(p_g) = 0.5$  and  $w^-(p_\ell) = 0.5$

Table 1: Four-Step Elicitation Procedure of Abdellaoui et al. (2007b)

Assessed quantity	Indifference	Under CPT	Choice variables*
Elicitation of $p_\ell$ and $p_g$ such that $w^-(p_\ell) = 0.5$ and $w^+(p_g) = 0.5$			
Step 1			
Loss domain			
$x_1$	$(x_0, R; p, 1-p) \sim (x_1, r; p, 1-p)$	$u(x_2) - u(x_1) = u(x_1) - u(x_0)$	$p = 0.33$
$x_2$	$(x_1, R; p, 1-p) \sim (x_2, r; p, 1-p)$		$r = -100$
$p_\ell$	$x_1 \sim (x_2, x_0; p_\ell, 1-p_\ell)$	$w^-(p_\ell) = 0.5$	$R = -600$
			$x_0 = -1000$
Gain domain			
$x_1$	$(x_0, R; p, 1-p) \sim (x_1, r; p, 1-p)$	$u(x_2) - u(x_1) = u(x_1) - u(x_0)$	$p = 0.33$
$x_2$	$(x_1, R; p, 1-p) \sim (x_2, r; p, 1-p)$		$r = 100$
$p_g$	$x_1 \sim (x_2, x_0; p_g, 1-p_g)$	$w^+(p_g) = 0.5$	$R = 600$
			$x_0 = 1000$
Elicitation of utility function			
Step 2	$L_r \in [L_1, 0]$	$L_r \sim (L_A, L_B; p_\ell, 1-p_\ell)$	$u(L_r) = 0.5u(L_A) + 0.5u(L_B)$
			$L_1 = -100,000$
Step 3	$\ell$	$L_1 \sim (\ell, 0; 0.5, 0.5)$	$u(\ell)w^-(0.5) = -1$
	$g$	$0 \sim (\ell, g; 0.5, 0.5)$	$u(g)w^+(0.5) = 1$
	$G_1$	$G_1 \sim (g, 0; 0.5, 0.5)$	$u(G_1) = u(g)w^+(0.5) = 1$
Step 4	$G_r \in [0, G_1]$	$G_r \sim (G_A, G_B; p_g, 1-p_g)$	$u(G_r) = 0.5u(G_A) + 0.5u(G_B)$

\* All monetary amounts are in French francs (FF).

Each elicitation requires three indifferences. First, three outcomes  $x_0$ ,  $x_1$  and  $x_2$  equally spaced in terms of utility are elicited by using (28) and (29) as in the tradeoff method. These two indifferences entail

$$u(x_1) = 0.5u(x_0) + 0.5u(x_2) \quad (40)$$

In the case of the loss domain, where  $x_2 \leq x_1 \leq x_0$ ,  $p_\ell$  is elicited with the following indifference

$$(x_2, x_0; p_\ell, 1-p_\ell) \sim x_1$$

This indifference entails

$$u(x_1) = w^-(p_\ell)u(x_2) + (1-w^-(p_\ell))u(x_0) \quad (41)$$

---

Using (40) and (41), by identification,  $w^-(p_\ell) = 0.5$  as wanted. We proceed similarly in the gain domain, where  $x_2 \geq x_1 \geq x_0$ .

**Second step:** Elicitation of utility in the loss domain

Once  $p_\ell$  is known from the first step, the utility midpoint of any two losses  $L_A$  and  $L_B$  for which the utilities are already known can be measured by eliciting just one indifference. By the uniqueness properties of the utility function in prospect theory, we can fix a loss  $L_1 < 0$  and set

$$u(L_1) = -1 \tag{42}$$

This allows the elicitation of the outcome  $L_{0.5}$  such that  $u(L_{0.5}) = -0.5$  by looking for the indifference  $(L_1, 0; p_\ell, 1 - p_\ell) \sim L_{0.5}$ . This process is used to elicit utility on the interval  $[L_1, 0]$ . For example, by setting  $L_A = 1$  and  $L_B = L_{0.5}$ , the outcome  $L_{0.75}$  such that  $u(L_{0.75}) = -0.75$  can be elicited via the following indifference  $(L_1, L_{0.5}; p_\ell, 1 - p_\ell) \sim L_{0.75}$ .

**Third step:** Mirror image technique to link the utility between the two domains

In the third step, utility in the loss domain is linked to utility in the gain domain by eliciting three indifferences. The first indifference consists in taking one of the outcomes that was obtained in the step 2, say  $L_1$ , and elicit  $\ell$  that satisfies  $(\ell, 0; 0.5, 0.5) \sim L_1$ . This indifference implies

$$u(\ell)w^-(0.5) = -1 \tag{43}$$

---

The second indifference consists in eliciting a gain  $g$  that satisfies  $(\ell, g; 0.5, 0.5) \sim 0$ . This indifference implies:

$$u(g)w^+(0.5) = 1 \tag{44}$$

Finally the gain  $G_1$  is elicited from the following indifference  $(g, 0; 0.5, 0.5) \sim G_1$ . This indifference implies

$$u(G_1) = 1 \tag{45}$$

$G_1$  has utility 1 and is the “mirror image” of  $L_1$  in terms of utility.

**Fourth step:**

Once  $p_g$  and  $G_1$  are elicited from step 1 and step 3, the fourth and final step of the elicitation determines utility on the interval  $[0, G_1]$  in a similar way as it is done in the loss domain in step 2.

Even though this method elicits utility function simultaneously in the gain and loss domains and then offer the possibility to estimate loss aversion, this method has three drawbacks. First, this method is not applicable in uncertainty contexts. Recognizing this limitation, [Abdellaoui et al. \(2016\)](#) extend this method in uncertainty contexts. Second, the method only tells us how to elicit probabilities that have a weight of 0.5. We can point out two solutions to this drawback. The first solution is to follow [Abdellaoui \(2000\)](#) procedure to elicit other points in the weighting function. The second solution is to generalize how  $w^+(p_g) = 0.5$  and  $w^-(p_\ell) = 0.5$  are elicited in the first step of this method as it is the case in the midweight method proposed by [Van De Kuilen and Wakker \(2011\)](#). The third drawback that this method shares with the previous

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(Abdellaoui, 2000; Bleichrodt and Pinto, 2000; Etchart-Vincent, 2009a) is due to the fact that before completely eliciting the weighting function, the utility function has to be elicited. This can be time-consuming for the experimenter if he is only interested in eliciting some features of the weighting function. It was the case for example of Etchart-Vincent (2009a,b). To avoid this, it is important to have a method that allows to elicit the weighting function without knowing utility function. The midweight method proposed by Van De Kuilen and Wakker (2011) was an important contribution in that direction.

### 0.2.3.3 Method of mirror image applicable in risky and uncertainty contexts

Since the mirror image method of Abdellaoui et al. (2007b) is only applicable in decision under risk, Abdellaoui et al. (2016) extended this method so that it could be applied in uncertainty and risky contexts.<sup>4</sup> As pointed out by Abdellaoui et al. (2016) and Bleichrodt et al. (2018), this method constitutes the first one that makes it possible to completely measure all the ingredients of prospect theory without making simplifying assumptions. The method is split in three steps.

#### First step: Connecting utility for gains and utility for losses (mirror image step)

This step determines the loss  $x_1^-$  and a gain  $x_1^+$  that have the same utility (in absolute value). The steps start by fixing a gain  $X$  and an event  $E$  (or probability  $p$  in a risky context). Then, the loss  $Y$  that satisfies the following indifference is elicited

$$0 \sim (X, Y; E, E^c) \tag{46}$$

---

<sup>4</sup>Blavatsky (2021) proposes a similar procedure.

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This indifference means

$$w^+(E)u(X) + w^-(E^c)u(Y) = u(0) = 0 \quad (47)$$

The gain  $x_1^+$  is determined from the following indifference

$$x_1^+ \sim (X, 0; E, E^c) \quad (48)$$

so that

$$u(x_1^+) = w^+(E)u(X) \quad (49)$$

The loss  $x_1^-$  is determined from the following indifference

$$x_1^- \sim (Y, 0; E^c, E) \quad (50)$$

so that

$$u(x_1^-) = w^-(E^c)u(Y) \quad (51)$$

The relations (47), (49) and (51) imply:

$$u(x_1^+) = -u(x_1^-) \quad (52)$$

### Second step: Measurement of utility for gains

The second step serves to elicit the remainder standard sequence of gains, *i.e.*  $x_2^+, x_3^+, x_1^+, \dots, x_n^+$ . The step starts by fixing a loss  $\ell$  and eliciting the loss  $\mathcal{L} < \ell$  that satisfies:

$$(x_1^+, \mathcal{L}; E, E^c) \sim (\ell, 0; E^c, E) \quad (53)$$

so that

$$w^+(E)u(x_1^+) + w^-(E^c)u(\mathcal{L}) = w^-(E^c)u(\ell) \quad (54)$$



---

or equivalently

$$u(x_1^+) - \underbrace{u(0)}_{=0} = \frac{w^-(E^c)}{w^+(E)} (u(\ell) - u(\mathcal{L})) \quad (55)$$

Next, the gain  $x_2^+$  is elicited with the following indifference

$$(x_2^+, \mathcal{L}; E, E^c) \sim (x_1^+, \ell; E, E^c) \quad (56)$$

so that

$$w^+(E)u(x_2^+) + w^-(E^c)u(\mathcal{L}) = w^+(E)u(x_1^+) + w^-(E^c)u(\ell) \quad (57)$$

or equivalently

$$u(x_2^+) - u(x_1^+) = \frac{w^-(E^c)}{w^+(E)} (u(\ell) - u(\mathcal{L})) \quad (58)$$

Then, we continue the elicitation sequentially as follows:

$$(x_j^+, \mathcal{L}; E, E^c) \sim (x_{j-1}^+, \ell; E, E^c) \quad , \quad j = 2, 3, \dots, n \quad (59)$$

so as to get

$$u(x_j^+) - u(x_{j-1}^+) = \frac{w^-(E^c)}{w^+(E)} (u(\ell) - u(\mathcal{L})) \quad (60)$$

Relations (55) and (60) imply that  $0, x_1^+, x_2^+, x_3^+, x_1^+, \dots, x_n^+$  is a standard sequence of gains, that is  $0, x_1^+, x_2^+, x_3^+, x_1^+, \dots, x_n^+$  are equally spaced in term of utility

$$u(x_1^+) - u(0) = u(x_j^+) - u(x_{j-1}^+) \quad , \quad j = 2, 3, \dots, n \quad (61)$$

$u(0) = 0$  and  $u(x_n^+) = 1$  lead to

$$u(x_j^+) = \frac{j}{n} \quad , \quad \text{for } j = 1, 2, \dots, n \quad (62)$$

---

### Third step: Measurement of utility for losses

Similar to the second step, the third steps serves to elicit the remainder standard sequence of losses, *i.e.*  $x_1^-, x_2^-, x_3^-, \dots, x_n^-$ . The step starts by fixing a gain  $g$  and eliciting the gain  $\mathcal{G} > g$  that satisfies

$$(\mathcal{G}, x_1^-; E, E^c) \sim (g, 0; E, E^c) \quad (63)$$

so that

$$w^+(E)u(\mathcal{G}) + w^-(E^c)u(x_1^-) = w^+(E)u(g) \quad (64)$$

or equivalently

$$\underbrace{u(0)}_{=0} - u(x_1^-) = \frac{w^+(E)}{w^-(E^c)} (u(\mathcal{G}) - u(g)) \quad (65)$$

Next, the loss  $x_2^-$  is elicited with the following indifference

$$(\mathcal{G}, x_2^-; E, E^c) \sim (g, x_1^-; E, E^c) \quad (66)$$

so that

$$w^+(E)u(\mathcal{G}) + w^-(E^c)u(x_2^-) = w^+(E)u(g) + w^-(E^c)u(x_1^-) \quad (67)$$

or equivalently

$$u(x_1^-) - u(x_2^-) = \frac{w^+(E)}{w^-(E^c)} (u(\mathcal{G}) - u(g)) \quad (68)$$

Then, we continue the elicitation sequentially as follows:

$$(\mathcal{G}, x_j^-; E, E^c) \sim (g, x_{j-1}^-; E, E^c) \quad , \quad j = 2, 3, \dots, n \quad (69)$$

---

so as to get

$$u(x_{j-1}^-) - u(x_j^-) = \frac{w^+(E)}{w^-(E^c)} (u(\mathcal{G}) - u(g)) \quad (70)$$

Relations (68) and (70) imply that  $0, x_1^-, x_2^-, x_3^-, x_1^-, \dots, x_n^-$  is a standard sequence of losses, that is:

$$u(0) - u(x_1^-) = u(x_{j-1}^-) - u(x_j^-) \quad , \quad j = 2, 3, \dots, n \quad (71)$$

Because  $u(0) = 0$  and  $u(x_1^+) = \frac{1}{n}$ , it follows from the first step that  $u(x_1^-) = -\frac{1}{n}$ . So, it also follows from (71) that:

$$u(x_j^-) = -\frac{j}{n} \quad , \quad \text{for } j = 1, 2, \dots, n \quad (72)$$

[Attema et al. \(2018\)](#) and [Bleichrodt et al. \(2018\)](#) complete this method by one further step to elicit probability (or event) weights. This fourth step consists in determining the following indifference

$$x_E^+ \sim (x_n^+, 0; E, E^c) \quad \text{and} \quad x_E^- \sim (x_n^-, 0; E, E^c) \quad (73)$$

These indifferences means that

$$w^+(E) = u(x_E^+) \quad \text{and} \quad w^-(E) = -u(x_E^-) \quad (74)$$

The values of  $u(x_E^+)$  and  $u(x_E^-)$  are approximated using the utility function elicited in steps 2 and 3. This way to elicit probability (or event) weight can also be found in [Etchart-Vincent \(2004, 2009a\)](#). Finally, it is worth to notice that this method is neither easy nor error-robust.

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#### 0.2.3.4 Midweight method

The midweight method proposed by [Van De Kuilen and Wakker \(2011\)](#) allows to elicit weighting function when the utility midpoint for at least one pair of outcomes is known. This method is applicable both in risky and uncertainty context.

In the risky context, this method can be viewed as a generalization of how the probability that has one half as weight is elicited in [Abdellaoui et al. \(2007b\)](#) and can be split in two steps.

##### **First step:**

The first step consists in determining the sequence of three outcomes  $x_0$ ,  $x_1$ ,  $x_2$  equally spaced in terms of utility by the *tradeoff* method proposed by [Wakker and Deneffe \(1996\)](#) to obtain the equation 40. Recall this equation:

$$u(x_1) = \frac{u(x_2) + u(x_0)}{2} \quad (75)$$

with  $x_0 < x_1 < x_2$  in gain domain and  $x_2 < x_1 < x_0$  in the loss domain.

##### **Second step:**

Once  $x_0$ ,  $x_1$  and  $x_2$  are determined in the first step, the method generalizes the relation (41) in [Abdellaoui et al. \(2007b\)](#). Formally, a lottery  $L = (x_2, x_1, x_0; p_2, p_1, p_0)$  is constructed and the quantity  $\epsilon$  is determined by looking for the following indifference

$$(x_2, x_1, x_0; p_2, p_1, p_0) \sim (x_2, x_0; p_2 + \epsilon, p_0 + p_1 - \epsilon) \quad (76)$$

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This indifference implies

$$u(x_1) = \left( \frac{w^i(p_2 + \epsilon) - w^i(p_2)}{w^i(p_2 + p_1) - w^i(p_2)} \right) u(x_2) + \left( 1 - \frac{w^i(p_2 + \epsilon) - w^i(p_2)}{w^i(p_2 + p_1) - w^i(p_2)} \right) u(x_0) \quad (77)$$

Using 75 and 77, by identification  $p_2$ ,  $p_2 + \epsilon$  and  $p_2 + p_1$  are equally spaced in terms of weight  $w^i$  as follows

$$w^i(p_2 + \epsilon) = \frac{w^i(p_2) + w^i(p_2 + p_1)}{2} \quad (78)$$

To use this formula, the weight of  $p_2$  and  $p_2 + p_1$  have to be known before computing  $w^i(p_2 + \epsilon)$ . Then, the experimenter has to start with the case  $(p_0, p_1, p_2) = (0, 1, 0)$  that corresponds to eliciting  $\epsilon$  so that  $w^i(\epsilon) = 0.5$ . Then, use this  $\epsilon$  to elicit other points on the weighting function and so on.

We can point out two drawbacks for this method. First, it only minimizes the need to elicit the utility function before eliciting the weighting function because the utility midpoint for at least one pair of outcomes is still required. Second this method does not allow direct measurement of the weight of any desired probability  $p$  in  $(0, 1)$ . For example, if the experimenter is only interested to measure the weight  $w^i(p)$  of  $p = 0.2$ , the midweight method will force him to elicit several points of the weighting function before reaching  $w^i(0.2)$ . This kind of criticism applies also to Abdellaoui (2000). Again, this can be particularly time-consuming for the experimenter.

Similarly to the decision under risk, one can elicit three outcomes  $x_0, x_1, x_2$  equally spaced in terms of utility by the *tradeoff* method proposed by Wakker and Deneffe (1996) in a context of uncertainty. Once the outcomes  $x_0, x_1, x_2$

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are elicited, the events  $G \subset D$  and  $B \subset D$  with  $D = G \cup B$  are determined as follows

$$(x_2, x_1, x_0; A, D, C) \sim (x_2, x_0; A \cup G, C \cup B) \quad (79)$$

This indifference implies under CPT that:

$$w^i(A \cup G) = \frac{w^i(A) + w^i(D \cup A)}{2} \quad (80)$$

Similar to the risky context, this formula can be used by starting with  $(A, D, C) = (\emptyset, \Omega, \emptyset)$  so as to exploit the fact that  $w^i(\emptyset) = 0$  and  $w^i(\Omega) = 1$ .

A main drawback of the midweight method under uncertainty is that it is not always applicable. In fact, to be able to elicit  $G$  and  $B$  in the indifference 79, the event space  $\Omega$  needs to be sufficiently rich such as a continuum (Van De Kuilen and Wakker, 2011). Thus, if for example the event space  $\Omega$  contains only two events the midweight method will not be able to provide the probability (or event) weights for that events. Finally, it is worth to notice that this method is neither easy nor not error-robust.

### 0.2.3.5 Alternating least squares estimation method

This method is proposed by Gonzalez and Wu (1999). To implement this method, the experimenter fixes the probabilities  $p_1, p_2, \dots, p_K$  for which he wants to elicit probability weights. He also fixes  $n$  pairs of positive (or negative) outcomes  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$  with  $0 \leq y_j < x_j, j = 1, 2, \dots, n$ . The experimenter elicits the following  $K \times n$  certainty equivalents

$$ce_{jk} \sim (x_j, y_j; p_k, 1 - p_k) \text{ for } j = 1, 2, \dots, n \text{ and } k = 1, 2, \dots, K$$

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The method assumes the equation that characterizes the certainty equivalent with an additive and normally distributed error term at the scale of the utility  $u$  as follows:

$$u(ce_{jk}) = w^+(p_k)u(x_j) + (1 - w^+(p_k))u(y_j) + \epsilon_{u_{jk}} \quad (81)$$

The values of  $w^+(p_k)$ ,  $u(x_j)$  and  $u(y_j)$  are determined based on an alternating least squares estimation method. The idea of the estimation is the following. First, the starting values of  $w^+(p_k)$ ,  $u(x_j)$  and  $u(y_j)$  are chosen. Based on these starting values of  $u(x_j)$  and  $u(y_j)$ , the values of  $u(ce_{jk})$  are approximated through linear interpolation. Finally, the values of  $w^+(p_k)$ ,  $u(x_j)$  and  $u(y_j)$  are determined iteratively.

The method is error-robust and easy. However, the method is not data-efficient and tractable (Van De Kuilen and Wakker, 2011). Furthermore, the method is applicable in the gain and loss domains separately so that there is no link between utility function in the two domains. As such, loss aversion cannot be measured (Abdellaoui et al., 2007b). Most importantly, as pointed out by Van De Kuilen and Wakker (2011), this method is not data-efficient (*i.e.* inefficient) and tractable. More importantly, defining the response error at the utility scale is problematic because it produces solutions that are characterized by unrealistic concavity of the utility and probability weighting functions. To illustrate this point, suppose that we are interested in eliciting utility only over strictly positive outcomes with a power utility function  $u(z) = z^\alpha$ . For an extremely concave utility function (*i.e.*,  $\alpha > 0$  and  $\alpha \rightarrow 0$ ) and an extremely concave weighting function (*i.e.*,  $w^+(p_k) = 1$  for  $k = 1, 2, \dots, K$ ) along with the PT assumptions  $w^+(0) = 0$  and  $w^+(1) = 1$ , we have  $\epsilon_{u_{jk}} = 0$  for all

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$j = 1, 2, \dots, n$  and  $k = 1, 2, \dots, K$ . For the the aim of estimating  $u(z)$  for  $z \in A(z) \equiv \{\$25, \$50, \$75, \$100, \$150, \$200, \$400, \$800\}$  and the probability weights  $w^+(p)$  for  $p \in B(p) \equiv \{0.01, 0.05, 0.10, 0.25, 0.40, 0.50, 0.60, 0.75, 0.90, 0.95, 0.99\}$ , it follows that the combination of an extremely concave utility function (i.e.,  $u(z) = \text{constant} > 0$  for  $z \in A(z)$  and  $u(0) = 0$ ) and an extremely concave weighting function (i.e.,  $w^+(p) = 1$  for  $p \in B(p)$  and  $w^+(0) = 1 - w^+(p) = 0$ ) is the solution of the minimization of least squares estimation.

### 0.3 Aims and outline of the thesis

The thesis is at the intersection of behavioral economics and decision theory. It has two main objectives. The first is to develop new methods to estimate the different components of decision models under risk and under uncertainty. For risk, the idea is to develop new methods for estimating (i) utility function, (ii) probability weighting function and, (iii) loss aversion. In the case of uncertainty, a fourth component must also be measured: (iv) beliefs (i.e. subjective probabilities) that the decision maker forms about the different possible events. The second objective is to use these methods to understand in a concrete way the decision-making of individuals in various fields of economics. For this second objective, the thesis focuses on applications related to incentive setting and strategic uncertainty in game theory.

To provide further details, Chapter 1, co-authored with Brice Corgnet and Adam Zylbersztein, establishes a comprehensive semi-parametric method that satisfies the four desirable properties of parametric methods: tractable, data-efficient, error-robust, easy. Doing so, we develop a method that increases the precision of parameter estimates of parametric methods while being easy



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to implement and estimate. The method can be seen as an extension of the semi-parametric method of [Abdellaoui et al. \(2008\)](#) with respect to three points.

First, our method uses a single step to estimate the probability weights and the utility function in the full domain, whereas [Abdellaoui et al. \(2008\)](#) propose a two-step procedure. This feature of our method allows for testing several important restrictions (partial reflection, identical probability weighting functions across domains, and duality) as well as imposing these restrictions whenever necessary. Imposing partial reflection helps avoid the problem of arbitrary measurement of loss aversion with power utility functions (see [Wakker, 2010](#)). The method allows for testing and imposing identical probability weighting functions across domains (*i.e.*,  $w^+(p) = w^-(p)$ ) thus allowing us to test a key assumption of OPT. Also, the method allows for testing and imposing duality (*i.e.*,  $w^+(p) = 1 - w^-(1 - p)$ ).<sup>5</sup> By allowing us to impose duality as well as identical probability weighting across domains, our method can be applied under RDU ([Quiggin, 1982](#); [Gilboa, 1987](#); [Schmeidler, 1989](#)) and Original Prospect Theory ([Kahneman and Tversky, 1979](#)).

Second, unlike [Abdellaoui et al. \(2008\)](#), we can estimate multiple probability weights and thus elicit the shape of the probability weighting function. This is done without losing error-robustness.

Third, certainty equivalents for mixed prospects are obtained using a different procedure than the one proposed by ABL. In ABL, subjects are asked to provide a loss amount  $L$  for which they are indifferent between the status-quo (0) and a binary lottery  $(G, L; p_g, 1 - p_g)$  where  $G$  is a fixed gain and  $L \in (-\infty, 0]$  is a loss. In this elicitation procedure, the researcher does not know the lower bound of the loss interval. By contrast, our method keeps track of the upper and lower

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<sup>5</sup>As pointed out by [Abdellaoui \(2000, pp. 1509-1510\)](#), testing for duality with parametric methods and non-parametric methods based on the tradeoff approach requires using the specific probability weighting function of [Goldstein and Einhorn \(1987\)](#) and [Lattimore et al. \(1992\)](#).

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bounds of the loss interval because  $ce_k$  belongs to the interval  $(y_k, x_k)$ . This is an appealing property of our method for two reasons. First, asking subjects to provide indifference values on unbounded intervals can be cognitively demanding (Wakker and Deneffe, 1996; Abdellaoui et al., 2007b). This may lead to errors that potentially inflate the estimates of loss aversion, as reported by ABL (see Table 11, pp. 263-264). Second, eliciting indifference values on bounded intervals allows us to use a standard switching outcome procedure (Booij and Van de Kuilen, 2009).

Chapter 2, single-authored, establishes a nonparametric method for measuring utility function, weighting function and loss aversion under risk and uncertainty. It satisfies three desirable properties of parametric methods: *tractable*, *error-robust*, and *easy*. The method builds upon the smoothing spline literature. As such, the method is more data consuming than parametric methods (e.g. Ahamada and Flachaire, 2010; Green and Silverman, 1993). This method should thus be used in two main cases. First, behavioral studies often elicit few observations per subject. In such cases, the method can be used to derive estimates at the aggregate level by pooling subjects as in Tversky and Kahneman (1992). Second, the method can be performed at the individual level if the number of observations per subject is sufficiently large as in Gonzalez and Wu (1999). The method includes smooth parameters. These parameters allow to control for the collinearity between the value and weighting functions (e.g. Zeisberger et al., 2012; l'Haridon and Vieider, 2019) by penalizing deviation from the linear value function.

Chapter 3, co-authored with another PhD student Maria Alejandra Erazo Diaz, develops a new method to measure beliefs, utility function and weighting function towards events that are not necessarily equally likely and belong to a discrete set (i.e., discrete sources of uncertainty). It is a multi-stage method.

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In the first stage, we only specify utility and estimate events weights non-parametrically. Based on event weights from the first stage, the method allows to estimate the parameters of any weighting function. Our method thus allows for more flexibility in the parametric choices of weighting function in comparison to existing methods (e.g. Baillon et al., 2018b, 2021, 2018a) that rely on the neo-additive weighting function of Chateauneuf et al. (2007). Using simulations, we show that the multi-stage approach is more robust to misspecification issues than the one-stage approach that specifies simultaneously the functional form for the utility and weighting functions (e.g. Baillon et al., 2018a). The method is based on simple choices that involve the lowest possible number of outcomes (i.e., three). As such, this method is easy for subjects, compared to methods that are based on *exchangeable events* or *matching probabilities* (e.g. Baillon et al., 2018b; Gutierrez and Kemel, 2021; Abdellaoui et al., 2020), in which each choice involves four outcomes (Kpegli et al., 2023; Abdellaoui et al., 2008). Finally, contrary to previous methods (e.g. Baillon et al., 2018b,a), our method accounts for response errors that are pervasive in experimental data (Kpegli et al., 2023). We implement the method experimentally to both equal and different sources of uncertainty in two contexts: trust and coordination games. The method successfully passes validity tests and provides plausible results, showing the reliability of the results derived from it. People are more insensitive to likelihood in the presence of asymmetric events than symmetric events, suggesting that belief formation is cognitively demanding. For equal sources of uncertainty, people exhibit *payoff dependence aversion* and *variety of payoffs seeking*. *Payoff dependence aversion* means that people dislike that their own payoffs depend on the preferences of others. This behavior is captured by a more concave utility function. *Variety of payoffs seeking* means that subjects prefer a greater number

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of possible payoffs when such possible payoffs depend on the preferences of others. This behavior is captured by more optimism.

Chapter 4, co-authored with Brice Corgnet, Roberto Hernán-González and Adam Zylbersztejn, provides new insights about the Risk Incentives Tradeoff (RIT) originally established under EUT. The RIT is a fundamental result of principal-agent theory (e.g. [Holmström, 1979](#); [Milgrom and Roberts, 1992](#)). Yet, empirical evidence has been elusive ([Corgnet and Hernan-Gonzalez, 2019](#); [Dohmen et al., 2021](#)). This could be due to a lack of robustness of the theory outside of the standard expected utility framework (EUT) or to confounding factors in the empirical tests. We first study RIT under alternative theories: Rank-Dependent Utility (RDU) and Mean-Variance-Skewness (MVS). We show that, under RDU, RIT is remarkably pervasive because it applies not only when agents are risk-averse but also when they are risk-neutral or risk-seeking. For example, RIT is present when risk-neutral or risk-seeking agents who are moderately risk-seeking in the probability domain (i.e., they moderately overweight probabilities) are risk-averse in the utility domain (i.e., their utility is concave). This result suggests RIT might be more widespread than predicted by EUT. This observation contrasts with the limited empirical evidence for RIT. However, MVS provides a setup in which, in line with existing evidence, RIT is less pervasive. Although RIT applies whenever agents are risk-averse under EUT, this is not the case under MVS. Indeed, RIT might not hold for risk-averse agents who value positive skewness. Furthermore, under MVS the optimal variable pay (fixed pay) can increase (decrease) with the shock, which is what we refer to as reversed RIT. This occurs when the distribution of the shock is positively skewed and the aversion to variance is less pronounced than the value of skewness for a risk-averse MVS agent.

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These theoretical results show that non-EUT models provide reasons for both hope and despair regarding the robustness of RIT. To test the predictions of the alternative theories, we develop a novel lab test of RIT to eliminate confounding factors. To do so, we directly elicit the minimum fixed pay agents are ready to accept given a value of the variable pay. In this setup, the focus is on agents' decisions because principals do not make contractual decisions (see e.g., [Dohmen et al., 2021](#)). This BareBone design (BB design, henceforth) allows us to discard confounding factors related to the risk attitudes of principals. It also eliminates any asymmetry of information between the principal and the agent whose preferences are unknown. We also use monetary effort instead of a real-effort task (e.g., [Anderhub et al., 2002](#); [Keser and Willinger, 2007](#); [Gächter and Königstein, 2009](#)) to discard other confounding factors often present in experimental data such as social motives and reference points (see [Corgnet and Hernan-Gonzalez, 2019](#)). More generally, our design is such that common confounding factors, such as organizational hierarchies, delegation, implicit incentives, tacit knowledge, uncertainty and market dynamics ([Jensen and Meckling, 1995](#); [Raith, 2008](#); [DeVaro and Kurtulus, 2010](#); [Edmans et al., 2012](#); [He et al., 2014](#)), are absent. We do not mean to underplay the importance of these confounding factors but implement a testbed for the basic mechanism underlying RIT. It follows that a lack of evidence supporting RIT in our setup would be a definitive blow for the theory. To ensure that our BB design can be used to study RIT, we analyze a BareBone (BB) principal-agent model.

Our experiment shows that RIT is remarkably robust and more pervasive than predicted by EUT. In line with RDU but in contrast with EUT and MVS, RIT arises even when agents are risk-seeking. This finding has direct implications for various applications of the theory in which agents are risk-seeking agents, as is the case of executive compensation ([Garen, 1994](#); [Edmans and Gabaix, 2011](#);

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[Edmans et al., 2012, 2017](#)) and highly-paid work packages ([Ma et al., 2019](#)). Risk-seeking is likely to be pervasive in these applications because of selection arguments ([MacCrimmon and Wehrung, 1990](#); [Brenner, 2015](#)). Furthermore, executive packages are often positively skewed due to, for example, the use of stock options ([Edmans et al., 2017](#)). As a result, an agent who appears to be risk-averse when rewarded according to linear contracts might appear to be risk-seeking when facing skewed compensation packages.

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# Chapter 1

## All at Once! A Comprehensive and Tractable Semi-Parametric Method to Elicit Prospect Theory Components

This chapter is based on a paper co-authored with Brice Corgnet and Adam Zylbersztejn.

## Abstract

Eliciting all the components of prospect theory –curvature of the utility function, weighting function and loss aversion– remains an open empirical challenge. We develop a semi-parametric method that keeps the tractability of parametric methods while providing more precise estimates. Applying the new method to the datasets of [Tversky and Kahneman \(1992\)](#) and [Bruhin et al. \(2010\)](#), we reject the convexity of the utility function in the loss domain and show that the probability weighting function does not exhibit duality and equality across domains, in line with cumulative prospect theory and in contrast with original prospect and rank dependent utility theories. Furthermore, our method highlights that the overweighting of tail probabilities is more pronounced in the gain domain than in the loss domain. Overall, our results show that the utility function varies little across domains, thus suggesting that probability distortions are key to capture differences in risk attitudes in the gain and loss domains.

**Keywords:** Prospect theory; semi-parametric elicitation; risk attitudes; weighting function; loss aversion.

**JEL codes :** D81, C91

## 1.1 Introduction

There is now a large body of empirical evidence showing systematic violations of expected utility theory (EUT; see [Starmer, 2000](#), for a review). The original version of prospect theory (OPT; see [Kahneman and Tversky, 1979](#), henceforth KT79) and its subsequent refinements, most notably cumulative prospect theory (CPT; see [Tversky and Kahneman, 1992](#), henceforth TK92), explain these empirical violations by introducing probability distortions ([Bleichrodt and Pinto, 2000](#)) and loss aversion ([Wakker, 2010](#)). Classical methods for eliciting risk attitudes (such as [Holt and Laury, 2002](#)) that are based on EUT may lead to biased estimates ([Abdellaoui et al. \(2011a\)](#) and [Abdellaoui et al. \(2008, Figure 1; henceforth ABL\)](#)) and produce incoherent results ([Bleichrodt et al., 2001; Hershey and Schoemaker, 1985](#)). New methods have thus been proposed that build on CPT instead of EUT (ABL). These methods fall into three broad categories: parametric (with parametric form of utility and probability weighting functions), semi-parametric (with parametric form of the utility function and parameter-free probability weighting function) and non-parametric (no parametric form for either function).

While all parametric methods rely on a parametric specification of both utility and probability weighting, they may differ in terms of the required data structures and the employed estimation procedures. The data used by parametric methods usually involve certainty equivalents (e.g. [Fehr-Duda et al., 2006; Bruhin et al., 2010; l'Haridon and Vieider, 2019, TK92](#)), binary choices (e.g. [Harrison and Rutström, 2008, 2009; Harrison and Swarthout, 2020](#)), as well as indifference between non-degenerate lotteries from the so-called tradeoff method ([Booij et al., 2010](#)). Then, commonplace estimation procedures range from simple arithmetic calculations ([Tanaka et al., 2010](#)) to more convoluted econometric techniques such as maximum likelihood estimation (MLE) (e.g. [Fehr-Duda et al., 2006;](#)

Stott, 2006; Harrison and Rutström, 2008, 2009; Harrison and Swarthout, 2020), nonlinear least squares (NLS)(e.g. TK92, Gonzalez and Wu, 1999, henceforth GW99), OLS (Fox and Poldrack, 2009), and Bayesian methods (e.g. Nilsson et al., 2011; Toubia et al., 2013; Murphy and ten Brincke, 2018; Spiliopoulos and Hertwig, 2019; Baillon et al., 2020; Gao et al., 2020).

Parametric methods are more often used in applied research than non-parametric and semi-parametric methods (ABL) because they have four appealing properties: *tractable*, *data-efficiency*, *easy* and *error-robust* (see Section 4.2 for definitions), which are associated with minimal data requirements and simple estimation procedures.

These virtues, however, come at a cost. First, empirical estimates are sensitive to the specification of the utility and probability weighting functions (Abdellaoui, 2000). Second, parametric methods only provide an overall measure of the goodness of fit of the model, rather than separate measures for each of its components – one for the utility function and one for the probability weighting function (see GW99).

The aim of this paper is to establish a comprehensive semi-parametric method that satisfies the four desirable properties of parametric methods (see Section 4.2 for definitions). Doing so, we develop a method that increases the precision of parameter estimates of parametric methods while being easy to implement and estimate. Our method also comes with an additional advantage because it can be implemented not only under CPT but also under OPT and alternative theories such as rank dependent utility theory (henceforth RDU; see Quiggin, 1982; Gilboa, 1987; Schmeidler, 1989)

This paper proceeds as follows. Section 4.2 outlines the existing semi-parametric and non-parametric methods. Section 4.3 presents our elicitation method under cumulative prospect theory. Section 1.4 focuses on identification



and misspecification. Section 4.4 provides two applications of the method. Section 3.7 concludes.

## 1.2 Existing semi-parametric and non-parametric methods

In this section, we review the existing semi- and non-parametric methods of eliciting risk attitudes under CPT. Table 1.1 provides an overview of these methods along the four desirable properties of parametric methods (*tractability*, *data-efficiency*, *easiness*, *error-robustness*) and *comprehensiveness*. We define these properties below.

**Tractable:** the method allows for estimating risk attitudes with standard tools, like OLS or NLS (Abdellaoui et al., 2007a, ABL).

**Error-robust:** the method accounts for the fact that subjects make response errors when answering questions (ABL).

**Easy (not cognitively demanding):** the method relies on *simple choices* involving the lowest possible number of outcomes, that is 3 (ABL). A useful benchmark comes from TK92 who ask their subjects to make *simple choices* between a sure outcome and binary lottery.

**Data-efficient:** the method requires few measurements (observations) to estimate the parameters of the utility function and the probability weights. As a rule of thumb, we take TK92 (with 28 measurements for 9 probability weights and one utility parameter per domain) as benchmark, and consider a method

data-efficient if it requires no more than three measurements per estimate of a probability weight.<sup>1</sup>

**Comprehensive:** Comprehensive: the method allows for estimating utility function, loss aversion and weighting function under risk (i.e. known probability) as well as under uncertainty (i.e. unknown probability).

The existing methods typically use the tradeoff approach of [Wakker and Deneffe \(1996\)](#) in three steps.<sup>2</sup> In the first step, the tradeoff method estimates the utility function by eliciting a sequence of outcomes  $(x_0, x_1, x_2, \dots, x_n)$  which are equally spaced in terms of utility:  $u(x_i) - u(x_{i-1}) = \text{constant}$  for  $i = 1, 2, \dots, n$ . In the second step, the utility function obtained in the first step is used to estimate the weighting function. If the utility function in the gain and loss domains is elicited on the same scale ([Abdellaoui et al., 2007b, 2016](#)), the loss aversion can then be inferred in a third step. The tradeoff method is not error-robust because it assumes that the first-step values  $(x_1, x_2, \dots, x_n)$  are elicited without errors. This assumption is particularly restrictive because the elicitation of these values is subject to error propagation: any error in the first-stage elicitation of a given value  $(x_i)$  affects the subsequent estimates of values  $(x_{i+1}, \dots, x_n)$ .<sup>3</sup> It

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<sup>1</sup>ABL use the term “efficient” instead. Since this property only relates to the physical resources (such as time and money) used for data collection, we coin the term *data-efficiency* to avoid confusion with the (unrelated) statistical notion of the efficiency of an estimator.

<sup>2</sup>See, e.g. [Abdellaoui \(2000\)](#); [Bleichrodt and Pinto \(2000\)](#); [Etchart-Vincent \(2004\)](#); [Abdellaoui et al. \(2007b\)](#); [Etchart-Vincent \(2009a\)](#); [Booij and Van de Kuilen \(2009\)](#); [Van De Kuilen and Wakker \(2011\)](#); [Abdellaoui et al. \(2016\)](#); [Attema et al. \(2018\)](#); [Bleichrodt et al. \(2018\)](#); [Blavatsky \(2021\)](#). The main reason of the popularity of the tradeoff method is that the elicitation of the utility function is robust to probability distortions.

<sup>3</sup>Another issue with the standard tradeoff method is strategic responding ([Harrison and Rutström, 2008](#); [Abdellaoui et al., 2020](#)). For the sake of illustration, suppose that the researcher is looking for outcomes  $x_1$  and  $x_2$  by eliciting a pair of chained indifference values  $x_1$  and  $x_2$  such that  $(x_1, \$1; 0.5, 0.5) \sim (\$10, \$5; 0.5, 0.5)$  and  $(x_2, \$1; 0.5, 0.5) \sim (x_1, \$5; 0.5, 0.5)$ . One of these four lotteries is picked at random for payoff at the end of the experiment. Hence, the decision-making problem boils down to calibrating the following lottery:  $R(x_1, x_2) = (\$1, \$5, \$10, x_1, x_2; 1/4, 1/4, 1/8, 1/4, 1/8)$ . This, in turn, provides incentives to overstate the values of  $x_1$  and  $x_2$ , since  $x_1^* > x_1$  and  $x_2^* > x_2$  yields a lottery  $R(x_1^*, x_2^*)$  that first-order

follows that semi-parametric and non-parametric elicitation techniques based on the tradeoff method are not error-robust (see Table 1.1). Moreover, ABL note that the complexity of the elicitation procedure makes the tradeoff method cognitively demanding.<sup>4</sup>

The literature proposes three notable alternatives to the tradeoff method (GW99; ABL; Abdellaoui et al., 2011c).<sup>5</sup> However, GW99 is not a comprehensive method because it does not elicit loss aversion. Also, Van De Kuilen and Wakker (2011) point to the lack of tractability and efficiency of this method. Furthermore, their method tends to produce an extremely concave (resp. convex) utility function in the gain (resp. loss) domain (see footnote 13).

The semi-parametric method of ABL, in turn, satisfies the four appealing properties of parametric methods, and provides information on the goodness of fit of the functional form chosen for estimating the utility function. Yet, ABL is not a comprehensive method because it cannot estimate the weighting function. Achieving comprehensiveness by including an additional step to estimate the weighting function, as in Abdellaoui et al. (2011c), comes at the cost of potentially multiplying response errors (Etchart-Vincent, 2004, pp. 221).

In addition, the approach in ABL and Abdellaoui et al. (2011c) has two caveats when it comes to measuring loss aversion. First, estimating the utility stochastically dominates  $R(x_1, x_2)$ . Recently, Johnson et al. (2019) have developed a new mechanism, called PRINCE, that alleviates this issue by *ex ante* fixing the real choice situation that determines the final payment.

<sup>4</sup>This is because under the tradeoff method subjects need to compare two binary lotteries, while other methods based on certainty equivalent elicitation only ask subjects to compare a certain amount with a binary lottery. Thus, the tradeoff method requires processing more information which makes it relatively cognitively demanding.

<sup>5</sup>A method related to Abdellaoui et al. (2011c) is the *source method* of Abdellaoui et al. (2011a) that allows for eliciting the source function and the utility function under the biseparable preference model of Ghirardato and Marinacci (2001). An additional assumption is that decision makers can assign subjective probabilities (*i.e.*, beliefs) to events even when they do not maximize subjective expected utility. Another method proposed by Bertani et al. (2019) elicits the probability weighting function. However, this method is restrictive because it is only valid for the dual theory of Yaari (1987) in which the utility function is assumed to be linear.

function separately in the gain and loss domains makes it impossible to impose partial reflection (*i.e.*, identical utility curvature in both domains) which is often required to circumvent the arbitrary measurement of loss aversion (see [Wakker, 2010](#), pp. 267-270).<sup>6</sup> By allowing for a joint estimation of the utility function in both domains, our method allows for testing and imposing partial reflection whenever needed.<sup>7</sup> The second problem, as pointed out by [Wakker and Deneffe \(1996, pp. 1148\)](#), comes from the fact that the elicitation of loss aversion in ABL and [Abdellaoui et al. \(2011c\)](#) is based on asking subjects to provide a loss amount  $L$  on an unbounded interval  $(-\infty, 0]$ . This procedure is more cognitively demanding than stating  $L$  on a bounded interval ([Abdellaoui et al., 2007b](#)). Then, not knowing the lowest possible value of the loss amount  $L$  could lead to large response errors that potentially inflate the estimates of loss aversion, as reported in ABL (see Table 11, pp. 263-264).

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<sup>6</sup>Note that this issue also applies to the parametric methods in TK92 and [Fehr-Duda et al. \(2006\)](#) which estimate the utility function in the gain and loss domains in two separate steps. Other parametric methods do not suffer from this problem ([Harrison and Rutström, 2008](#); [Post et al., 2008](#); [Tanaka et al., 2010](#)).

<sup>7</sup>With our one-step procedure, it is also possible to test whether the probability weighting functions are the same in the gain and loss domains. Outside the framework of CPT, our method also allows for testing the duality of the probability weighting function under RDU.

Table 1.1: Summary of literature on semi-parametric and non-parametric methods

Method or combination of methods	<i>Tractable</i>	<i>Data-efficient</i>	<i>Easy</i>	<i>Error-robust</i>	<i>Comprehensive</i>
Non-parametric methods based on tradeoff method					
Abdellaoui et al. (2007b) and Abdellaoui (2000)	Yes	Yes	No	No	No (only risk)
Abdellaoui et al. (2016)					
Bleichrodt et al. (2018) and Attema et al. (2018)	Yes	Yes	No	No	Yes
Van De Kuilen and Wakker (2011)	Yes	Yes	No	No	No (only $w$ )
Blavatsky (2021)	Yes	Yes	No	No	No (only $u$ and $\lambda$ )
Semi-parametric methods based on tradeoff method					
Etchart-Vincent (2004, 2009a)	Yes	Yes	No	No	No (only $u$ and $w$ )
Bleichrodt and Pinto (2000)	Yes	Yes	No	No	No (only $u$ and $w$ )
Chai and Ngai (2020)	Yes	Yes	No	No	No (only $w$ )
Non-parametric method <i>not</i> based on tradeoff method					
GW99	No	No	Yes	Yes	No (only $u$ and $w$ )
Semi-parametric methods <i>not</i> based on tradeoff method					
ABL	Yes	Yes	Yes	Yes	No (only $u$ and $\lambda$ )
Abdellaoui et al. (2011c)	Yes	Yes	Yes	No	Yes
<b>This paper</b>	Yes	Yes	Yes	Yes	Yes

## 1.3 Method

### 1.3.1 Notations

Consider a binary lottery  $L = (x, y; p, 1 - p)$  yielding outcome  $x$  with probability  $p$  and outcome  $y$  with probability  $1 - p$ , both outcomes being real numbers.<sup>8</sup> For notational convenience, let  $x > y \geq 0$  ( $x < y \leq 0$ ) for non-mixed prospects involving only gains (losses). For mixed prospects (*i.e.*, involving both gains and losses), let  $y < 0 < x$ .  $\succsim$  is a preference relation over prospects with  $\succ$  ( $\sim$ ) denoting strict preference (indifference). Preferences are represented by CPT with a probability weighting function  $w^i$  and a value function  $v$  as defined in equation (2.1) for non-mixed prospects and in equation (2.2) for the mixed ones:

$$CPT(L) = (v(x) - v(y)) w^i(p) + v(y) \quad (1.1)$$

$$CPT(L) = w^+(p)v(x) + w^-(1 - p)v(y) \quad (1.2)$$

where  $w^i$  and  $v$  are both continuous, strictly increasing and satisfying  $v(0) = 0$ ,  $w^i(0) = 0$  and  $w^i(1) = 1$ , and  $i = "+"$  ( $i = "-"$ ) stands for the gain (loss) domain.<sup>9</sup>

Following the seminal study by TK92, as well as the subsequent developments in Köbberling and Wakker (2005) and ABL, we assume that the value function  $v(\cdot)$  is composed of the loss aversion index  $\lambda > 0$  which reflects the exchange rate between gain and loss utility units, and the utility function  $u(\cdot)$  that reflects the intrinsic value of outcomes:

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<sup>8</sup>This notation is related to decision under risk. In the case of decisions under uncertainty, one would simply replace  $p$  and  $1 - p$  by  $E$  and  $E^c$  respectively.  $E$  denotes an event in a state space  $\Omega$  and  $E^c$  denotes its complement in  $\Omega$ . In that case,  $L = (x, y; E, E^c)$  is a binary prospect that gives outcome  $x$  if  $E$  occurs, and  $y$  otherwise.

<sup>9</sup>CPT makes no explicit link between weighting functions  $w^+(\cdot)$  and  $w^-(\cdot)$  which makes it more general than OPT in which  $w^+(p) = w^-(p)$ , or RDU that includes the duality condition  $w^+(p) = 1 - w^-(1 - p)$ .

$$v(x) = \begin{cases} u(x) & \text{if } x \geq 0 \\ \lambda u(x) & \text{if } x < 0 \end{cases} \quad (1.3)$$

However, without further assumptions, loss aversion ( $\lambda$ ) as defined in (1.3) is not empirically identifiable. Indeed, we can rescale the utility function  $u(\cdot)$  in the gain and loss domains with two different linear transformations  $u^*(x) = \rho u(x)$  for  $x \geq 0$  and  $u^*(x) = \tau u(x)$  for  $x < 0$ , so that we have a linear transformation  $v^*(x) = \rho v(x)$  for the value function by defining  $\lambda^* = \lambda \frac{\rho}{\tau}$  (Wakker, 2010, p. 248):

$$v^*(x) = \begin{cases} u^*(x) & \text{if } x \geq 0 \\ \lambda^* u^*(x) & \text{if } x < 0 \end{cases} \quad \text{with} \quad \lambda^* = \lambda \frac{\rho}{\tau}$$

As a result, as long as  $\rho \neq \tau$ , we have two different values for the loss aversion index ( $\lambda$  and  $\lambda^*$ ) that represent the same underlying preferences. However, one can avoid this arbitrary measurement of loss aversion using utility functions that are differentiable at 0 with  $u'(0) \neq 0$  (e.g. exponential utility in equation (3.17)). In the case of power utility functions (see equation (3.16)), the issue of identification of loss aversion is present unless *partial reflection* (i.e., identical utility curvature in the full domain) is imposed.

### 1.3.2 Elicitation

We start by considering two standard utility functions that have been previously shown to provide a good fit to experimental data: the power utility function (see, e.g. GW99; Stott, 2006) and the exponential utility function (see, e.g. Attema

et al., 2013).<sup>10</sup> Next, we detail the steps for estimating the probability weighting function, the curvature of the utility function, and the loss aversion index.

### 1.3.2.1 Utility function

As in [Booij et al. \(2010\)](#), we use the following notation for the power (3.16) and exponential (3.17) utility functions:

$$u(x) = (\mathbf{1}_{(x \geq 0)} - \mathbf{1}_{(x < 0)}) |x|^{\alpha_p \mathbf{1}_{(x \geq 0)} + \beta_p \mathbf{1}_{(x < 0)}} \quad (1.4)$$

$$u(x) = (\mathbf{1}_{(x \geq 0)} - \mathbf{1}_{(x < 0)}) \frac{1 - \exp\left((\beta_e \mathbf{1}_{(x < 0)} - \alpha_e \mathbf{1}_{(x \geq 0)})x\right)}{\alpha_e \mathbf{1}_{(x \geq 0)} + \beta_e \mathbf{1}_{(x < 0)}} \quad (1.5)$$

where  $\mathbf{1}_{(\cdot)}$  refers to the indicator function. The important properties of these functions are related to domain-specific curvature, loss aversion, and partial reflection, and can be summarized as follows. For gains (losses), the power function in (3.16) is concave if  $\alpha_p < 1$  ( $\beta_p > 1$ ), linear if  $\alpha_p = 1$  ( $\beta_p = 1$ ), and convex if  $\alpha_p > 1$  ( $\beta_p < 1$ ). For gains (losses), the exponential function in (3.17) is concave if  $\alpha_e > 0$  ( $\beta_e < 0$ ), linear if  $\alpha_e \rightarrow 0$  ( $\beta_e \rightarrow 0$ ), and convex if  $\alpha_e < 0$  ( $\beta_e > 0$ ). Furthermore, the two functions imply two different definitions of loss aversion. For (3.16), the loss aversion index is  $\lambda = -\frac{v(-\$1)}{v(\$1)}$  which corresponds to the standard definition in TK92. For (3.17), the loss aversion index is given by the definition in [Köbberling and Wakker \(2005\)](#), that is  $\lambda = \frac{v'_\uparrow(0)}{v'_\downarrow(0)}$  with  $v'_\uparrow(0)$  and  $v'_\downarrow(0)$  representing the left and right derivatives of the value function at the reference point.<sup>11</sup> Finally, partial reflection corresponds to  $\alpha_p = \beta_p$  and  $\alpha_e = \beta_e$  in (3.16) and (3.17).

In addition, we use the following method for curvature comparisons of different utility functions for a given interval, such as  $[0, \bar{x}]$  in the gain domain or  $[\underline{x}, 0]$  in

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<sup>10</sup>Note, however, that our method is compatible with any utility function.

<sup>11</sup>Regardless of the exact definition, it is always the case that loss aversion (loss seeking) corresponds to  $\lambda > 1$  ( $\lambda < 1$ ), whereas  $\lambda = 1$  captures loss neutrality.



the loss domain. We compute the following measure of utility curvature (see also [Abdellaoui et al., 2016](#)):

$$\alpha = \frac{1}{\bar{x}u(\bar{x})} \int_0^{\bar{x}} u(t)dt \quad \text{if} \quad \bar{x} \geq 0 \quad (1.6)$$

$$\beta = \frac{1}{\underline{x}u(\underline{x})} \int_{\underline{x}}^0 u(t)dt \quad \text{if} \quad \underline{x} < 0 \quad (1.7)$$

For power (exponential) utility function, this yields  $\alpha = \frac{1}{1+\alpha_p}$  and  $\beta = -\frac{1}{1+\beta_p}$   
(  $\alpha = \frac{1}{1-\exp(-\alpha_e \bar{x})} - \frac{1}{\alpha_e \bar{x}}$  and  $\beta = \frac{1}{\exp(\beta_e \underline{x})-1} - \frac{1}{\beta_e \underline{x}}$ .)

Then,  $\alpha > 0.5$  /  $\alpha = 0.5$  /  $\alpha < 0.5$  correspond to concave / linear / convex utility functions in the gain domain. In the loss domain we have  $\beta > -0.5$  /  $\beta = -0.5$  /  $\beta < -0.5$  that correspond to concave / linear / convex utility functions.

### 1.3.2.2 Estimating probability weighting functions and utility curvature

The first step of our estimation procedure consists of three parts. First, we select the set of probabilities  $\{p_k : k = 1, 2, \dots, K\}$  for which weights are estimated in the gain and loss domains, with  $p_k < p_{k+1}$ . For any  $p_k$ , its complement  $1 - p_k$  must also be included in the set of probabilities, so that  $p_{K-k+1} = 1 - p_k$  for  $k = 1, 2, \dots, K$ . Then, in a given domain, one elicits (at least) two certainty equivalents for each probability  $p_k$ :

$$ce_{j,k}^i \sim (x_{j,k}^i, y_{j,k}^i; p_k, 1 - p_k) \quad , \quad j = 1, 2, \dots, N_k^i \quad \text{and} \quad N_k^i \geq 2 \quad (1.8)$$

where  $N_k^i$  stands for the number of certainty equivalents for  $p_k$  in domain  $i \in \{“+”; “-”\}$ , and  $x_{j,k}^i$  and  $y_{j,k}^i$  are outcomes such that  $x_{j,k}^+ > y_{j,k}^+ \geq 0$  and  $x_{j,k}^- < y_{j,k}^- \leq 0$ .<sup>12</sup>

Thus, in total one needs to elicit  $N^+ = \sum_{k=1}^K N_k^+ \geq 2 \times K$  certainty equivalents in the gain domain and  $N^- = \sum_{k=1}^K N_k^- \geq 2 \times K$  certainty equivalents in the loss domain. For invertible  $u$  and using (2.1) and (1.3), these certainty equivalents satisfy the following condition:

$$ce_{j,k}^i = u^{-1} \left[ \left( u(x_{j,k}^i) - u(y_{j,k}^i) \right) w^i(p_k) + u(y_{j,k}^i) \right] \quad (1.9)$$

Let  $\mathbf{ce}$ ,  $\mathbf{x}$  and  $\mathbf{y}$  be column vectors containing all the realizations of  $ce_{j,k}^i$ ,  $x_{j,k}^i$  and  $y_{j,k}^i$ , respectively. Any column vector  $\mathbf{z} \in \{\mathbf{ce}, \mathbf{x}, \mathbf{y}\}$  is constructed as follows:

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<sup>12</sup>Note that having the same outcomes for each probability ( $x_{j,k}^i = x_j^i$  and  $y_{j,k}^i = y_j^i$  for all  $k$ ) allows for an immediate test of the monotonicity of preferences by checking if certainty equivalents increase with probabilities for given pairs of outcomes  $(x_j^i, y_j^i)$ . This choice of outcomes could also reduce the cognitive burden of the task.

$$z = \begin{pmatrix} z_1^+ \\ z_2^+ \\ \cdot \\ \cdot \\ z_K^+ \\ z_1^- \\ z_2^- \\ \cdot \\ \cdot \\ \cdot \\ z_K^- \end{pmatrix} \quad \text{with } z_k^+ = \begin{pmatrix} z_{1,k}^i \\ z_{2,k}^i \\ \cdot \\ \cdot \\ z_{N_k^i,k}^i \end{pmatrix}, i \in \{“+” ; “-”\} \text{ and } k = 1, 2, \dots, K$$

As in the literature (e.g. ABL; Hey et al., 2009; Bruhin et al., 2010, henceforth BFE10), we assume that certainty equivalents are observed with additive response error with mean 0. Thus, the empirical counterpart of (2.9) is given by:<sup>13</sup>

<sup>13</sup>An alternative approach would be to introduce the response error term at the utility level (GW99, eq. 7):  $u(\mathbf{c}e_l) = (u(\mathbf{x}_l) - u(\mathbf{y}_l)) \times \left( \sum_{k=1}^K (\delta_k^+ \mathbf{D}_l^+ + \delta_k^- \mathbf{D}_l^-) \mathbf{I}_l^k \right) + u(\mathbf{y}_l) + e_l^i$ .

However, defining the response error at the utility level is problematic when using certainty equivalents data because it produces solutions that are characterized by unrealistic concavity of the utility and probability weighting functions. To illustrate this point, suppose that we are interested in eliciting utility only over strictly positive outcomes with a power utility function  $u(z) = z^\alpha$ . For an extremely concave utility function (i.e.,  $\alpha > 0$  and  $\alpha \rightarrow 0$ ) and an extremely concave weighting function (i.e.,  $\delta_k^+ = 1$  for  $k = 1, 2, \dots, K$ ) along with the PT assumptions  $w^+(0) = 0$  and  $w^+(1) = 1$ , we have  $e_l^+ = 0$  for all  $l = 1, 2, \dots, N^+$ . For the non-parametric method of GW99 which aims at estimating  $u(z)$  for  $z \in A(z) \equiv \{\$25, \$50, \$75, \$100, \$150, \$200, \$400, \$800\}$  and the probability weights  $w(p)$  for  $p \in B(p) \equiv \{0.01, 0.05, 0.10, 0.25, 0.40, 0.50, 0.60, 0.75, 0.90, 0.95, 0.99\}$ , it follows that an extremely concave utility function (i.e.,  $u(z) = \text{constant} > 0$  for  $z \in A(z)$  and  $u(0) = 0$ ) and an extremely concave weighting function (i.e.,  $w(p) = 1$  for  $p \in B(p)$  and  $w(0) = 1 - w(p) = 0$ ) are solutions of the

$$\mathbf{ce}_l = u^{-1} \left[ (u(\mathbf{x}_l) - u(\mathbf{y}_l)) \times \left( \sum_{k=1}^K (\delta_k^+ \mathbf{D}_l^+ + \delta_k^- \mathbf{D}_l^-) \mathbf{I}_l^k \right) + u(\mathbf{y}_l) \right] + \mathbf{e}_l^i \quad (1.10)$$

where  $\mathbf{I}^k$  is a dummy variable set to 1 if the probability equals  $p_k$  and 0 otherwise,  $\mathbf{D}^+$  ( $\mathbf{D}^-$ ) is a dummy variable set to 1 for a positive (negative) certainty equivalent and 0 otherwise,  $\mathbf{e}^i$  the response error term and  $l$  is the  $l^{\text{th}}$  line in  $\mathbf{ce}$ ,  $\mathbf{x}$ ,  $\mathbf{y}$ ,  $\mathbf{I}^k$  and  $\mathbf{e}^i$ . Probability weights correspond to:<sup>14 15</sup>

$$w^+(p_k) = \delta_k^+ \quad \text{and} \quad w^-(p_k) = \delta_k^- \quad \text{for } k = 1, \dots, K \quad (1.11)$$

Note that  $u^{-1}$  in (1.10) should be written in the full domain. To do that, one can first write  $u$  in the full domain using indicator functions as in (3.16) and (3.17), and  $u^{-1}$  can be derived using standard algebra. Finally, the parameters in (1.10) can be estimated as long as one provides a functional form for  $u$  (and thus for  $u^{-1}$ ), such as (3.16) or (3.17).<sup>16</sup>

The estimation of equation (1.10) can be done with either NLS or MLE. Under standard assumptions of normally distributed error terms and homoscedasticity, optimization problem. A similar issue can be found in Section 4.3 of [Green and Silverman \(1993\)](#).

<sup>14</sup>Take a probability  $p_s$  for  $s \in 1, 2, \dots, K$ .  $\mathbf{I}_l^s$  equals 1 for any observation  $l$  that involves  $p_s$ , and all the other probability dummy variables  $\mathbf{I}_l^c$  for  $c \neq s$  are set to 0. In that case, we have  $\sum_{k=1}^K (\delta_k^+ \mathbf{D}_l^+ + \delta_k^- \mathbf{D}_l^-) \mathbf{I}_l^k = \delta_s^+ \mathbf{D}_l^+ + \delta_s^- \mathbf{D}_l^-$ . In the gain domain, the dummy variable  $\mathbf{D}_l^+$  equals 1 while  $\mathbf{D}_l^-$  equals 0 so that we get  $\sum_{k=1}^K (\delta_k^+ \mathbf{D}_l^+ + \delta_k^- \mathbf{D}_l^-) \mathbf{I}_l^k = \delta_s^+ \mathbf{D}_l^+ + \delta_s^- \mathbf{D}_l^- = \delta_s^+$ . Hence,  $w^+(p_k) = \delta_k^+$  in (1.10) for  $k = 1, 2, \dots, K$ . Analogously,  $w^-(p_k) = \delta_k^-$  in (1.10) for  $k = 1, 2, \dots, K$ .

<sup>15</sup>Note that we do not require monotonicity of the weighting function as is commonly done in the literature (see e.g. [GW99](#), p. 147). Requiring monotonicity in our method can be achieved by adding the following restriction on weights:  $\delta_k^i = \delta_1^i + \sum_{j=2}^k \exp(a_j^i)$  for  $k \geq 2$ . In this case, the estimated parameters are  $\delta_1^i, a_2^i, a_3^i, \dots, a_K^i$ .

<sup>16</sup>One can choose the functional form that best performs in terms of goodness of fit (e.g. [Hey and Orme, 1994](#); [Fehr-Duda et al., 2006](#); [Stott, 2006](#)).

both methods provide identical point estimates for risk-attitude components, with MLE being a more efficient method (see, e.g. [Wooldridge, 2010](#), p. 470).<sup>17</sup>

In addition, two sources of heteroscedasticity can be present at the level of individual data: the variance of the error term may vary (*i*) with respect to the range  $|x_l - y_l|$  of a lottery, but also (*ii*) across domains  $i = +, -$  (gains vs. losses). Both of them can be accounted for by MLE ([l'Haridon and Vieider, 2019](#), BFE10). Herein, we adopt a more general form of heteroscedasticity than these two studies by assuming that  $\sigma_{i,l} = \sigma_i |x_l - y_l|^\psi$  with  $\psi \geq 0$  where  $\psi \neq 0$  implies there is heteroscedasticity due to the range of outcomes.<sup>18</sup>

Our method allows us to account for these various sources of heteroscedasticity by applying MLE to equation (1.10). The log-likelihood function is:

$$\begin{aligned} \log L(\theta^i, \delta^i, \sigma_i, \psi) = & - (N^+ + N^-) \log(\sqrt{2\pi}) - \sum_{l=1}^{N^+ + N^-} \log(\sigma_i |\mathbf{x}_l - \mathbf{y}_l|^\psi) \\ & - \frac{1}{2} \sum_{l=1}^{N^+ + N^-} \left( \frac{e_l^i}{\sigma_i |\mathbf{x}_l - \mathbf{y}_l|^\psi} \right)^2 \end{aligned} \quad (1.12)$$

where  $\theta^i$  stands for the parameters associated with the utility function in domain  $i$ . Maximizing the log-likelihood with respect to all the parameters provides a simultaneous estimation of the utility function and probability weights for the gain and loss domains.

We use two criteria to assess the achieved goodness of fit: Akaike Information Criterion (AIC) and leave-one-out Cross Validation (CV). AIC is a standard measure in the literature (see, e.g. [Fehr-Duda et al., 2006](#); [Stott, 2006](#); [Hey and Orme, 1994](#)) and is given as  $AIC = 2n_p - 2\log L$ , where  $\log L$  is the log-

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<sup>17</sup>In Appendix 1.D, we also provide an illustration of how to apply Bayesian techniques with our semi-parametric method using data from [l'Haridon and Vieider \(2019\)](#).

<sup>18</sup>A third source of heteroscedasticity may arise at the aggregate level (pooled data) when the variance of response errors differs across individuals (e.g. [Harrison and Rutström, 2008, 2009](#); [l'Haridon and Vieider, 2019](#), BFE10)

likelihood function given in equation (1.12) and  $n_p$  is the total number of estimated parameters in the utility function, the probability weights and the variance of response error. For a one-parameter and domain-specific utility function (as in equations 3.16 and 3.17), there are  $n_p = 2K + 5$  parameters in the AIC computation:  $2K$  probability weights (gain and loss domains), 2 utility parameters (gain and loss domains), and 3 variance parameters  $\sigma_+$ ,  $\sigma_-$  and  $\psi$ . As a descriptive alternative to AIC, we also compute CV based on the following multi-step procedure (see, e.g. Baillon et al., 2020, for a similar approach). In each step, we estimate the model on  $N^+ + N^- - 1$  non-mixed lotteries and predict the certainty equivalent for the remaining (excluded) lottery. The (absolute) difference between the predicted and actual certainty equivalents is the (absolute) prediction error for that lottery. This out-of-sample prediction procedure is repeated over  $N^+ + N^-$  steps such that each lottery is left out of the sample once. Then, the value of the criterion is the mean absolute prediction error.

The certainty equivalent in equation (1.10) is given by equations (1.13) and (1.14) for power and exponential utility functions, respectively

$$ce_l = (D_l^+ - D_l^-) \left[ \left( |x_l|^{\alpha_p D_l^+ + \beta_p D_l^-} - |y_l|^{\alpha_p D_l^+ + \beta_p D_l^-} \right) \times \left( \sum_{k=1}^K (\delta_k^+ D_l^+ + \delta_k^- D_l^-) I_l^k \right) + |y_l|^{\alpha_p D_l^+ + \beta_p D_l^-} \right]^{\frac{1}{\alpha_p D_l^+ + \beta_p D_l^-}} + e_l^i \quad (1.13)$$

$$\begin{aligned}
 ce_l = \ln & \left[ \left( \exp((\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+) \mathbf{x}_l) - \exp((\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+) \mathbf{y}_l) \right) \times \right. \\
 & \left. \left( \sum_{k=1}^K (\delta_k^+ \mathbf{D}_l^+ + \delta_k^- \mathbf{D}_l^-) \mathbf{I}_l^k \right) + \exp((\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+) \mathbf{y}_l) \right] \times \\
 & \frac{1}{\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+} + \mathbf{e}_l^i
 \end{aligned} \tag{1.14}$$

### 1.3.2.3 Estimating loss aversion

As a second step, we measure the loss aversion index  $\lambda$  as defined in (1.3) based on the estimates of the utility function and the probability weights outlined in subsection 1.3.2.2. Following Abdellaoui et al. (2007b), the estimation of the loss aversion index can be done using a set of  $K$  indifference relationships that involve mixed binary prospects:

$$ce_k \sim (x_k, y_k; p_k, 1 - p_k), \quad k = 1, 2, \dots, K \tag{1.15}$$

where  $y_k < 0 < x_k$ . Under CPT, these indifferences imply that:

$$ce_k = v^{-1} \left[ w^+(p_k)v(x_k) + w^-(1 - p_k)v(y_k) \right] \tag{1.16}$$

Because  $ce_k$  belongs to the interval  $(y_k, x_k)$ , it could either be a gain or a loss. Also, note that for each  $k$  both  $w^+(p_k)$  and  $w^-(1 - p_k)$  are known since they have been elicited in the previous step. Echoing our previous notation, let  $\mathbf{ce}$ ,  $\mathbf{x}$  and  $\mathbf{y}$  contain the realizations of  $ce_k$ ,  $x_k$  and  $y_k$ . In addition, denote by  $\boldsymbol{\delta}^+$  and  $\boldsymbol{\delta}^-$  the column vectors such that  $\boldsymbol{\delta}^{+'} \equiv (\delta_1^+, \delta_2^+, \dots, \delta_K^+)$  and  $\boldsymbol{\delta}^{-'} \equiv (\underline{\delta}_1^-, \underline{\delta}_2^-, \dots, \underline{\delta}_K^-) = (\delta_K^-, \delta_{K-1}^-, \dots, \delta_1^-)$ .<sup>19</sup> Assuming that certainty equivalents are

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<sup>19</sup>For clarity of exposition, we use underscores to refer to the loss domain so that:  $\underline{\delta}_k^- \equiv \delta_{K-k+1}^- = w^-(1 - p_k)$  for  $k = 1, 2, \dots, K$ .

observed with an additive and normally distributed response error term ( $\mathbf{e}_k$ ), the empirical counterpart of equation (1.16) then becomes:

$$\mathbf{c}\mathbf{e}_k = v^{-1} \left[ \delta_k^+ v(\mathbf{x}_k) + \underline{\delta}_k^- v(\mathbf{y}_k) \right] + \mathbf{e}_k \quad (1.17)$$

$v^{-1}$  in (1.17) can be derived similarly to  $u^{-1}$  in (1.10). Then, the respective certainty equivalent equations for power and exponential utility functions become:

$$\mathbf{c}\mathbf{e}_k = (D_k^+ - D_k^-) \left[ \frac{\delta_k^+ (\mathbf{x}_k)^{\alpha_p} - \lambda \underline{\delta}_k^- (-\mathbf{y}_k)^{\beta_p}}{D_k^+ - \lambda D_k^-} \right]^{\frac{1}{\alpha_p D_k^+ + \beta_p D_k^-}} + \mathbf{e}_k \quad (1.18)$$

$$\mathbf{c}\mathbf{e}_k = \frac{\ln \left[ 1 - \frac{\alpha_e D_k^+ + \beta_e D_k^-}{D_k^+ - \lambda D_k^-} \left( \delta_k^+ \left( \frac{1 - \exp(-\alpha_e \mathbf{x}_k)}{\alpha_e} \right) - \lambda \underline{\delta}_k^- \left( \frac{1 - \exp(\beta_e \mathbf{y}_k)}{\beta_e} \right) \right) \right]}{\beta_e D_k^- - \alpha_e D_k^+} + \mathbf{e}_k \quad (1.19)$$

Using the values of the probability weights and the parameters of  $u(\cdot)$  from the first step, we can estimate (1.18) or (1.19) by NLS or MLE to obtain  $\lambda$ .

#### 1.3.2.4 Key properties of our method

**Comparison with ABL.** We refine and extend the method previously proposed by ABL in several ways.

First, unlike ABL, we can estimate multiple probability weights and thus elicit the shape of the probability weighting function.

Second, our method uses a single step to estimate the probability weights and the utility function in the full domain, whereas ABL propose a two-step procedure. This feature of our method allows for testing several important



restrictions (partial reflection, identical probability weighting functions across domains, and duality) as well as imposing these restrictions whenever necessary.

Imposing partial reflection helps avoid the problem of arbitrary measurement of loss aversion with power utility functions (see [Wakker, 2010](#)). Testing for identical probability weighting functions across domains (*i.e.*,  $w^+(p_k) = w^-(p_k)$  for all  $k$ ) allows us to test a key assumption of OPT. In addition, this assumption must also be made under CPT whenever loss aversion is present and preferences are homogeneous ([Al-Nowaihi et al., 2008](#)).<sup>20</sup> Our method allows for testing and imposing duality (*i.e.*,  $w^+(p_k) = 1 - w^-(1 - p_k)$  for all  $k$ ).<sup>21</sup> By allowing for testing and imposing duality as well as identical probability weighting across domains, our method can be applied under RDU ([Quiggin, 1982](#); [Gilboa, 1987](#); [Schmeidler, 1989](#)) and OPT (KT79). This is not the case for existing parametric, semi-parametric, or non-parametric methods.

Third, certainty equivalents for mixed prospects are obtained using a different procedure than the one proposed by ABL. In ABL, subjects are asked to provide a loss amount  $L$  for which they are indifferent between the status-quo (0) and a binary lottery  $(G, L; p_g, 1 - p_g)$  where  $G$  is a fixed gain and  $L \in (-\infty, 0]$  is a loss. In this elicitation procedure, the researcher does not know the lower bound of the loss interval. By contrast, equation (1.15) keeps track of the upper and lower bounds of the loss interval because  $ce_k$  belongs to the interval  $(y_k, x_k)$ . This is an appealing property of our method for two reasons. First, asking subjects to provide indifference values on unbounded intervals can be cognitively demanding ([Wakker and Deneffe, 1996](#); [Abdellaoui et al., 2007b](#)). This may lead to errors

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<sup>20</sup>Homogeneity of preferences holds whenever multiplying all the payoffs of a non-mixed lottery by a positive constant  $c$  also leads the certainty equivalent of the lottery to be multiplied by  $c$ .

<sup>21</sup>As pointed out by [Abdellaoui \(2000, pp. 1509-1510\)](#), testing for duality with parametric methods and non-parametric methods based on the tradeoff approach requires using the specific probability weighting function of [Goldstein and Einhorn \(1987\)](#) and [Lattimore et al. \(1992\)](#).

that potentially inflate the estimates of loss aversion, as reported by ABL (see Table 11, pp. 263-264). Second, eliciting indifference values on bounded intervals allows us to use a standard switching outcome procedure (Booij and Van de Kuilen, 2009).

**Comparison to standard parametric methods.** Our method retains all the appealing properties of parametric methods. First, it is as data-efficient as parametric methods because, for  $K$  probability weights to be elicited, the smallest number of certainty equivalents required to measure all the three components of risk attitudes in the full domain is  $5K$  (*i.e.*,  $2K$  certainty equivalents in the gain domain,  $2K$  in the loss domain and  $K$  for mixed lotteries). Second, we use simple choices (comparisons of certain outcomes and binary lotteries) so that the method is not cognitively demanding for subjects. Third, our method is tractable because we can measure risk attitudes using standard econometric tools. Fourth, our estimation method accounts for response errors.

In parametric methods, it is key to assess the validity of the functional forms used for the probability weighting and utility functions. However, parametric methods do not allow the researcher to separately assess the goodness of fit of each of these functions (GW99). In contrast, our semi-parametric method does not make any parametric assumption regarding the probability weighting function and allows the researcher to evaluate the goodness of fit of the utility function separately. Thus, one can select the utility function with the best fit, further improving the accuracy of the elicitation of risk attitudes of the semi-parametric method compared to the parametric one.

**Applicability to unknown probabilities.** Our method is also directly applicable to cases of uncertainty where probabilities are unknown. It does not require setting any specific conditions on the event space, and hence can be

applied to real-life uncertainty situations (Baillon et al., 2018).<sup>22</sup> Extending our method to the case of uncertainty can thus be done by replacing probability dummy variables by event dummy variables in equations (1.10) and (1.17).

**Robustness to monotonicity problem.** We further note that the monotonicity problem raised by Apesteguia and Ballester (2018), which could lead to identification issues, does not apply to our case. First, our method is not based on binary choices (as in random utility models), but on eliciting certainty equivalents. Second, we define the error term at the certainty equivalent level and not at the utility level. For power and exponential utility functions, the certainty equivalent is monotonic in the utility parameters and probability weights. This is also true for a broad range of utility functions once we use the Arrow-Pratt approximation for binary lotteries in the context of RDU and CPT. A related problem to Apesteguia and Ballester (2018) can arise with the certainty equivalent method when the error term is defined at the utility level, as in the non-parametric method of GW99 (see footnote 13 for a discussion of these issues).

**Spline extension.** Our semi-parametric method requires specifying a utility function which allows us to keep the data-efficiency property of parametric methods. However, in the case of an extensive dataset (as in GW99), our semi-parametric method can be extended to use spline approximation of the utility function. In appendix 1.C, we provide a linear spline extension for our semi-parametric method.

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<sup>22</sup>Non-parametric methods (e.g. Van De Kuilen and Wakker, 2011; Abdellaoui et al., 2020) require the event space to be rich (e.g. continuous). This means that in applied contexts, the universal event is an interval on a real scale (e.g. temperature in town). The semi-parametric method of Abdellaoui et al. (2011a) requires equally likely events either with (i) preset priors (like in Ellsberg's urn experiments), or (ii) a rich event space analogous to non-parametric methods.

## 1.4 Parameter recovery and misspecification

Following [Gao et al. \(2020\)](#), [Nilsson et al. \(2011\)](#) and [Murphy and ten Brincke \(2018\)](#), we report in this section two types of simulation exercises: parameter recovery and robustness to misspecification. In the parameter recovery exercise, we estimate a model assuming that we know the specification of the utility and weighting functions used to simulate the data. Our aim is to assess the extent to which an estimation method can identify the parameters underlying the simulated data. In the robustness to misspecification exercise, we estimate a model assuming an incorrect specification of the utility and weighting functions and check for the extent to which an estimation method identifies the underlying parameters from simulated data. For the sake of comparison, the simulations are made for both our semi-parametric method and parametric methods. Subsections [1.4.1](#) and [1.4.2](#) explain the simulation exercises and results are presented in subsection [1.4.3](#).

### 1.4.1 Parameter recovery

The calibration of lotteries follows TK92. We consider 9 probabilities – 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95, and 0.99 – along with possible outcomes  $(x, y)$  in each domain:  $(0, 100)$ ,  $(0, 400)$  and  $(50, 150)$  for the gain domain, and  $(-100, 0)$ ,  $(-400, 0)$  and  $(-150, -50)$  for the loss domain. Each of the 9 probabilities is combined with each pair of outcomes, resulting in a lottery  $(x, y; p, 1 - p)$ . This gives a total of 27 lotteries in each domain, and each probability occurs three times in the dataset.

### 1.4.1.1 Our method

**Simulation 1: Power utility function.** We simulate data for 1000 ( $s = 1, 2, \dots, 1000$ ) hypothetical subjects. For each subject  $s$ , we generate random parameters of the power utility functions in the gain and loss domains from a uniform distribution  $U(0.1, 2.1)$  (Spiliopoulos and Hertwig, 2019, ABL).

For the 9 probabilities involved in the lotteries, we generate probability weights using a uniform distribution  $U(0, 1)$ , making sure that higher probabilities are assigned to higher weights.

Then, these simulated power utility parameters (one per domain) and probability weights (9 per domain) are plugged into CPT formulas to generate *noiseless* certainty equivalents. In the last step of the data generation process, we use two random variables from  $U(0, 0.025)$  to simulate standard deviations  $\sigma_{s,i}$  in each domain  $i \in \{+, -\}$ , and then draw 27 random values from  $N(0, \sigma_{s,i}|x - y|)$  which we add to the previously generated 27 *noiseless* certainty equivalents to obtain the *noisy* ones.<sup>23</sup> Finally, we use the *noisy* certainty equivalents as input data and compute MLE outcomes for our semi-parametric method.

**Simulation 2: Exponential utility function.** This simulation exercise is based on the same principles as Simulation 1, the sole difference being the utility function. This time, we draw exponential utility parameters for each domain from  $U(-0.01, 0.01)$ .<sup>24</sup>

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<sup>23</sup>A standard deviation of  $0.025 \times |x - y|$  implies response errors of +/- \$20 around the true certainty equivalent value, which seems large given the range of lottery outcomes [0, \$400].

<sup>24</sup>Note that the scale of the exponential utility parameter depends on the scale of the outcomes used in the lotteries. Taking into account the midpoint of the outcome range [0, 400], the index of absolute risk aversion generated by a power utility function with a parameter in the range (0, 2) is approximately equal to the index generated by an exponential utility with a parameter in the range  $(-\frac{1}{200}, \frac{1}{200})$ . In the simulation exercise, we allow for a wider range for that parameter:  $(-0.01, 0.01)$ .

### 1.4.1.2 Parametric methods

We consider eight common parametric specifications. These parametric specifications arise from the combination of the two standard utility functions (power and exponential) (see [Stott, 2006](#)) and four popular weighting functions (see TK92; [Goldstein and Einhorn, 1987](#); [Lattimore et al., 1992](#); [Prelec, 1998](#)). These weighting functions are:

$$w^i(p) = \frac{p^{(a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)})}}{\left[p^{(a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)})} + (1-p)^{(a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)})}\right]^{\frac{1}{a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)}}}} \quad (1.20)$$

where  $a, c \in (0, 1]$

$$w^i(p) = \exp\left[-\left(-\ln(p)\right)^{b\mathbf{1}_{(i=+)}+d\mathbf{1}_{(i=-)}}\right] \quad (1.21)$$

where  $b > 0, d > 0$

$$w^i(p) = \exp\left[-\left(b\mathbf{1}_{(i=+)} + d\mathbf{1}_{(i=-)}\right) \times \left(-\ln(p)\right)^{a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)}}\right] \quad (1.22)$$

where  $a > 0, b > 0, c > 0, d > 0$

$$w^i(p) = \frac{(b\mathbf{1}_{(i=+)} + d\mathbf{1}_{(i=-)})p^{(a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)})}}{(b\mathbf{1}_{(i=+)} + d\mathbf{1}_{(i=-)})p^{(a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)})} + (1-p)^{(a\mathbf{1}_{(i=+)}+c\mathbf{1}_{(i=-)})}} \quad (1.23)$$

where  $a > 0, b > 0, c > 0, d > 0$ . Equation (1.20) represents the one-parameter weighting function (per domain) of TK92. Equations (1.21) and (1.22) refer to the one- and two-parameter weighting functions of [Prelec \(1998\)](#), and (1.23) is the two-parameter weighting function of [Goldstein and Einhorn \(1987\)](#) and [Lattimore et al. \(1992\)](#). The vast majority of parametric estimations in the literature rely on one of these four weighting functions in combination with a standard utility function ([Stott, 2006](#)). Henceforth, we refer to (1.20), (1.21),

(1.22) and (1.23) as TK92, P98-I, P98-II and GE87 respectively.<sup>25</sup>

**Simulation 3 and 4.** We then run two additional series of simulations (Simulations 3 and 4) that are based on the same principles as Simulations 1 and 2 (respectively), the sole difference being the weighting function. Depending on the simulation, we specify one of the four parametric weighting functions. For the weighting function of TK92, we draw the values for  $a$  and  $c$  from  $U(0.2, 1)$  (e.g. [Dhami, 2016](#), p. 122). For the remaining weighting functions, we draw  $a$ ,  $b$ ,  $c$  and  $d$  from  $U(0.1, 1.5)$ .

## 1.4.2 Parameter recovery under model misspecification

### 1.4.2.1 Our method

**Simulation 5: Power utility function.** We consider the data generated in Simulation 4 under an exponential utility function in combination with each of the four weighting functions in turn. We apply our estimation procedure to each of these four simulated datasets, while misspecifying the utility function which is assumed to be power instead of exponential.

**Simulation 6: Exponential utility function.** We follow the same procedure as in Simulation 5, this time using the data generated in Simulation 3 with power utility function. For the sake of model misspecification, we assume utility to be exponential.

### 1.4.2.2 Parametric methods

**Simulation 7 and 8.** As before, we run two additional series of simulations for parametric methods. In Simulation 7 (8), we rely on data previously generated

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<sup>25</sup>For these specifications, identical probability weighting across domains corresponds to  $a = c$  and  $b = d$ . Note that an appealing property of the GE87 specification is that it allows for a straightforward test of duality ([Abdellaoui, 2000](#)) by checking whether  $a = c$  and  $b = \frac{1}{d}$ .

in Simulation 2 (1) and misspecify the model in the same way as in Simulation 5 (6).

### 1.4.3 Result of parameter recovery and misspecification

Table 1.2 shows the average absolute error in parameter estimates, which is defined as the absolute difference between the true parameter value and its estimate. Figure 1.1 plots the average absolute error in parameter estimates across all parameters and all simulations. When a point is above the  $45^\circ$  line, this means that the average absolute error in the parametric specification is greater than the corresponding simulation in the semi-parametric specification. For parameter recovery exercises (Figure 1.1, panel (a)), parametric specifications tend to perform better than the semi-parametric method. However, for misspecification exercises, the semi-parametric method performs better than parametric methods (Figure 1.1, panel (b)). Taking both types of simulations into account (figure 1.1, panel (c)), we highlight that average absolute errors in parameter recovery exercises are substantially smaller than misspecification errors. Overall, we conclude that the semi-parametric method (*i*) is less sensitive to model misspecification and (*ii*) produces more reliable estimates when the model is misspecified than standard parametric methods.



Figure 1.1: Absolute error in estimates: semi-parametric vs. parametric methods

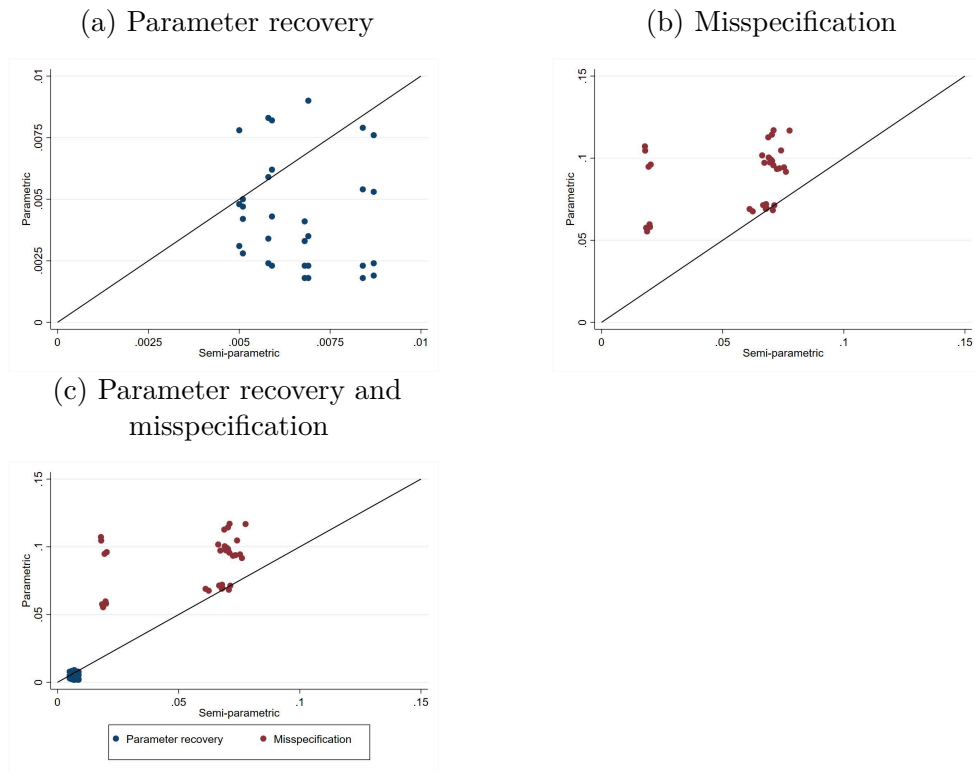


Table 1.2: Simulation results

Simulation n°	Estimation		Data generation		Average absolute value of error			
	$u()$	$w()$	$u()$	$w()$	$\alpha$	$w^+$	$\beta$	$w^-$
Parameter recovery								
1	Power	our method	Power	our method	0.0059	0.0087	0.0058	0.0084
2	Expo	our method	Expo	our method	0.0050	0.0069	0.0051	0.0068
3	Power	TK92	Power	TK92	0.0043	0.0024	0.0034	0.0023
3	Power	P98-I	Power	P98-I	0.0023	0.0019	0.0024	0.0018
3	Power	P98-II	Power	P98-II	0.0062	0.0053	0.0059	0.0054
3	Power	GE87	Power	GE87	0.0082	0.0076	0.0083	0.0079
4	Expo	TK92	Expo	TK92	0.0048	0.0023	0.0042	0.0023
4	Expo	P98-I	Expo	P98-I	0.0031	0.0018	0.0028	0.0018
4	Expo	P98-II	Expo	P98-II	0.0078	0.0090	0.0050	0.0041
4	Expo	GE87	Expo	GE87	0.0048	0.0035	0.0047	0.0033
Misspecification								
5	Power	our method	Expo	TK92	0.0703	0.0180	0.0710	0.0179
5	Power	our method	Expo	P98-I	0.0672	0.0194	0.0690	0.0203
5	Power	our method	Expo	P98-II	0.0611	0.0198	0.0624	0.0200
5	Power	our method	Expo	GE87	0.0667	0.0184	0.0681	0.0188
6	Expo	our method	Power	TK92	0.0688	0.0776	0.0663	0.0741
6	Expo	our method	Power	P98-I	0.0695	0.0724	0.0699	0.0753
6	Expo	our method	Power	P98-II	0.0707	0.0709	0.0713	0.0704
6	Expo	our method	Power	GE87	0.0678	0.0761	0.0679	0.0734
7	Power	TK92	Expo	our method	0.1143	0.1046	0.1170	0.1072
7	Power	P98-I	Expo	our method	0.0972	0.0948	0.1004	0.0961
7	Power	P98-II	Expo	our method	0.0690	0.0597	0.0676	0.0581
7	Power	GE87	Expo	our method	0.0714	0.0576	0.0696	0.0554
8	Expo	TK92	Power	our method	0.1127	0.1168	0.1017	0.1047
8	Expo	P98-I	Power	our method	0.0974	0.0934	0.0992	0.0944
8	Expo	P98-II	Power	our method	0.0683	0.0957	0.0713	0.0983
8	Expo	GE87	Power	our method	0.0691	0.0917	0.0720	0.0938

## 1.5 Applications

In this section we use existing experimental data to compare our semi-parametric method and parametric methods. Because our method relies on the elicitation of certainty equivalents, we compare it to parametric methods that also make

use of certainty equivalents. Since our exercise requires the use of datasets that allow for the elicitation of certainty equivalents, we start this section by detailing our choice of datasets before comparing the methods in terms of goodness of fit and providing estimation results.

### 1.5.1 Data

To apply our method, we need to elicit certainty equivalents in the gain and loss domains for two-outcome lotteries. These lotteries should vary each of the outcomes as well as the corresponding probabilities, and at least two certainty equivalents should be elicited for each probability.

We made an extensive search of the literature to identify available datasets from which we could make individual estimates. We reviewed the datasets from [Harrison and Rutström \(2009\)](#); [Eisenberg et al. \(2019\)](#); [l’Haridon and Vieider \(2019\)](#); [Pedroni et al. \(2017\)](#); [Andersson et al. \(2020\)](#); BFE10; GW99 and TK92. The data used in [Harrison and Rutström \(2009\)](#); [Eisenberg et al. \(2019\)](#); [Pedroni et al. \(2017\)](#); [Andersson et al. \(2020\)](#) rely on binary choices, which cannot be used as input in our method. The data of [Bruhin et al. \(2010\)](#); [l’Haridon and Vieider \(2019\)](#); GW99 and TK92 contain certainty equivalents for binary lotteries. However, the dataset in [l’Haridon and Vieider \(2019\)](#) does not match our criteria at the individual level because it only contains one certainty equivalent for some of the probability weights. The dataset of GW99 satisfies our criteria, with an important caveat that it contains observations from only 10 subjects and solely in the gain domain. By contrast, BFE10 [and more specifically, their “Zurich 03” experiment]<sup>26</sup> collected data on 179 subjects in the gain and loss domains with several certainty equivalents per probability, thus

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<sup>26</sup>The authors also conducted two other experiments, but these datasets do not match our criteria at the individual level since they include only one certainty equivalent for some of the probability weights.

fully matching our selection criteria. However, this dataset does not include mixed lotteries, thus not allowing us to estimate loss aversion. In addition, TK92 provide median data that contain several certainty equivalents per probability in the gain and loss domains, also in line with our selection criteria. They also include mixed lotteries so that we can elicit loss aversion. We thus apply our method to the median data of TK92 and to the individual data of BFE10.

### 1.5.2 Goodness of fit across models

We start by evaluating the goodness of fit of our method relative to parametric alternatives. The corresponding values of AIC and CV are reported in Tables 1.3 and 1.4.

For the data of TK92 (BFE10), power (exponential) utility function best fits the data under our semi-parametric method according to both AIC and CV. The best parametric specification is the combination of a power utility function and the one-parameter weighting function of TK92 (an exponential utility function and the two-parameter weighting function of GE87) for the data of TK92 (BFE10).

For each dataset and each criterion, the best-fitting specification under our semi-parametric method outperforms the best-fitting parametric specification. This implies that our semi-parametric method fits the data better than standard parametric methods.

Table 1.3: Goodness of fit across methods: data of TK92

		Parametric								Semi-parametric	
		AIC*				CV*				AIC	CV
$w(\cdot)$ \ / \ $u(\cdot)$		TK92 <sup>†</sup>	P98-I <sup>†</sup>	P98-II <sup>†</sup>	LG92 <sup>†</sup>	TK92 <sup>†</sup>	P98-I <sup>†</sup>	P98-II <sup>†</sup>	LG92 <sup>†</sup>	-	-
Power		320	327	321	318	3.41	3.57	3.52	3.87	284 <sup>‡</sup>	3.15 <sup>‡</sup>
Exponential		339	347	328	320	6.21	4.35	4.06	5.39	286	3.31

\* AIC: Akaike information criterion, CV: Leave one out of sample cross-validation. The best specification is the one that minimizes a considered criterion (AIC or CV).

<sup>†</sup> TK92 (one-parameter weighting function of [Tversky and Kahneman \(1992\)](#)), P98-I (one-parameter weighting function of [Prelec \(1998\)](#)), P98-II (two-parameter weighting function of [Prelec \(1998\)](#)), LG92 (two-parameter weighting function of [Lattimore et al. \(1992\)](#))

<sup>‡</sup> The semi-parametric method with power utility function provides smaller AIC and CV

Table 1.4: Goodness of fit across methods: data of BFE10

		Parametric								Semi-parametric	
		AIC*				CV*				AIC	CV
$w(\cdot)$ \ / \ $u(\cdot)$		TK92 <sup>†</sup>	P98-I <sup>†</sup>	P98-II <sup>†</sup>	LG92 <sup>†</sup>	TK92 <sup>†</sup>	P98-I <sup>†</sup>	P98-II <sup>†</sup>	LG92 <sup>†</sup>	-	-
Power		51110	50980	50895	50828	10.005	4.381	4.383	4.375	50776	4.400
Exponential		51489	51066	50704	50636	4.842	4.512	4.304	4.253	50601 <sup>‡</sup>	4.249 <sup>‡</sup>

\* AIC: Akaike information criterion, CV: Leave one out of sample cross-validation. The best specification is the one that minimizes a considered criterion (AIC or CV).

<sup>†</sup> TK92 (one-parameter weighting function of [Tversky and Kahneman \(1992\)](#)), P98-I (one-parameter weighting function of [Prelec \(1998\)](#)), P98-II (two-parameter weighting function of [Prelec \(1998\)](#)), LG92 (two-parameter weighting function of [Lattimore et al. \(1992\)](#))

<sup>‡</sup> The semi-parametric method with exponential utility function provides smaller AIC and CV

### 1.5.3 Results

In this section, we focus our analysis on the best-fitting specifications under parametric and semi-parametric methods, as highlighted in the previous section.

### 1.5.3.1 Curvature of the utility function for gains and losses

Table 1.5 summarizes the semi-parametric and parametric estimates of the main components of the CPT value function (curvature in each domain and loss aversion) for the data of TK92 and BFE10.<sup>27</sup> In the remainder of the results section, we use z-tests to assess whether a coefficient is equal to a specific value and whether two coefficients are equal, and  $\chi^2$ -tests for joint hypotheses. Tests are two-sided, unless stated otherwise.

Our semi-parametric estimations show that the utility function is concave in the gain domain: the estimated values of  $\alpha = 0.525$  (TK92) and  $\alpha = 0.587$  (BFE10) are significantly greater than 0.5 ( $p$ -values  $< 0.0292$ ). In the loss domain, the estimated values also suggest the utility function is concave because  $\beta = -0.483$  and  $\beta = -0.425$  are greater than -0.5 ( $p$ -value  $< 0.0757$  and  $p$ -value  $< 0.0001$ , respectively). Concavity in the loss domain is in line with the findings of ABL, [Attema et al. \(2013\)](#) and [Etchart-Vincent and l'Haridon \(2011\)](#). Furthermore, we reject partial reflection ( $H_0 : \alpha + \beta = 0, p$ -values  $< 0.0058$ ).

### 1.5.3.2 Loss aversion

With our semi-parametric method, we replicate the standard finding of loss aversion, with  $\lambda = 1.751$ .<sup>28</sup> Our estimate of the loss aversion index is close to the estimated value of 1.6 that was elicited in both [Booij et al. \(2010\)](#) who use

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<sup>27</sup>The utility curvature is computed based on equations (2.14) and (2.19). Detailed results for the semi-parametric method are reported in Appendix 1.A.2 for TK92 and in Appendix 1.B for BFE10.

<sup>28</sup>In section 4.3, we propose to estimate loss aversion  $\lambda$  in a second step after estimating utility and weighting functions in a first step. This two-step procedure we propose can be applied regardless of whether elicitation of loss aversion is of interest (which requires both steps) or not (which only requires the first step of estimation). In the former case, one could alternatively apply a one-step procedure (e.g. [l'Haridon and Vieider, 2019](#)) that simultaneously estimates equations (1.10) and (1.17). Table 1.A.11 in appendix 1.A.4.1 summarizes the maximum likelihood estimates of utility curvature, probability weights and loss aversion obtained through a one-step procedure. In the one-step procedure, estimated loss aversion is 1.688 compared to the median value of 1.751 in the two-step procedure.

structural estimation techniques, and ABL for pooled data. It is also similar to the estimates reported by Tom et al. (2007), Pennings and Smidts (2003), and Booij and Van de Kuilen (2009):  $\lambda = 1.93$ ,  $\lambda = 1.8$ , and  $\lambda = 1.87$ , respectively. Note that a large meta-analytical study by Brown et al. (2021) suggests that the mean loss aversion coefficient lies between 1.8 and 2.1. From that perspective, our estimates are on the conservative side and come close to the lower bound of that interval.

Table 1.5: Curvature of the utility function and loss aversion

	Data of TK92		Data of BFE10	
	Semi-parametric	Parametric	Semi-parametric	Parametric
Curvature Gain ( $\alpha$ )	0.525	0.544	0.587	0.589
Curvature Loss ( $\beta$ )	-0.483	-0.525	-0.425	-0.428
Loss aversion ( $\lambda$ )	1.751	1.730	-	-

### 1.5.3.3 Probability weighting function

**Data of TK92.** Figure 4.2.1 presents the estimates of the probability weighting function across domains (labeled *Semi-para*) for the data of TK92. In the gain domain, probabilistic risk neutrality  $w^+(p) = p$  is rejected for most probabilities (all  $p$  - values  $< 0.0258$ ), except for 0.25 ( $p$  - value = 0.0671). Overall, we reject the joint hypothesis of linearity of the probability weighting function over the whole range of probabilities in the gain domain ( $p$  - value  $< 0.0001$ ). The resulting weighting function is inverse S-shaped because there is overweighting for  $p \in (0, 0.25]$ , and underweighting for  $p \in (0.25, 1)$ . Similar patterns emerge in the loss domain, with overweighting starting for lower probabilities  $p \in (0, 0.1]$ , and then shifting to underweighting for  $p \in (0.1, 1)$ . We cannot reject  $H_0 : w^-(0.1) = 0.1$  ( $p$  - value = 0.7042).

Over the 9 probabilities in the data of TK92, the hypothesis of identical probability weights across domains ( $w^+(p_k) = w^-(p_k)$ ) is rejected for 4 probabil-

ities (0.01, 0.05, 0.25 and 0.90; all  $p$  – values  $< 0.0241$ ), but not for others (0.1, 0.5, 0.75, 0.95 and 0.99; all  $p$  – values  $> 0.1192$ ). For tail probabilities ( $p = 0.01$  and 0.05 in this dataset),<sup>29</sup> overweighting is more pronounced in the gain than in the loss domain ( $p$  – values  $< 0.0121$ ). Using a joint test, the hypothesis of identical probability weights across domains is rejected ( $p$  – value  $< 0.0001$ ).

The hypothesis of duality ( $w^+(p_k) = 1 - w^-(1 - p_k)$ ) is rejected for 7 probabilities (all  $p$  – values  $< 0.001$ ), with the exception of probabilities 0.01 and 0.05 (both  $p$  – values  $> 0.2365$ ). Using a joint test, the duality hypothesis is rejected ( $p$  – value  $< 0.0001$ ).

**Data of BFE10.** Figure 1.3 presents the estimates of the probability weighting function across domains (once again, labeled *Semi-para*) for the data of BFE10.

In the gain domain, probabilistic risk neutrality  $w^+(p) = p$  is rejected for all probabilities (all  $p$  – values  $< 0.0001$ ), except for 0.5 ( $p$  – value = 0.9496). Overall, we reject the hypothesis of linearity of the probability weighting function over the whole range of probabilities in the gain domain. The resulting weighting function is once again inverse S-shaped with overweighting for  $p \in (0, 0.5]$  and underweighting for  $p \in (0.5, 1)$ .

Similar patterns emerge in the loss domain with overweighting for  $p \in (0, 0.5]$ , and underweighting for  $p \in (0.5, 1)$ . We cannot reject  $H_0 : w^-(0.5) = 0.5$  ( $p$  – value = 0.8881).

Over the 7 probabilities in the data of BFE10, the hypothesis of identical probability weights across domains ( $w^+(p_k) = w^-(p_k)$ ) is rejected for the probability  $p = 0.05$  ( $p$  – values  $< 0.0204$ ), but not for others (all  $p$  – values  $> 0.0553$ ). For tail probability ( $p = 0.05$  in this dataset), overweighting is more pronounced for gains than for losses. Using a joint test, the hypothesis of identical probability weights across domains is rejected ( $p$  – value  $< 0.0001$ ).

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<sup>29</sup>Tail probabilities are typically considered to be equal to 5% or less (see Barron and Erev, 2003; Erev, 2007; Erev et al., 2017; Hertwig et al., 2004; Corgnet et al., 2020).



Finally, the hypothesis of duality ( $w^+(p_k) = 1 - w^-(1 - p_k)$ ) is rejected for  $p = 0.9$  ( $p - value < 0.0146$ ) but not for the remaining probabilities (all  $p - values > 0.1159$ ). A joint test rejects the duality hypothesis ( $p - value < 0.0467$ ).

Figure 1.2: Semi-parametric and parametric measurements of the probability weighting function (median data from TK92)

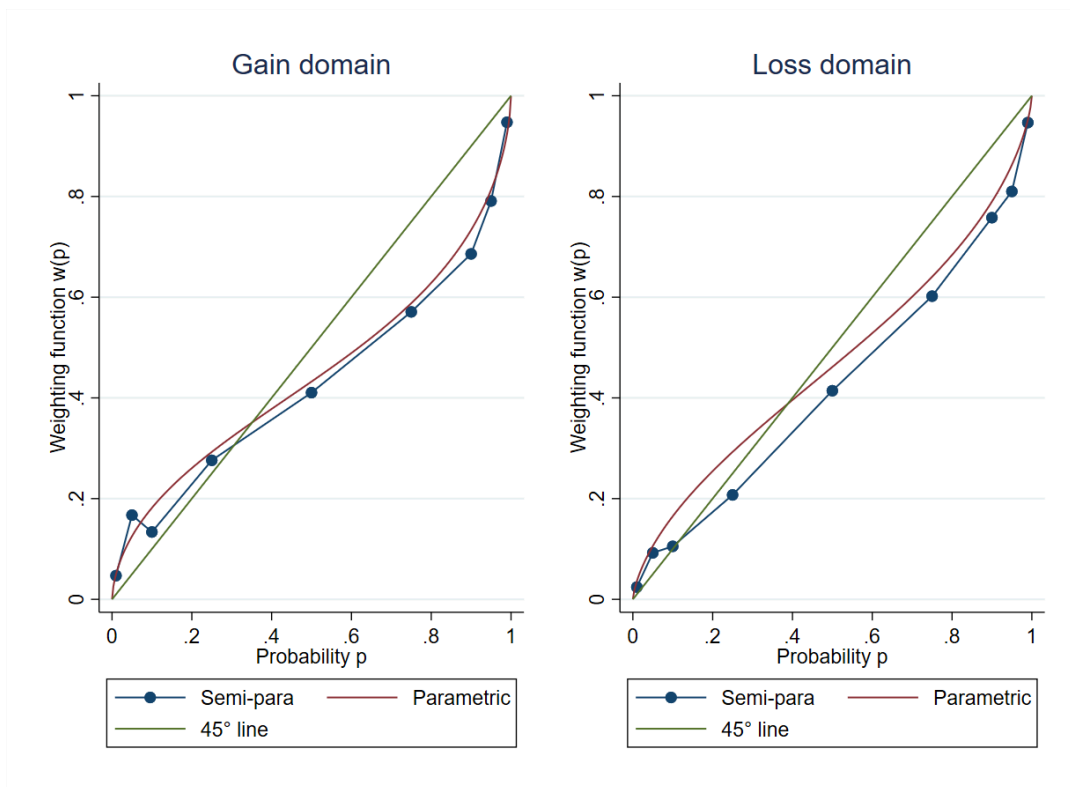
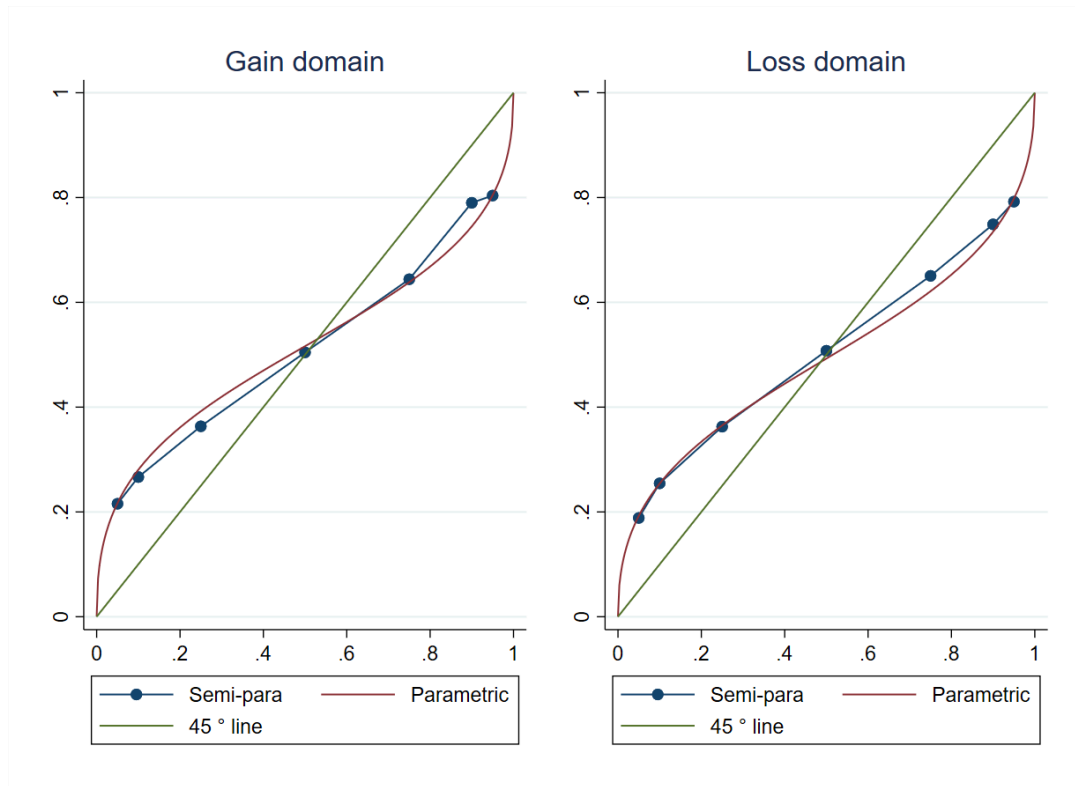


Figure 1.3: Semi-parametric and parametric measurements of the probability weighting function (results on pooled data of BFE10)



#### 1.5.3.4 Discussion

Table 1.6 summarizes the discussion for both datasets. Echoing the seminal findings in TK92,<sup>30</sup> the parametric estimates reported in Table 1.5 imply concavity in the gain domain ( $\alpha = 0.544$ , statistically different from 0.5 with  $p - value < 0.0001$ ) and convexity in the loss domain ( $\beta = -0.525$ , statistically different from  $-0.5$  with  $p - value = 0.001$ ). In addition, partial reflection cannot be rejected at the 5% significance level ( $H_0 : \alpha + \beta = 0$ ,  $p - value = 0.0936$ ). When considering the data of BFE10, the parametric estimates imply concavity in both gain ( $\alpha = 0.589$ , statistically different from 0.5 with  $p - value < 0.0001$ ) and loss

<sup>30</sup>See Appendix 1.A.4 for detailed information about parametric specifications and results.

( $\beta = -0.428$ , statistically different from  $-0.5$  with  $p - value < 0.0001$ ) domains. In addition, partial reflection is rejected ( $H_0 : \alpha + \beta = 0$ ,  $p - value < 0.0001$ ). We note that parametric estimates lead to inconsistent results across datasets for utility curvature in the loss domain and partial reflection. By contrast, semi-parametric estimates lead to different findings: (i) concave utility in both domains and (ii) rejection of partial reflection. Unlike parametric methods, these findings are consistent across datasets. The absence of convexity of the utility function in the loss domain is consistent with a number of previous studies (ABL; BFE10 Abdellaoui et al., 2011c; Attema et al., 2013, 2016; Kemel and Mun, 2020). ABL, Attema et al. (2013, 2016), Abdellaoui et al. (2011c) and Kemel and Mun (2020) use the semi-parametric method developed by ABL, whereas BFE10<sup>31</sup> use a parametric method with the two-parameter probability weighting function of GE87. In contrast, studies based on the tradeoff method find support for the convexity of the utility function in the loss domain (Abdellaoui, 2000; Etchart-Vincent, 2004, 2009b; Abdellaoui et al., 2007b, 2013, 2016; Booij and Van de Kuilen, 2009; Hajimoladarvish, 2017; Attema et al., 2018; Bleichrodt et al., 2018). From a theoretical standpoint, people who exhibit a concave utility in the loss domain can still be risk seeking (Chateauneuf and Cohen, 1994). Our semi-parametric method thus allows for such a possibility.

The empirical evidence on partial reflection in the literature is mixed. Our rejection of partial reflection is consistent with some studies (Abdellaoui et al., 2013, 2016; Attema et al., 2013, 2016, ABL) but not others (e.g. Abdellaoui, 2000; Andersen et al., 2006; Abdellaoui et al., 2007b; Booij and Van de Kuilen, 2009; Harrison and Rutström, 2009; Booij et al., 2010).

Parametric estimates on the data of TK92 lead to a rejection of equality of probability weighting function across domains ( $p - value < 0.0001$ ). As observed

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<sup>31</sup>We also report similar results in Table 1.5.

by TK92, parametric estimates imply that both  $w^+(0.5)$  and  $w^-(0.5)$  are less than 0.5 so that the duality condition is rejected. When considering the data of BFE10, identical probability weighting cannot be rejected ( $p - value < 0.0001$ ). Using data of BFE10, parametric estimates imply the equality of probability weighting functions across domains ( $p - value = 0.9172$ ) and the rejection of duality ( $p - value < 0.0001$ ). Again, parametric estimates lead to inconsistent results across datasets for the comparison of probability weighting functions across domains.

In contrast, our method provides consistent results for the comparison of probability weighting functions across domains. We reject duality (RDU, [Quiggin, 1982](#); [Gilboa, 1987](#); [Schmeidler, 1989](#)) and identical probability weights across domains across datasets (OPT, [Kahneman and Tversky, 1979](#)). Tests of duality and identical probability weightings that cover the whole range of probabilities are scarce in the literature. Our findings echo [Abdellaoui \(2000\)](#) who reject both duality and identical probability weighting functions across domains under risk. However, under uncertainty, [Abdellaoui et al. \(2005\)](#) do not reject duality, although they reject identical weighting functions across domains. Importantly, our rejection of both duality and identical probability weights provides support for CPT.<sup>32</sup>

Our method also reveals an interesting pattern in the probability weighting function – more overweighting of tail probabilities in the gain domain than in the loss domain – which fully stands in line with CPT, but does not arise under the parametric approach.<sup>33</sup> Hence, the level of optimism for very small probabilities of gains is more pronounced than the level of pessimism for very small probabilities of losses.

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<sup>32</sup>Even though we reject both duality and identical probability weights, in Appendix 1.A.3 we show how to impose such constraints in our method.

<sup>33</sup>In addition, this pattern also holds for the Bayesian estimations reported in Appendix 1.D.

Two important similarities with TK92 also emerge. First, our estimates of loss aversion ( $\lambda$ ) are close to 2, in line with the estimate provided by TK92. Second, echoing the central tenets of CPT, we find that the probability weighting function is domain-specific. Furthermore, in both domains it is characterized by the overweighting of small probabilities and the underweighting of large ones.

Altogether, our results mesh well with CPT. In both domains, the inverse S-shaped probability weighting function affects risk preferences alongside the utility function.

Table 1.6: Summary of the discussion

	Data of TK92		Data of BFE10		Consistent	
	Semi-para	Para	Semi-para	Para	Semi-para	Para
Curvature Gain ( $\alpha$ )	Concave	Concave	Concave	Concave	Yes	Yes
Curvature Loss ( $\beta$ )	Concave	Convex	Concave	Concave	Yes	No
Loss aversion ( $\lambda$ )	Loss aversion	Loss aversion	-	-	-	-
Partial reflection	No	Yes	No	No	Yes	No
OPT: $w^+(\cdot) = w^-(\cdot)$	No	No	No	Yes	Yes	No
RDU: $w^+(p) = 1 - w^-(1 - p)$	No	No	No	No	Yes	Yes

## 1.6 Conclusion

ABL and [Abdellaoui et al. \(2011b\)](#) deploy a semi-parametric method to elicit the utility function and loss aversion. In this paper, we go one step further by developing a semi-parametric method that elicits all dimensions of risk attitudes, including the whole range of probability weights. Importantly, it retains the four appealing properties of the parametric methods that have been discussed at length in the literature.

Our method is also flexible because it can be applied to both risk and uncertainty. Furthermore, it can be used to extend the popular elicitation technique of [Holt and Laury \(2002\)](#) to the case in which probabilities are distorted, following the approach of [Abdellaoui et al. \(2011b\)](#). Finally, even though our method does not readily apply to the context envisioned by [Kőszegi and Rabin \(2007\)](#),<sup>34</sup> one can speculate on a possible procedure combining Kőszegi and Rabin's approach and our semi-parametric method. This procedure could start by introducing probability weighting functions in [Kőszegi and Rabin \(2007\)](#) following the work of [Baillon et al. \(2020\)](#). We see this as a promising avenue for future research.

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<sup>34</sup>They assume a stochastic reference point and the absence of any probability distortions, whereas we assume a fixed reference point and probability distortions.

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## 1.A Appendix on TK92 data

### 1.A.1 Data

#### a) Source

We use median data previously reported by TK92. They run a computerized experiment with 25 graduate students from Berkeley and Stanford with no particular training in decision theory. Each subject participated in three separate one-hour sessions organized over several days, and received \$25 for participation. We use all the median observations from non-mixed prospects (see their Table 3) as well as the first six median observations from mixed prospects (see their Table 6).

#### b) Procedure

The data are generated via the switching outcome procedure in which an indifference value is inferred through a list of equally spaced certain outcomes, ranging from the admissible maximum indifference value to the admissible minimum indifference value. Note that an alternative approach, the direct matching procedure in which subjects are directly asked to provide their indifference values, tends to produce more inconsistencies ([Bostic et al., 1990](#); [Booij and Van de Kuilen, 2009](#)). Internal consistency of the responses to each prospect is monitored by the computer software to reduce response errors.

#### c) Data for the first step

All outcomes are expressed in US dollars. In Table 3 of TK92, there are 28 median values of certainty equivalents for binary lotteries that involve 7 pairs of positive monetary outcomes  $(0, 50)$ ,  $(0, 100)$ ,  $(0, 200)$ ,  $(0, 400)$ ,  $(50, 100)$ ,  $(50, 150)$  and  $(100, 200)$ , and 9 probabilities of getting the higher outcome: 0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95 and 0.99.

Also, the same Table 3 in TK92 provides 28 median values of certainty equivalents for binary lotteries that involve 7 pairs of negative monetary outcomes  $(0, -50)$ ,  $(0, -100)$ ,  $(0, -200)$ ,  $(0, -400)$ ,  $(-50, -100)$ ,  $(-50, -150)$  and  $(-100, -200)$ , and the same list of 9 probabilities as in the gain domain. These probabilities are now associated to losing the higher outcome.

As required by our method, at least two certainty equivalents for each of the nine probabilities are available per domain so as to perform a simultaneous measurement of the utility function and the probability weighting function in the full domain.

c) Data for the second step

All outcomes are expressed in US dollars. In Table 6 of TK92, there are 6 cases of indifferences involving mixed prospects. The first four items consist in eliciting the values of gains  $x$  to make subjects indifferent between the mixed prospects  $(x, y; 0.5, 0.5)$  and 0. The values of  $y$  are -25, -50, -100 and -150. The two others cases consist in eliciting gains  $x$  that make subjects indifferent between two mixed prospects  $(x, y; 0.5, 0.5)$  and  $(z, w; 0.5, 0.5)$ . The triplets  $(y, z, w)$  take the values of either  $(-50, 50, -20)$  or  $(-125, 150, -50)$ . Note that here the experimenter has no control over the maximum level of  $x$  which may hinder the use of the switching outcome procedure for finding indifference value. For this reason, we make changes in the third step of the original method of ABL

through equations (1.16) - (1.19). Also, our method is based on the comparisons of binary lotteries and sure outcomes. Hence, these data do not exactly fit our method. With the present data, we compute loss aversion for each of the six questions and take the median as estimated value to account for response error (following ABL). For the first four items, we compute loss aversion as follows:

$$\lambda = \frac{w^+(0.5)}{w^-(0.5)} \times \frac{x^{\alpha_p}}{(-y)^{\beta_p}} \quad (1.24)$$

$$\lambda = \frac{w^+(0.5)}{w^-(0.5)} \times \frac{1 - \exp(-\alpha_e x)}{1 - \exp(\beta_e y)} \times \frac{\beta_e}{\alpha_e} \quad (1.25)$$

Formulas (1.24) and (1.25) correspond to power and exponential specifications, respectively.

For the last two questions, we compute loss aversion as follows:

$$\lambda = \frac{w^+(0.5)}{w^-(0.5)} \times \frac{z^{\alpha_p} - x^{\alpha_p}}{(-w)^{\beta_p} - (-y)^{\beta_p}} \quad (1.26)$$

$$\lambda = \frac{w^+(0.5)}{w^-(0.5)} \times \frac{\exp(-\alpha_e x) - \exp(-\alpha_e z)}{\exp(\beta_e y) - \exp(\beta_e w)} \times \frac{\beta_e}{\alpha_e} \quad (1.27)$$

Formulas (1.26) and (1.27) correspond to the power and exponential specifications, respectively. Finally, following ABL, we compute the median loss aversion.

## 1.A.2 Our main semi-parametric measurements

Our semi-parametric measurements are presented in Tables 1.A.1 and 1.A.2.



Table 1.A.1: Results of the first step

	Power utility				Exponential utility	
	No constraint		Constraint $\alpha_p = \beta_p$			
	Gain domain					
$\alpha_p$ or $\alpha_e$	0.904***	(0.0366)	0.976***	(0.0314)	0.00158*	(0.000886)
$\alpha$	0.525***	(0.0101)	0.506***	(0.00804)	0.552***	(0.0290)
$w(0.01)$	0.0471***	(0.00828)	0.0369***	(0.00659)	0.0445***	(0.00874)
$w(0.05)$	0.167***	(0.0138)	0.157***	(0.0138)	0.164***	(0.0143)
$w(0.10)$	0.134***	(0.0151)	0.115***	(0.0133)	0.124***	(0.0142)
$w(0.25)$	0.276***	(0.0142)	0.263***	(0.0142)	0.274***	(0.0155)
$w(0.50)$	0.410***	(0.0139)	0.388***	(0.0123)	0.409***	(0.0176)
$w(0.75)$	0.571***	(0.0137)	0.558***	(0.0140)	0.573***	(0.0164)
$w(0.90)$	0.686***	(0.0137)	0.666***	(0.0133)	0.692***	(0.0201)
$w(0.95)$	0.791***	(0.0124)	0.783***	(0.0133)	0.793***	(0.0139)
$w(0.99)$	0.947***	(0.00474)	0.943***	(0.00520)	0.957***	(0.00834)
	Loss domain					
$\beta_p$ or $\beta_e$	1.069***	(0.0485)	0.976***	(0.0314)	-0.00154*	(0.000931)
$\beta$	-0.483***	(0.0113)	-0.506***	(0.00804)	-0.449***	(0.0305)
$w(0.01)$	0.0244***	(0.00570)	0.0337***	(0.00646)	0.0236***	(0.00551)
$w(0.05)$	0.0924***	(0.0127)	0.103***	(0.0136)	0.0932***	(0.0123)
$w(0.10)$	0.105***	(0.0139)	0.127***	(0.0135)	0.106***	(0.0126)
$w(0.25)$	0.207***	(0.0140)	0.222***	(0.0140)	0.205***	(0.0141)
$w(0.50)$	0.414***	(0.0152)	0.440***	(0.0123)	0.405***	(0.0186)
$w(0.75)$	0.602***	(0.0146)	0.617***	(0.0139)	0.595***	(0.0168)
$w(0.90)$	0.758***	(0.0139)	0.776***	(0.0121)	0.746***	(0.0190)
$w(0.95)$	0.810***	(0.0133)	0.819***	(0.0132)	0.805***	(0.0148)
$w(0.99)$	0.947***	(0.00552)	0.951***	(0.00512)	0.936***	(0.0107)
Log Likelihood	-120.9645		-124.5477		-121.9931	
$N$	56		56		56	
AIC criterion	283.9289		289.0954		285.9861	
CV	3.149		3.344		3.305	

Standard errors in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  to test the significance of coefficients.

Table 1.A.2: Results of the second step (loss aversion)

Observations	Power utility		Exponential utility
	No constraint	Constraint $\alpha_p = \beta_p$	
1	1.304	2.106	2.306
2	0.981	1.751	1.815
3	0.875	1.751	1.616
4	0.762	1.622	1.355
5	0.892	1.786	1.741
6	0.739	1.735	1.247
<b>Median</b>	<b>0.884</b>	<b>1.751</b>	<b>1.679</b>

### 1.A.3 Semi-parametric results under identical probability weighting function and duality assumptions

This appendix show results under the constraints of identical probability weighting (OPT) and duality assumption (RDU). Tables 1.A.3 and 1.A.4 present these results.

Table 1.A.3: Results under identical probability weighting assumption

	Power utility		Exponential utility	
$\alpha_p$ or $\alpha_e$	0.904***	(0.0456)	0.00132	(0.000942)
$\alpha$	0.525***	(0.0126)	0.544***	(0.0310)
$\beta_p$ or $\beta_e$	1.053***	(0.0523)	-0.00127	(0.000961)
$\beta$	-0.487***	(0.0124)	-0.458***	(0.0316)
$w^+(0.01) = w^-(0.01)$	0.0326***	(0.00760)	0.0301***	(0.00700)
$w^+(0.05) = w^-(0.05)$	0.128***	(0.0148)	0.125***	(0.0137)
$w^+(0.10) = w^-(0.10)$	0.119***	(0.0161)	0.114***	(0.0137)
$w^+(0.25) = w^-(0.25)$	0.242***	(0.0156)	0.237***	(0.0153)
$w^+(0.50) = w^-(0.50)$	0.414***	(0.0159)	0.408***	(0.0184)
$w^+(0.75) = w^-(0.75)$	0.587***	(0.0155)	0.584***	(0.0169)
$w^+(0.90) = w^-(0.90)$	0.720***	(0.0151)	0.715***	(0.0200)
$w^+(0.95) = w^-(0.95)$	0.801***	(0.0141)	0.799***	(0.0147)
$w^+(0.99) = w^-(0.99)$	0.947***	(0.00557)	0.950***	(0.00962)
$N$	56		56	
Log Likelihood	-145.7		-143.2982	
AIC	315.400		310.596	
CV	3.456		3.518	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.A.4: Results under duality assumption  $w^+(p) = 1 - w^-(1 - p)$

	Power utility		Exponential utility	
$\alpha_p$ or $\alpha_e$	0.738***	(0.0476)	0.00771***	(0.00174)
$\alpha$	0.575***	(0.0157)	0.724***	(0.0381)
$\beta_p$ or $\beta_e$	0.754***	(0.0465)	0.00270*	(0.00155)
$\beta$	-0.570***	(0.0151)	-0.588***	(0.0488)
$w^+(0.01) = 1 - w^-(0.99)$	0.0431***	(0.00819)	0.0330***	(0.0125)
$w^+(0.05) = 1 - w^-(0.95)$	0.170***	(0.0200)	0.178***	(0.0220)
$w^+(0.10) = 1 - w^-(0.90)$	0.182***	(0.0190)	0.187***	(0.0267)
$w^+(0.25) = 1 - w^-(0.75)$	0.327***	(0.0208)	0.347***	(0.0255)
$w^+(0.50) = 1 - w^-(0.50)$	0.478***	(0.0195)	0.516***	(0.0297)
$w^+(0.75) = 1 - w^-(0.25)$	0.662***	(0.0205)	0.693***	(0.0241)
$w^+(0.90) = 1 - w^-(0.10)$	0.755***	(0.0203)	0.817***	(0.0272)
$w^+(0.95) = 1 - w^-(0.05)$	0.834***	(0.0196)	0.856***	(0.0189)
$w^+(0.99) = 1 - w^-(0.01)$	0.953***	(0.00812)	0.989***	(0.00555)
Log Likelihood	-165.9685		-161.7984	
$N$	56		56	
AIC	355.937		347.597	
CV	4.977		9.024	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  to test the significance of coefficients.

## 1.A.4 Parametric measurements

We consider the following parametric specifications (1.28) and (1.29)

$$\begin{aligned}
 \mathbf{c}e_l = & (D_l^+ - D_l^-) \left[ \left( |\mathbf{x}_l|^{\alpha_p D_l^+ + \beta_p D_l^-} - |\mathbf{y}_l|^{\alpha_p D_l^+ + \beta_p D_l^-} \right) \times W_l + \right. \\
 & \left. |\mathbf{y}_l|^{\alpha_p D_l^+ + \beta_p D_l^-} \right]^{\frac{1}{\alpha_p D_l^+ + \beta_p D_l^-}} + \mathbf{e}_l^i
 \end{aligned} \tag{1.28}$$

$$\begin{aligned}
 \mathbf{c}e_l = \ln & \left[ \left( \exp((\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+) \mathbf{x}_l) - \exp((\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+) \mathbf{y}_l) \right) \times W_l + \right. \\
 & \left. \exp((\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+) \mathbf{y}_l) \right] \frac{1}{\beta_e \mathbf{D}_l^- - \alpha_e \mathbf{D}_l^+} + \mathbf{e}_l^i
 \end{aligned} \tag{1.29}$$

with  $W_l$  can be one of the four specifications of TK92, P98-I, P98-II and GE87:

$$\begin{aligned}
 W_l &= \frac{p_l^{(a\mathbf{D}_l^+ + c\mathbf{D}_l^-)}}{\left( p_l^{(a\mathbf{D}_l^+ + c\mathbf{D}_l^-)} + (1 - p_l)^{(a\mathbf{D}_l^+ + c\mathbf{D}_l^-)} \right)^{\frac{1}{a\mathbf{D}_l^+ + c\mathbf{D}_l^-}}} \\
 W_l &= \exp \left[ - \left( - \ln(p_l) \right)^{a\mathbf{D}_l^+ + c\mathbf{D}_l^-} \right] \\
 W_l &= \exp \left[ - \left( b\mathbf{D}_l^+ + d\mathbf{D}_l^- \right) \times \left( - \ln(p_l) \right)^{a\mathbf{D}_l^+ + c\mathbf{D}_l^-} \right] \\
 W_l &= \frac{(b\mathbf{D}_l^+ + d\mathbf{D}_l^-) \times p_l^{(a\mathbf{D}_l^+ + c\mathbf{D}_l^-)}}{(b\mathbf{D}_l^+ + d\mathbf{D}_l^-) \times p_l^{(a\mathbf{D}_l^+ + c\mathbf{D}_l^-)} + (1 - p_l)^{(a\mathbf{D}_l^+ + c\mathbf{D}_l^-)}}
 \end{aligned}$$

Equation (1.28) and (1.29) allow us to elicit the utility and probability weighting function parameters in the full domain.

Once the parameters of the utility function and the probability weighting function are obtained, we estimate loss aversion as described in equations (1.24) - (1.27).

Table 1.A.5 presents the results of the first step that simultaneously estimates the utility and probability weighting functions in the full domain. Table 1.A.6 summarizes the estimates of loss aversion using parameters of the utility and probability weighting functions from the first step as inputs.

Table 1.A.5: Results of the first step: power utility (without constraint)

	TK92		P98-I		P98-II		GE87	
Gain domain								
$\alpha_p$	0.839***	(0.0280)	0.772***	(0.0224)	0.834***	(0.0510)	0.907***	(0.0537)
$\alpha$	0.544***	(0.00828)	0.564***	(0.00715)	0.545***	(0.0151)	0.524***	(0.0148)
$a$	0.643***	(0.0120)	0.589***	(0.0158)	0.590***	(0.0145)	0.620***	(0.0181)
$b$					1.076***	(0.0557)	0.693***	(0.0555)
Loss domain								
$\beta_p$	0.906***	(0.0286)	0.867***	(0.0254)	1.042***	(0.0709)	1.058***	(0.0641)
$\beta$	-0.525***	(0.00786)	-0.536***	(0.00729)	-0.490***	(0.0170)	-0.486***	(0.0151)
$a$	0.704***	(0.0153)	0.676***	(0.0205)	0.680***	(0.0189)	0.708***	(0.0239)
$b$					1.186***	(0.0687)	0.673***	(0.0568)
$N$	56		56		56		56	
Log Likelihood	-155.124		-158.499		-153.315		-152.111	
AIC	320		327		321		318	
CV	3.41		3.57		3.52		3.87	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.A.6: Results of the second step for Loss aversion: power utility (without constraint)

Observations	TK92	P98-I	P98-II	GE87
1	1.618	1.429	1.143	1.405
2	1.318	1.156	0.846	1.066
3	1.258	1.082	0.734	0.979
4	1.253	1.058	0.732	0.961
5	1.146	0.980	0.630	0.841
6	1.127	0.920	0.580	0.822
<b>Median</b>	<b>1.256</b>	<b>1.070</b>	<b>0.773</b>	<b>0.970</b>

Table 1.A.7: Results of the first step: power utility (with constraint)

	TK92		P98-I		P98-II		GE87	
Gain domain								
$\alpha_p$	0.872***	(0.0204)	0.814***	(0.0179)	0.926***	(0.0441)	0.978***	(0.0425)
$\alpha$	0.534***	(0.00582)	0.551***	(0.00544)	0.519***	(0.0119)	0.506***	(0.0109)
$a$	0.635***	(0.0110)	0.583***	(0.0165)	0.590***	(0.0152)	0.629***	(0.0185)
$b$					1.166***	(0.0511)	0.632***	(0.0422)
Loss domain								
$\beta_p$	0.872***	(0.0204)	0.814***	(0.0179)	0.926***	(0.0441)	0.978***	(0.0425)
$\beta$	-0.534***	(0.00582)	-0.551***	(0.00544)	-0.519***	(0.0119)	-0.506***	(0.0109)
$a$	0.713***	(0.0152)	0.681***	(0.0225)	0.678***	(0.0199)	0.695***	(0.0226)
$b$					1.083***	(0.0474)	0.741***	(0.0477)
$N$	56		56		56		56	
Log Likelihood	-156.499		-162.219		-156.147		-153.719	
AIC	321		332		324		319	
CV	3.313		3.586		3.426		3.589	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.A.8: Results of the second step for Loss aversion: power utility (with constraint)

Observations	TK92	P98-I	P98-II	GE87
1	2.040	2.009	2.076	2.175
2	1.738	1.723	1.764	1.844
3	1.730	1.723	1.743	1.808
4	1.730	1.716	1.743	1.808
5	1.668	1.637	1.704	1.792
6	1.615	1.616	1.496	1.674
<b>Median</b>	<b>1.730</b>	<b>1.720</b>	<b>1.743</b>	1.808

Table 1.A.9: Results of the first step: exponential utility

	TK92		P98-I		P98-II		GE87	
Gain domain								
$\alpha_e$	0.00168***	(0.0006)	0.00314***	(0.0005)	0.0004	(0.0008)	-0.000550	(0.0007)
$\alpha$	0.556***	(0.0193)	0.602***	(0.0157)	0.513***	(0.0257)	0.482***	(0.0243)
$a$	0.649***	(0.0189)	0.639***	(0.0243)	0.595***	(0.0190)	0.628***	(0.0179)
$b$					1.216***	(0.0540)	0.588***	(0.0405)
Loss domain								
$\beta_e$	0.0016**	(0.0007)	0.00225***	(0.0006)	-0.0006	(0.0011)	-0.0006	(0.0007)
$\beta$	-0.551***	(0.0222)	-0.574***	(0.0189)	-0.479***	(0.0368)	-0.459***	(0.0326)
$a$	0.721***	(0.0238)	0.709***	(0.0281)	0.673***	(0.0221)	0.695***	(0.0213)
$b$					1.183***	(0.0670)	0.658***	(0.0552)
$N$	56		56		56		56	
Log Likelihood	-164.567		-168.725		-157.124		-152.808	
AIC	339		347		328		320	
CV	6.21		4.35		4.06		5.39	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.A.10: Results of the second step for Loss aversion: exponential utility

Observations	TK92	P98-I	P98-II	GE87
1	2.234	2.238	2.328	2.300
2	1.824	1.794	1.906	2.028
3	1.800	1.701	1.897	1.979
4	1.747	1.637	1.832	1.940
5	1.577	1.434	1.700	1.912
6	1.496	1.192	1.641	1.807
<b>Median</b>	<b>1.774</b>	<b>1.669</b>	<b>1.865</b>	<b>1.960</b>



### 1.A.4.1 One step estimation of utility function, weighting function and loss aversion

Table 1.A.11: Simultaneous estimation of utility function, weighting function and loss aversion

	Power utility				Exponential utility	
	No constraint		Constraint $\alpha_p = \beta_p$			
Gain domain						
$\alpha_p$ or $\alpha_e$	0.896***	(0.0433)	0.991***	(0.0326)	-0.000209	(0.000922)
$\alpha$	0.528***	(0.0121)	0.502***	(0.0082)	0.493***	(0.0307)
$w^+(0.01)$	0.0484***	(0.00990)	0.0351***	(0.00696)	0.0327***	(0.00798)
$w^+(0.05)$	0.169***	(0.0161)	0.155***	(0.0154)	0.152***	(0.0162)
$w^+(0.10)$	0.136***	(0.0179)	0.111***	(0.0143)	0.107***	(0.0149)
$w^+(0.25)$	0.278***	(0.0166)	0.260***	(0.0158)	0.256***	(0.0175)
$w^+(0.50)$	0.412***	(0.0165)	0.384***	(0.0134)	0.377***	(0.0185)
$w^+(0.75)$	0.572***	(0.0160)	0.555***	(0.0157)	0.551***	(0.0190)
$w^+(0.90)$	0.688***	(0.0161)	0.662***	(0.0147)	0.656***	(0.0227)
$w^+(0.95)$	0.792***	(0.0143)	0.781***	(0.0150)	0.778***	(0.0172)
$w^+(0.99)$	0.948***	(0.00547)	0.943***	(0.00590)	0.940***	(0.0111)
Loss domain						
$\beta_p$ or $\beta_e$	1.045***	(0.0383)	0.991***	(0.0326)	-0.000979	(0.000723)
$\beta$	-0.489	(0.0092)	0.502***	(0.0082)	-0.467***	(0.0239)
$w^+(0.01)$	0.0265***	(0.00496)	0.0320***	(0.00554)	0.0262***	(0.00470)
$w^+(0.05)$	0.0950***	(0.0107)	0.101***	(0.0113)	0.0957***	(0.0100)
$w^+(0.10)$	0.110***	(0.0117)	0.123***	(0.0120)	0.111***	(0.0103)
$w^+(0.25)$	0.211***	(0.0116)	0.220***	(0.0119)	0.210***	(0.0114)
$w^+(0.50)$	0.421***	(0.0123)	0.436***	(0.0115)	0.415***	(0.0146)
$w^+(0.75)$	0.606***	(0.0120)	0.615***	(0.0119)	0.602***	(0.0132)
$w^+(0.90)$	0.762***	(0.0112)	0.773***	(0.0107)	0.755***	(0.0147)
$w^+(0.95)$	0.812***	(0.0109)	0.818***	(0.0110)	0.809***	(0.0116)
$w^+(0.99)$	0.948***	(0.00448)	0.950***	(0.00436)	0.941***	(0.00800)
Mixed Prospect						
$\lambda$	0.864***	(0.242)	1.688***	(0.0786)	1.684***	(0.135)
Log Likelihood	-131.289		-134.001		-133.181	
$N$	60		60		60	
AIC criterion	308.5782		312.0025		312.3615	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

## **1.B Appendix for the application to the data of BFE10**

In this appendix, we provide details on individual and pooled results based on the data of BFE10. We also allow for heteroscedastic errors, as discussed in Section 1.3.2.2.

### **1.B.0.1 Pooled data**

Tables 1.B.1 and 1.B.2 summarize our pooled data estimates that we present in the main text.

Table 1.B.1: Semi-parametric estimation results: pooled data

	Power		Exponential	
	Gain domain			
Utility				
parameter	1.031***	(0.0216)	0.00710***	(0.0007)
$w^+(0.05)$	0.191***	(0.0062)	0.220***	(0.0063)
$w^+(0.10)$	0.250***	(0.0083)	0.276***	(0.0068)
$w^+(0.25)$	0.330***	(0.0076)	0.359***	(0.0067)
$w^+(0.50)$	0.450***	(0.0067)	0.501***	(0.0060)
$w^+(0.75)$	0.606***	(0.0074)	0.635***	(0.0064)
$w^+(0.90)$	0.734***	(0.0075)	0.756***	(0.0063)
$w^+(0.95)$	0.779***	(0.0069)	0.799***	(0.0061)
	Loss domain			
Utility				
parameter	1.088***	(0.0259)	-0.00606***	(0.00072)
$w^-(0.05)$	0.193***	(0.0077)	0.195***	(0.0065)
$w^-(0.10)$	0.263***	(0.0091)	0.270***	(0.0068)
$w^-(0.25)$	0.374***	(0.0083)	0.373***	(0.0068)
$w^-(0.50)$	0.518***	(0.0073)	0.501***	(0.0063)
$w^-(0.75)$	0.659***	(0.0078)	0.655***	(0.0069)
$w^-(0.90)$	0.730***	(0.0082)	0.730***	(0.0071)
$w^-(0.95)$	0.798***	(0.0064)	0.787***	(0.0065)
$N$	8906		8906	
Log Likelihood	-25191.14		-25103.62	
AIC	50776.27		50601.23	
CV	4.400		4.2494	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.B.2: Parametric estimation results with power utility: pooled data

	TK92		P98-I		P98-II		GE87	
Gain domain								
$\alpha_p$	1.219***	(0.0152)	1.102***	(0.0115)	1.043***	(0.0212)	1.040***	(0.0215)
$\alpha$	0.451***	(0.00310)	0.476***	(0.00260)	0.490***	(0.00509)	0.490***	(0.00517)
$a$	0.591***	(0.00490)	0.484***	(0.00704)	0.483***	(0.00705)	0.870***	(0.0196)
$b$					0.955***	(0.0140)	0.475***	(0.00708)
Loss domain								
$\beta_p$	1.442***	(0.0186)	1.330***	(0.0148)	1.091***	(0.0257)	1.078***	(0.0249)
$\beta$	-0.409***	(0.00312)	-0.429***	(0.00274)	-0.478***	(0.00587)	-0.481***	(0.00577)
$a$	0.616***	(0.00539)	0.508***	(0.00792)	0.506***	(0.00799)	1.049***	(0.0256)
$b$					0.853***	(0.0147)	0.477***	(0.00753)
$N$	8906		8906		8906		8906	
Log Likelihood	-25369		-25305		-25260		-25227	
AIC	51110		50980		50895		50828	
CV	10.005		4.381		4.383		4.375	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 1.B.3: Parametric estimation results with exponential utility: pooled data

	TK92		P98-I		P98-II		GE87	
Gain domain								
$\alpha_e$	-0.0008	(0.0005)	0.0004	(0.0004)	0.0066***	(0.0007)	0.0072***	(0.0007)
$\alpha$	0.490***	(0.0065)	0.505***	(0.0056)	0.581***	(0.0079)	0.589***	(0.0079)
$a$	0.345***	(0.0132)	0.502***	(0.0071)	0.492***	(0.0072)	1.025***	(0.0163)
$b$					0.862***	(0.0093)	0.467***	(0.0068)
Loss domain								
$\beta_e$	-0.0171***	(0.0009)	-0.0144***	(0.0007)	-0.0068***	(0.0007)	-0.0059***	(0.00069)
$\beta$	-0.307***	(0.0087)	-0.333***	(0.0067)	-0.416***	(0.0083)	-0.428***	(0.0083)
$a$	0.319***	(0.0146)	0.492***	(0.0077)	0.490***	(0.0079)	1.015***	(0.0167)
$b$					0.871***	(0.0096)	0.468***	(0.0071)
$N$	8906		8906		8906		8906	
Log Likelihood	-25560		-25348		-25165		-25131	
AIC	51489		51066		50704		50636	
CV	4.842		4.512		4.304		4.253	

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Standard errors in parentheses

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

### 1.B.1 Individual results

This appendix provides results based on individual estimates. We focus on the exponential utility function which is found to provide a better fit to the data than the power utility function under both our semi-parametric method and the parametric one. Analyses presented below are based on median comparisons of coefficients using Sign Rank tests. All tests are two-sided, unless stated otherwise.

### 1.B.1.1 Curvature of the utility function

The distributions of the curvature coefficients obtained under both methods are plotted in Figures 1.B.1 and 1.B.2, and their median values are summarized in Table 1.B.4.

Figures 1.B.1 and 1.B.2 indicate that, regardless of the estimation method at hand, the dominant pattern is the concavity of the utility function in both domains.

For gains, the estimated median exponential utility parameter under the semi-parametric method is 0.0068 and significantly greater than 0 ( $p$ -value  $< 0.0001$ , one-sided Sign Rank test). In the loss domain, the median exponential utility parameter is estimated at -0.0065 and significantly below 0 ( $p$ -value  $< 0.0001$ ). Furthermore, partial reflection is rejected: comparing the median estimates of both coefficients yields  $p$ -value  $< 0.0001$ . The parametric method leads to very similar results.<sup>35</sup>

### 1.B.2 Probability weighting function

Table 1.B.5 and Figure 1.B.3 summarize the estimated probability weighting functions across domains. In addition, Figures 1.B.4 and 1.B.5 show the underlying distributions of individual estimates. Both methods consistently point to an inverse S-shaped weighting function across domains, with a crossover point around  $p = 0.5$ . We cannot reject  $H_0 : w^+(0.5) = 0.5$  or  $H_0 : w^-(0.5) = 0.5$  with  $p$ -values  $> 0.3698$ .

Focusing on our semi-parametric method, we report that the median difference in probability weights between gains and losses is positive and significant ( $p$ -

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<sup>35</sup>The corresponding median values are 0.0081 and -0.0063. The respective statistical tests all yield  $p$ -values  $< 0.0001$ . In addition, the differences between the median estimates obtained through both methods are small and insignificant for gains ( $p$ -value = 0.6539) as well as for losses ( $p$ -value = 0.8812).

$values < 0.0361$ ) for the probabilities  $p = 0.05$  and  $p = 0.10$ , and insignificant for the remaining probabilities (all  $p - values > 0.1347$ ). This suggests that there is stronger overweighting of probabilities  $p = 0.05$  and  $p = 0.10$  in the gain domain than in the loss domain. Hence, subjects are more optimistic about very small probabilities of gaining money than they are pessimistic about very small probabilities of losing money. In contrast, identical probability weighting cannot be refuted with the parametric method because the median differences in the estimated probability weights are systematically insignificant (all  $p - values > 0.7651$ ).<sup>36</sup>

Table 1.B.4: Median estimates for exponential utility function using individual estimates

	Semi-parametric		Parametric	
	Median	IQR <sup>†</sup>	Median	IQR <sup>†</sup>
Utility parameter (Gain)	0.0068	[-0.0001; 0.0152]	0.0081	[0.0007; 0.0136]
Utility parameter (Loss)	-0.0065	[-0.0172; 0.0001]	-0.0063	[-0.0158; 0.0002]
AIC*	50,601.23		50,636.95	
CV*	4.2494		4.2529	

<sup>†</sup> IQR stands for interquartile range

\* AIC and CV are from pooled estimates

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<sup>36</sup>The same results hold on the median differences of the parameters of the probability weighting function (all  $p - values > 0.6539$ )

Table 1.B.5: Median values of probability weights based on individual estimates

	Semi-parametric		Parametric	
	Median	IQR <sup>+</sup>	Median <sup>+</sup>	IQR <sup>+</sup>
	Gain			
$w^+(0.05)$	0.2156	0.1339; 0.3181	0.2033	0.1273; 0.3030
$w^+(0.10)$	0.2666	0.1826; 0.3696	0.2670	0.1865; 0.3502
$w^+(0.25)$	0.3635	0.2763; 0.4521	0.3741	0.2971; 0.4437
$w^+(0.50)$	0.5046	0.4196; 0.5660	0.5163	0.4302; 0.5685
$w^+(0.75)$	0.6441	0.5251; 0.7269	0.6323	0.5549; 0.7067
$w^+(0.90)$	0.7900	0.6524; 0.8720	0.7315	0.6420; 0.8135
$w^+(0.95)$	0.8038	0.6916; 0.8961	0.7991	0.6999; 0.8698
	Loss			
$w^-(0.05)$	0.1886	0.0908; 0.3026	0.1922	0.1184; 0.3000
$w^-(0.10)$	0.2545	0.1490; 0.3811	0.2521	0.1729; 0.3688
$w^-(0.25)$	0.3628	0.2750; 0.4907	0.3663	0.2906; 0.4568
$w^-(0.50)$	0.5076	0.4289; 0.5724	0.4928	0.4345; 0.5645
$w^-(0.75)$	0.6506	0.5770; 0.7392	0.6398	0.5463; 0.6967
$w^-(0.90)$	0.7488	0.6340; 0.8353	0.7560	0.6564; 0.8118
$w^-(0.95)$	0.7922	0.6867; 0.8821	0.8131	0.7123; 0.8721
IQR stands for interquartile range				
+ For parametric methods, the median weights and IQR are computed from the individual probability weighting function				



Figure 1.B.1: Curvature of the utility function across domains: semi-parametric estimates



Figure 1.B.2: Curvature of the utility function under different estimation methods

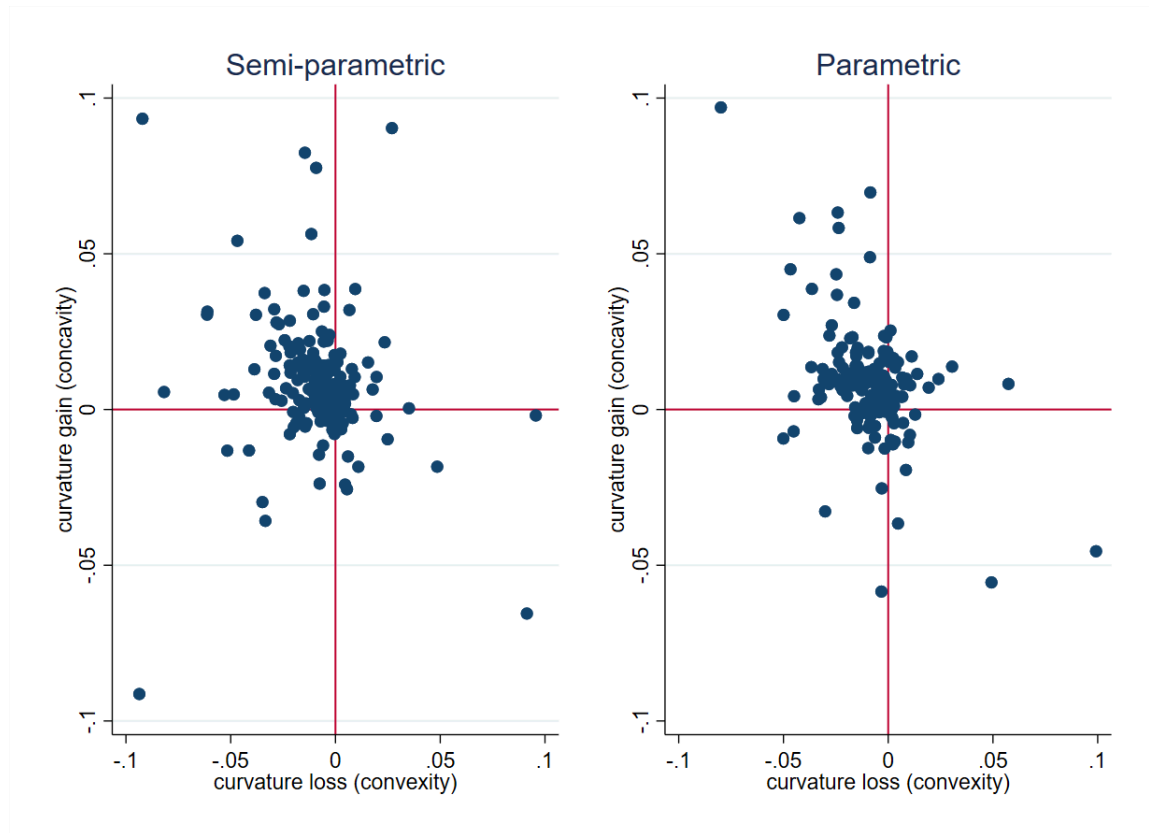


Figure 1.B.3: Median probability weights under different estimation methods

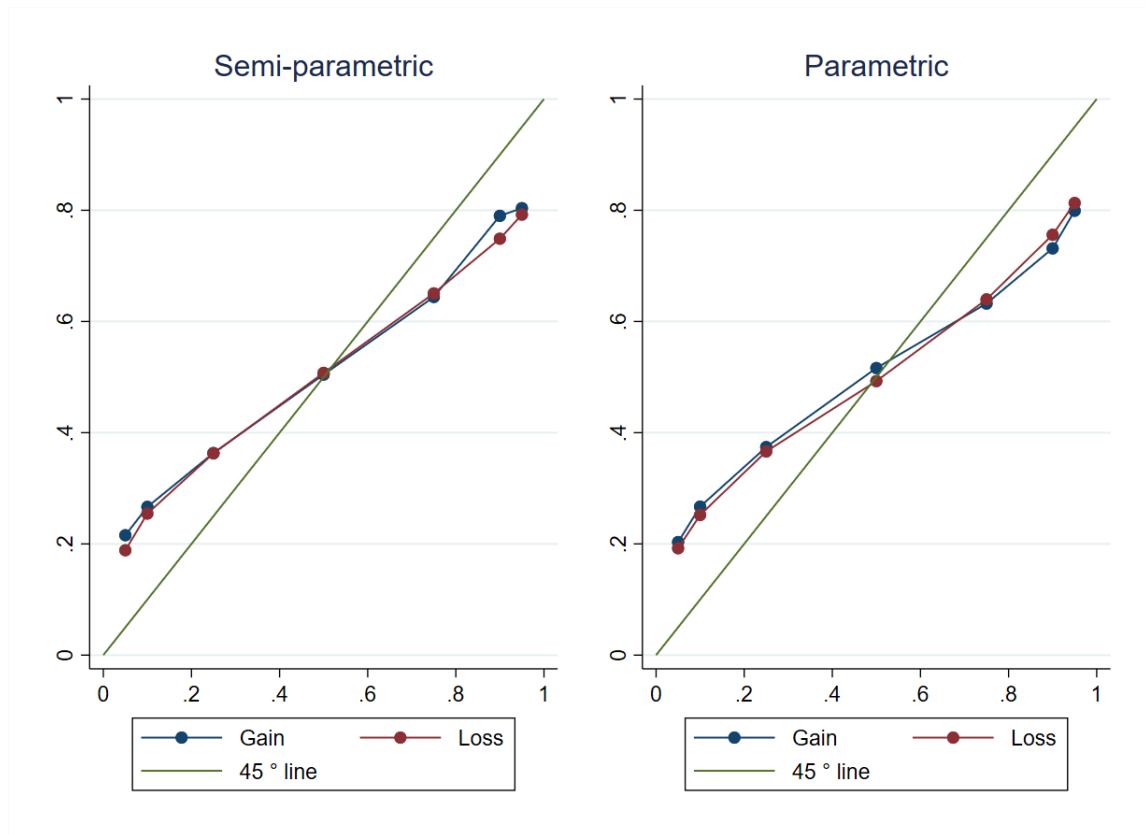


Figure 1.B.4: Distribution of probability weights for gains

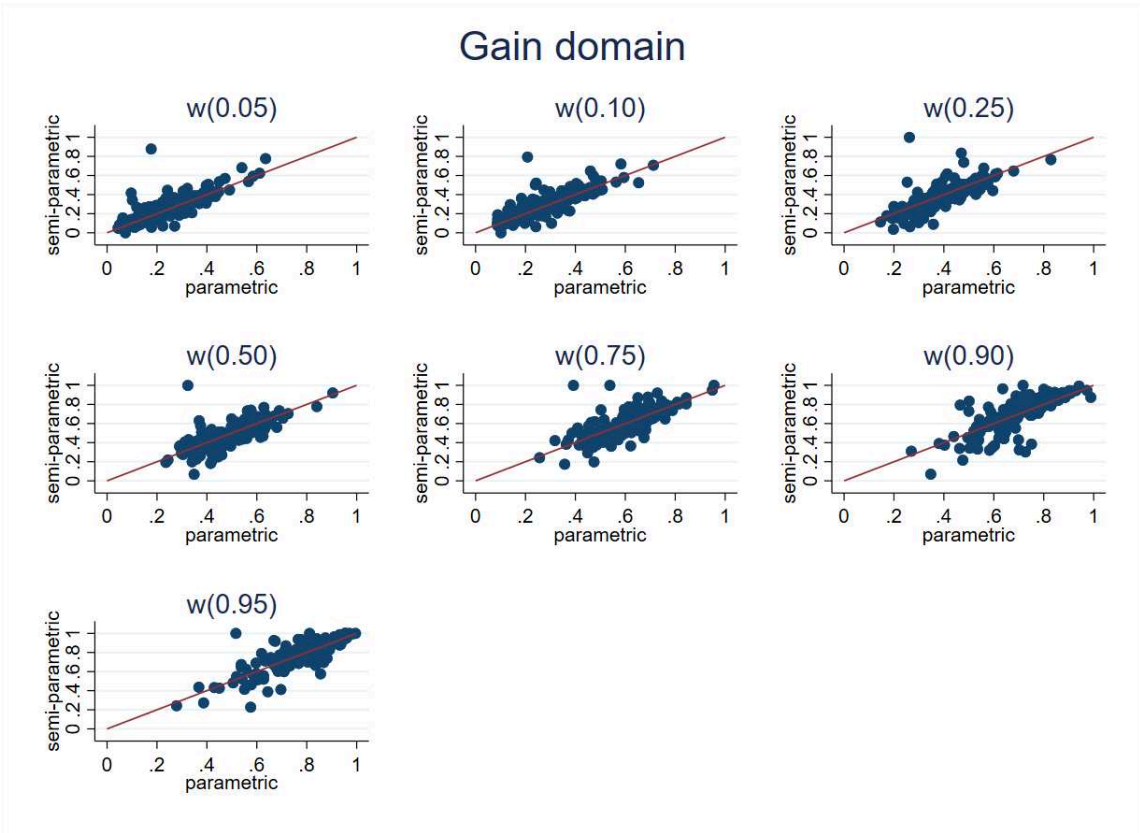
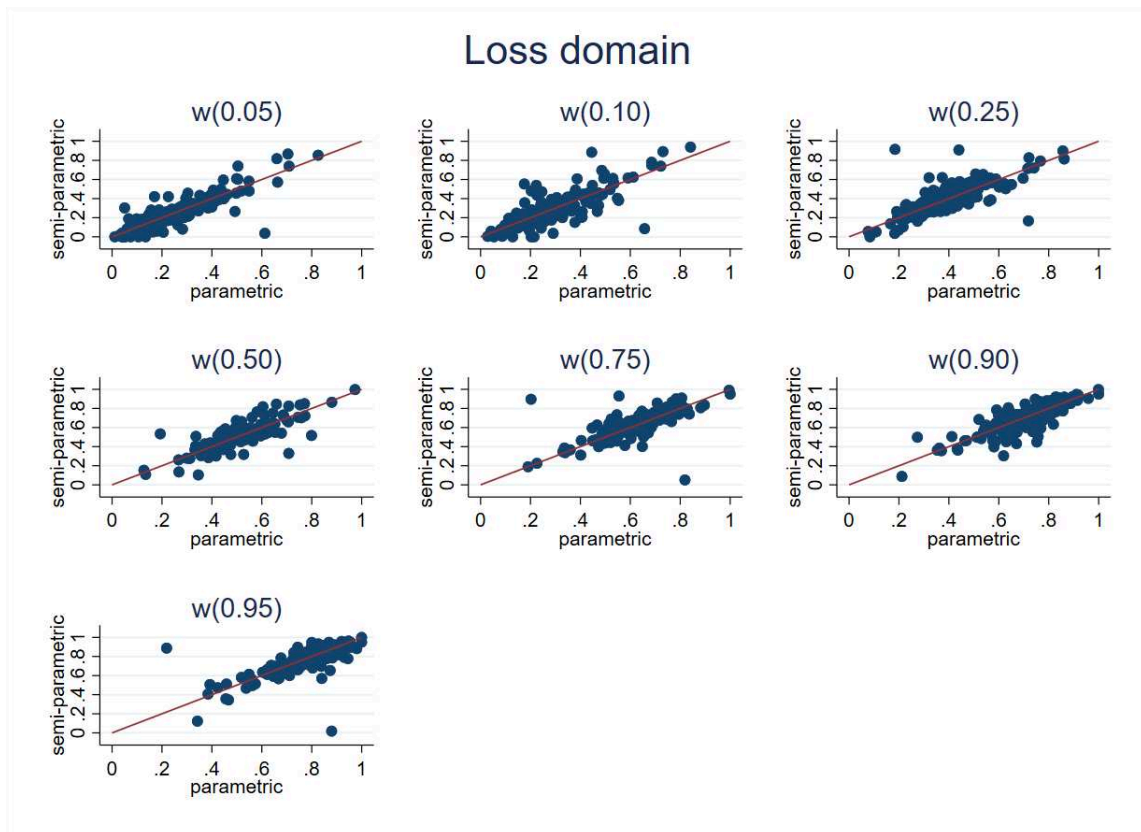


Figure 1.B.5: Distribution of probability weights for losses



## 1.C Spline extension

Our semi-parametric method requires specifying a utility function. Using spline instead may further serve to reduce or eliminate such parametric assumptions. In this section, we provide a linear spline extension for our semi-parametric method.<sup>37</sup>

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<sup>37</sup>The use of linear spline to approximate the utility function meshes well with the observation that utility is quasi-linear over a small range of outcomes (see [Wakker and Deneffe, 1996](#); [Bleichrodt and Pinto, 2000](#); [Rabin, 2000](#); [Fehr-Duda et al., 2006](#)).

### 1.C.1 Estimating probability weighting functions and utility curvature

We consider utility function over a range  $[\underline{q}, 0] \cup [0, \bar{q}]$ . We divide this range in arbitrarily small intervals  $[q_j, q_{j+1}]$  over which utility is assumed to be linear, with  $\underline{q} \equiv q_{-\tau^-} < q_{-\tau^-+1} < \dots < q_0 \equiv 0 < q_1 < \dots < q_{\tau^+-1} < q_{\tau^+} \equiv \bar{q}$  and  $j \in \{-\tau^-, -\tau^- + 1, \dots, -1, 0, 1, \dots, \tau^+ - 1, \tau^+\}$ . Notations  $(\mathbf{ce}_l, \mathbf{x}_l, \mathbf{y}_l, \mathbf{I}_l^k, \mathbf{D}_l^+$  and  $\mathbf{D}_l^-)$  are the same as in Sections 1.3.2.2 and 1.3.2.3. We assume that all the outcomes  $\mathbf{x}_l$  and  $\mathbf{y}_l$  in the binary lotteries are such that  $\{\mathbf{x}_l, \mathbf{y}_l\} \in \{q \equiv q_{-\tau^-}, q_{-\tau^-+1}, \dots, q_0 \equiv 0, q_1, \dots, q_{\tau^+-1}, q_{\tau^+} \equiv \bar{q}\}$ . A linear spline approximation of the utility of any certainty equivalent  $\mathbf{ce}_l \in [q_j, q_{j+1}]$  is thus given by:

$$u(\mathbf{ce}_l) = u(q_j) + \frac{u(q_{j+1}) - u(q_j)}{q_{j+1} - q_j}(\mathbf{ce}_l - q_j) \quad (1.30)$$

where  $u(0) = 0$ . The subsequent identification of loss aversion as in [Köbberling and Wakker \(2005\)](#) requires the utility function to be differentiable at 0 with  $u'(0) = 1$ . This implies that  $u(q_{-1}) = q_{-1}$  and  $u(q_1) = q_1$ . We assume response errors at the level of the utility ratio and get the equation:<sup>38</sup>

$$\frac{u(\mathbf{ce}_l) - u(\mathbf{y}_l)}{u(\mathbf{x}_l) - u(\mathbf{y}_l)} = \sum_{k=1}^K (\delta_k^+ \mathbf{D}_l^+ + \delta_k^- \mathbf{D}_l^-) \mathbf{I}_l^k + \mathbf{e}_l^i \quad (1.31)$$

with the scaling  $u(0) = 0$ ,  $u(q_{-1}) = q_{-1}$  and  $u(q_1) = q_1$ . Equation (1.31) then allows us to estimate the probability weights and the utility evaluated at the knots:  $q_{-\tau^-}, q_{-\tau^-+1}, \dots, q_{-2}, q_2, \dots, q_{\tau^+-1}, q_{\tau^+}$ .

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<sup>38</sup>We choose to define the error term at the level of the utility ratio rather than the utility itself so as to circumvent the problem of extreme utility curvature (see footnote 13 for further explanation).

## 1.C.2 Estimating loss aversion

With utility function and probability weights estimated in the previous steps, we can rewrite equation (1.16) as follows:

$$\left(1_{(ce_k \geq 0)} + \lambda 1_{(ce_k < 0)}\right) u(ce_k) = w^+(p_k)u(x_k) + \lambda w^-(1 - p_k)u(y_k) \quad (1.32)$$

where  $\{\mathbf{x}_k, \mathbf{y}_k\} \in \{q \equiv q_{-\tau^-}, q_{-\tau^-+1}, \dots, q_0 \equiv 0, q_1, \dots, q_{\tau^+-1}, q_{\tau^+} \equiv \bar{q}\}$  and  $1_{(\cdot)}$  refers to the indicator function. Using the same notation as in Section 1.3.2.3 and assuming an additive error at the basic utility scale ( $\mathbf{e}_k$ ), the empirical counterpart of equation (2.21) then becomes:

$$\left(\mathbf{D}_k^+ + \lambda \mathbf{D}_k^-\right) \hat{u}(ce_k) = \hat{\boldsymbol{\delta}}_k^+ \hat{u}(\mathbf{x}_k) + \lambda \hat{\boldsymbol{\delta}}_k^- \hat{u}(\mathbf{y}_k) + \mathbf{e}_k \quad (1.33)$$

We can then estimate the loss aversion index of [Köbberling and Wakker \(2005\)](#) from equation (2.22) by minimizing the sum of squared errors with respect to  $\lambda$ .

## 1.C.3 Comparing our semi-parametric method with its non-parametric spline version

To conduct spline estimations, we need data with a high number of certainty equivalents per subject. Among the several existing datasets that we reviewed (e.g. GW99; BFE10; [l'Haridon and Vieider, 2019](#); [Harrison and Rutström, 2009](#); [Andersson et al., 2020](#); [Pedroni et al., 2017](#); [Eisenberg et al., 2019](#)), the one of GW99 is best suited for our analysis because it includes 165 certainty equivalents per subject.

The 165 values of certainty equivalents correspond to binary lotteries that involve 15 pairs of positive monetary outcomes (0, 25), (0, 50), (0, 75), (0, 100), (0, 150), (0, 200), (0, 400), (0, 800), (25, 50), (50, 75), (50, 100), (50,

150), (100, 150), (100, 200) and (150, 200) and 11 probabilities of obtaining the higher outcome: 0.01, 0.05, 0.1, 0.25, 0.4, 0.5, 0.6, 0.75, 0.9, 0.95 and 0.99. The subjects are 10 graduate students in psychology. GW99 use the switching outcome procedure for eliciting certainty equivalents, resulting in a total of 1650 certainty equivalents.

### 1.C.4 Results

We perform both semi-parametric and linear spline estimations using individual-level and median data. Figures 1.C.1 and 1.C.2 show the estimates for the utility and probability weighting functions.<sup>39</sup> For the median data, both methods lead to remarkably similar estimates for both the utility and probability weighting functions. Both methods estimate a concave utility function and an inverse S-shaped weighting function with crossover point around  $p = 0.4$ . Even though we cannot reject the absence of differences in probability weights between the two methods (all  $p$ -values  $> 0.3438$ ), the concavity of the utility function is more pronounced in the spline estimation ( $p$ -value = 0.0010).

At the individual level, the utility function is also found to be predominantly concave in both methods. The typical inverse S-shaped weighting function is also pervasive across methods, with the exception of Subject 6 whose weighting function is weakly concave.

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<sup>39</sup>To compare the utility function over the range [\$0, \$800] from these two estimations, we convert them into a common scale, so that  $u(\$800) = 1$  and  $u(0) = 0$ .



Figure 1.C.1: Estimated utility functions

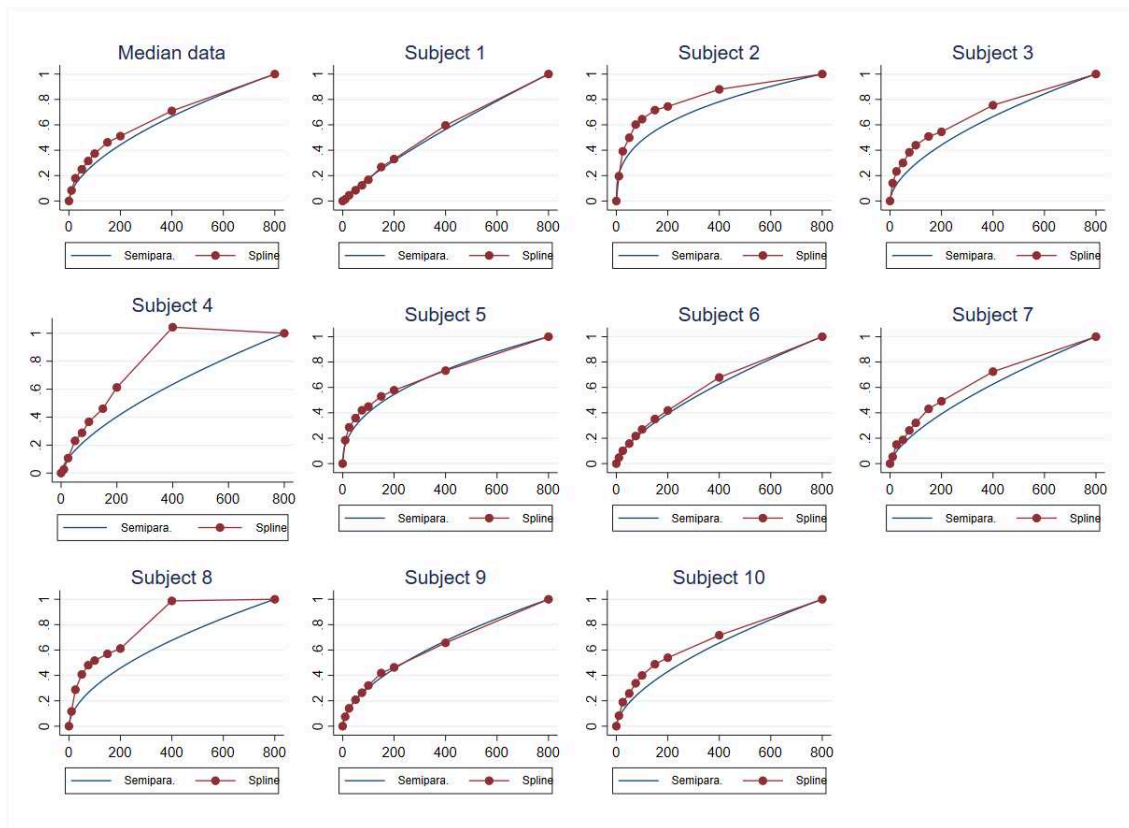
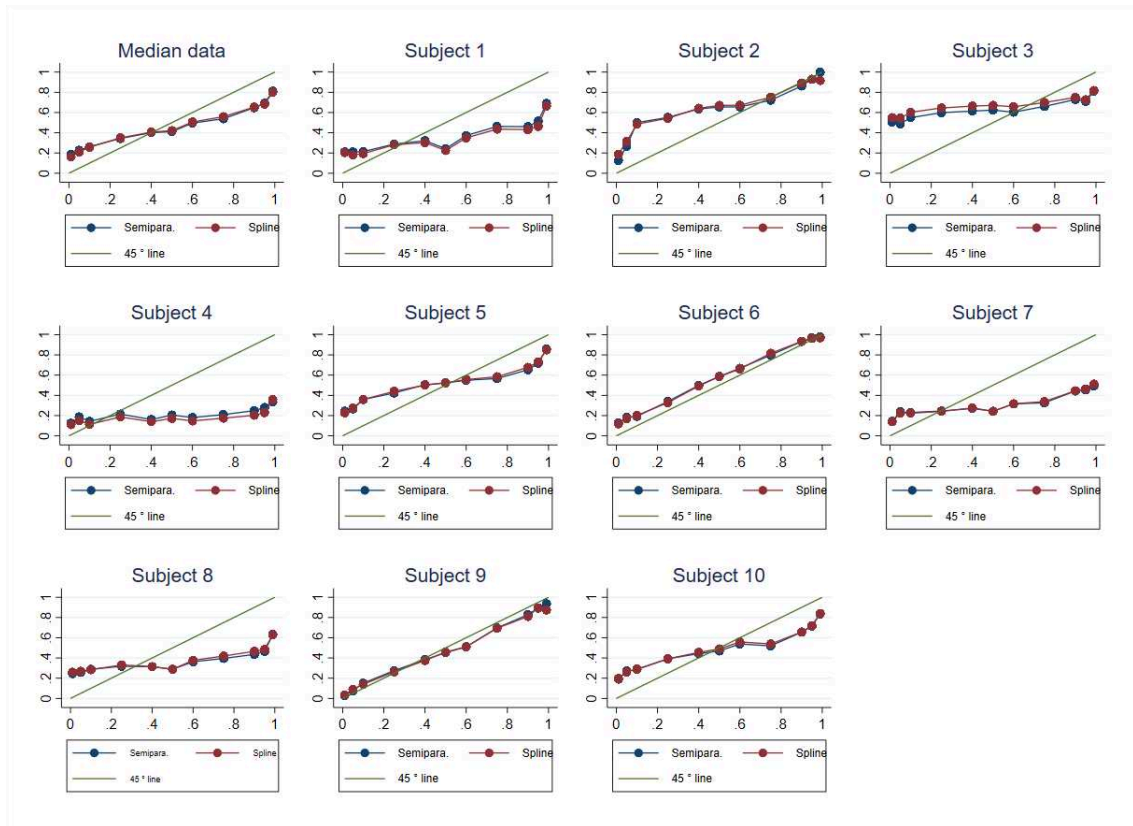


Figure 1.C.2: Estimated weighting functions



## 1.D Hierarchical Bayesian Parameter Estimation

The goal of this application is to illustrate how to deploy Bayesian techniques with our method. To that end, we use the data of [l'Haridon and Vieider \(2019\)](#) who elicit risk parameters from individual decisions of 2,939 subjects across 30 countries.

We use Hierarchical Bayesian Parameter Estimation (HBPE) ([Nilsson et al., 2011](#); [Murphy and ten Brincke, 2018](#); [Baillon et al., 2020](#); [Gao et al., 2020](#)) to

estimate world-level and country-level utility functions, probability weights and loss aversion. To perform HBPE, we rewrite equation (1.10) to account for the fact that risk preferences are elicited at the country level ( $c$ ):

$$\mathbf{c}e_{s,c,l} = u_c^{-1} \left[ (u_c(\mathbf{x}_l) - u_c(\mathbf{y}_l)) \times \left( \sum_{k=1}^K (\delta_k^{c,+} \mathbf{D}_l^+ + \delta_k^{c,-} \mathbf{D}_l^-) \mathbf{I}_l^k \right) + u_c(\mathbf{y}_l) \right] + e_{s,c,l}^i \quad (1.34)$$

with  $\delta_k^{c,+} = F(z_k^{c,+})$ ,  $\delta_k^{c,-} = F(z_k^{c,-})$ ,  $F(\cdot)$  is the normal cumulative distribution function,  $c$  refers to the country of residence and  $e_{s,c,l}^i$  is a normally distributed error term  $N(0, \sigma_i^2)$ . As in [l'Haridon and Vieider \(2019\)](#), we consider a country-specific exponential utility function  $u_c(\cdot)$  characterized by  $\alpha_e^c$  and  $\beta_e^c$ .

Following [Rouder and Lu \(2005\)](#), [Nilsson et al. \(2011\)](#) and [Gao et al. \(2020\)](#), we assume the following prior and hyperprior distributions. As priors we take:  $\alpha_e^c \rightsquigarrow N(\alpha_e, \sigma_{\alpha_e^2})$ ,  $\beta_e^c \rightsquigarrow N(\beta_e, \sigma_{\beta_e^2})$ ,  $z_k^{c,i} \rightsquigarrow N(z_k^i, \sigma_{z_k^i}^2)$ ,  $\sigma_+^2 \rightsquigarrow IG(0.001, 0.001)$  and  $\sigma_-^2 \rightsquigarrow IG(0.001, 0.001)$  where  $IG(\cdot)$  stands for inverse gamma distribution.

As hyperpriors, we take:  $\alpha_e \rightsquigarrow N(0, 10)$ ,  $\beta_e \rightsquigarrow N(0, 10)$ ,  $z_k^i \rightsquigarrow N(0, 1)$ ,  $\sigma_{\alpha_e}^2 \rightsquigarrow IG(0.001, 0.001)$ ,  $\sigma_{\beta_e}^2 \rightsquigarrow IG(0.001, 0.001)$ ,  $\sigma_{z_k^i}^2 \rightsquigarrow IG(0.001, 0.001)$ . We estimate the posterior distributions of world- and country- specific parameters by using Markov Chain Monte Carlo (MCMC) with blocked Gibbs sampling ([Baillon et al., 2020](#); [Gao et al., 2020](#)). After discarding a burn-in of 10000 samples, we collect 40000 samples to approximate the posterior distributions of the parameters of interest. We confirm the convergence of the MCMC chain by visual inspection of the trace plots, the autocorrelation plots and kernel densities of parameters based on the first and second halves of the sample.

We then use mean estimates of utility curvature and probability weights as inputs to estimate loss aversion. Like [Nilsson et al. \(2011\)](#), [Spiliopoulos and Hertwig \(2019\)](#) and [Gao et al. \(2020\)](#), we assume that the country-specific loss

aversion  $\lambda^c$  follows a log-normal distribution  $LN(\lambda, \sigma_\lambda^2)$  with  $\lambda \rightsquigarrow N(0, 10)$  and  $\sigma_\lambda^2 \rightsquigarrow IG(0.001, 0.001)$ .

## Results

### Utility and probability weighting functions

Figures 1.D.1 and 1.D.2 show the posterior distributions of the world-level utility curvature in the gain and loss domains. The mean of the posterior distribution of the utility curvature in the gain (loss) domain is 0.0085 (-0.0055) suggesting that the utility function is generally concave. In the gain domain, the 95% credible interval is [0.0021, 0.0150] showing that the utility function deviates significantly from linearity. In the loss domain, linearity of the utility function cannot be rejected at the 5% significance level with the 95% credible interval of [-0.0165, 0.0057].

Figure 1.D.1: Posterior distributions of curvature and probability weights in the gain domain (world-level)

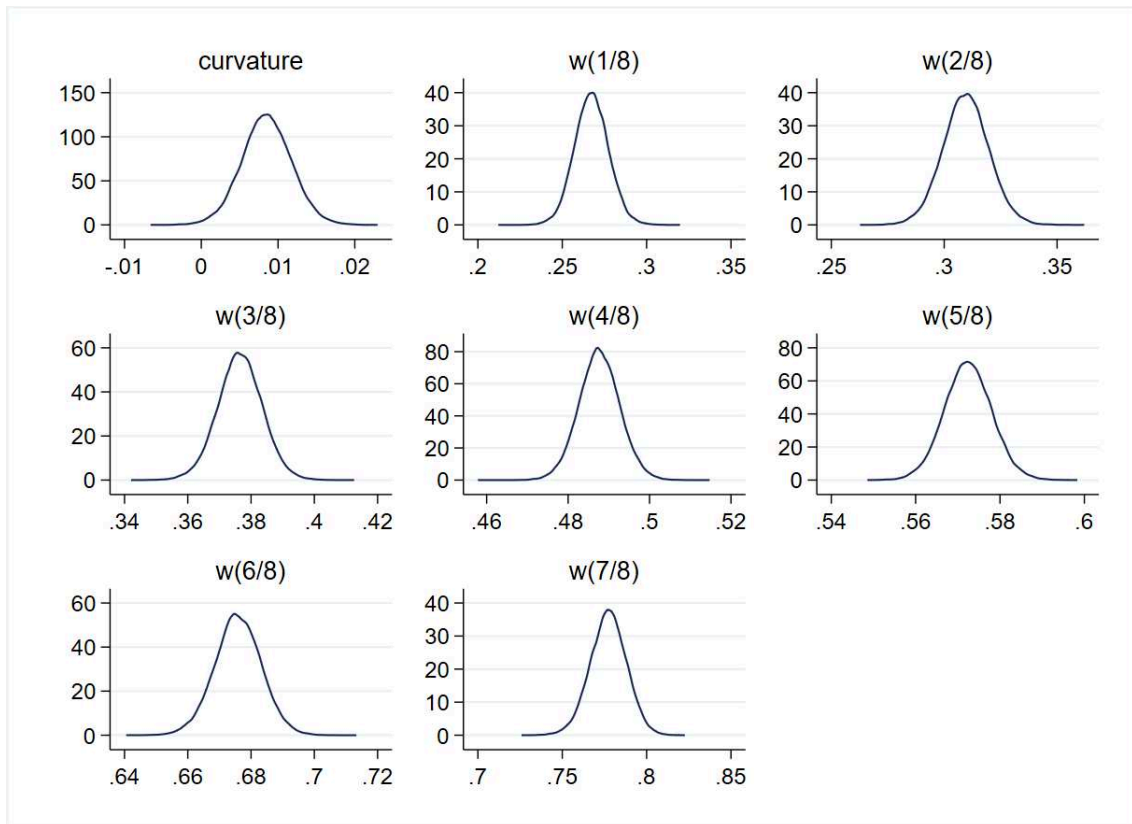
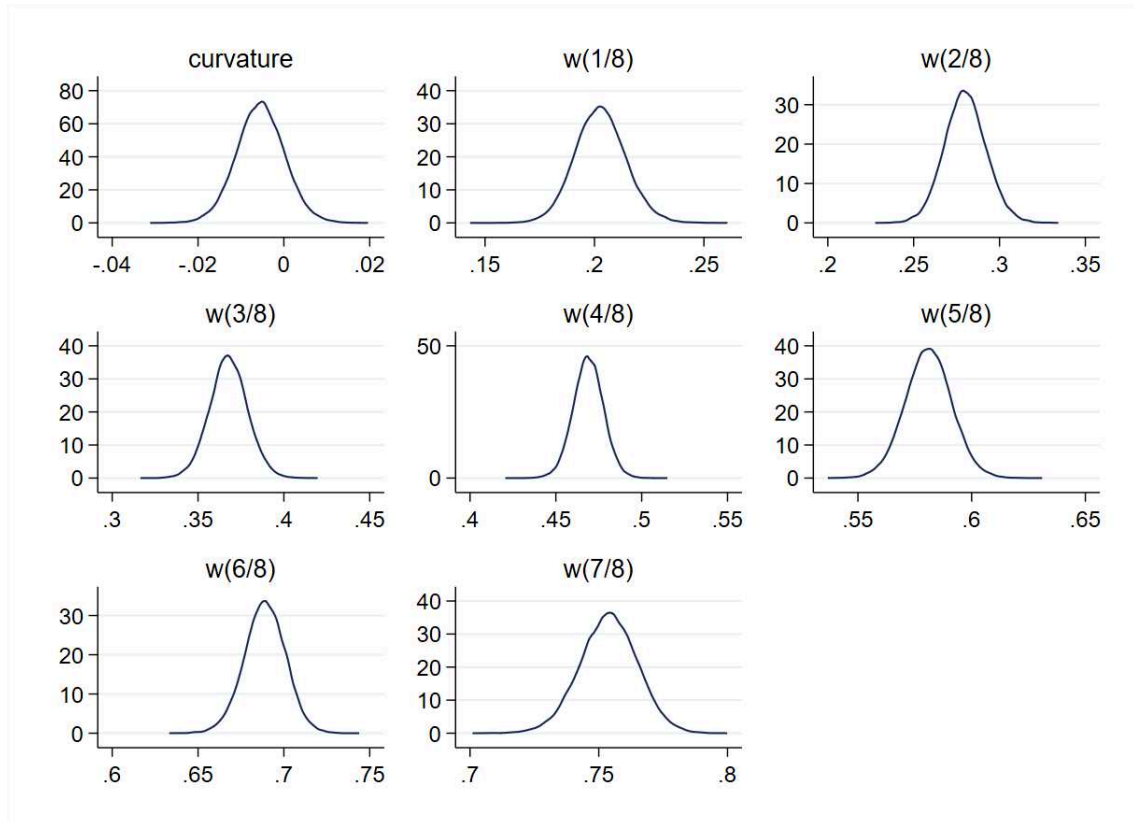


Figure 1.D.2: Posterior distributions of curvature and probability weights in the loss domain (world-level)



Turning to probability weights (see the posterior distributions in Figures 1.D.1 and 1.D.2 in the gain and loss domains for each weight), we present the mean of the posterior distribution for each weight in Figure 1.D.3. We observe the standard results of an underweighting of small probabilities and an overweighting of large probabilities in both domains (l'Haridon and Vieider, 2019). The crossover point is around  $3/8$  in both domains as the estimated mean lies within the 95% credible interval (see Table 1.D.1). We have overweighting for probabilities of  $1/8$  and  $2/8$ , and underweighting for probabilities  $4/8$ ,  $5/8$ ,  $6/8$  and  $7/8$ .

Figure 1.D.3: Estimated weighting functions

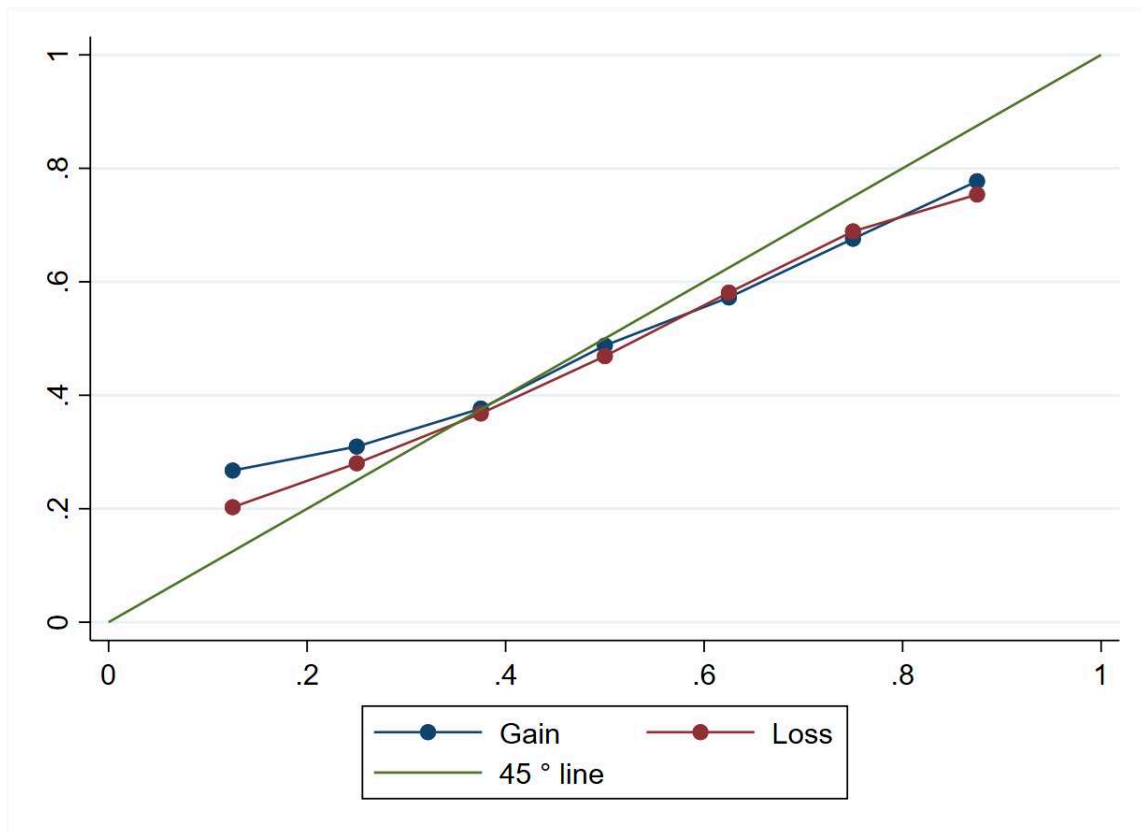


Table 1.D.1: Posterior statistics for utility and probability weights

	Mean	Std. Dev.	MCSE	Median	95% credible interval
Gain domain					
$\alpha_e$	0.0085	0.0033	0.0000	0.0085	0.0021 ; 0.0150
$w^+(1/8)$	0.2674	0.0102	0.0001	0.2673	0.2477 ; 0.2874
$w^+(2/8)$	0.3096	0.0102	0.0001	0.3096	0.2895 ; 0.3301
$w^+(3/8)$	0.3765	0.0071	0.0004	0.3765	0.3624 ; 0.3904
$w^+(4/8)$	0.4877	0.0050	0.0002	0.4876	0.4777 ; 0.4977
$w^+(5/8)$	0.5724	0.0056	0.0002	0.5724	0.5614 ; 0.5837
$w^+(6/8)$	0.6758	0.0074	0.0001	0.6758	0.6610 ; 0.6903
$w^+(7/8)$	0.7773	0.0108	0.0001	0.7774	0.7556 ; 0.7981
Loss domain					
$\beta_e$	-0.0055	0.0056	0.0000	-0.0055	-0.0165 ; 0.0057
$w^-(1/8)$	0.2027	0.0116	0.0001	0.2025	0.1805 ; 0.2263
$w^-(2/8)$	0.2801	0.0122	0.0001	0.2799	0.2565 ; 0.3047
$w^-(3/8)$	0.3678	0.0111	0.0003	0.3677	0.3461 ; 0.3898
$w^-(4/8)$	0.4689	0.0088	0.0003	0.4689	0.4516 ; 0.4862
$w^-(5/8)$	0.5810	0.0103	0.0003	0.5810	0.5606 ; 0.6013
$w^-(6/8)$	0.6889	0.0120	0.0001	0.6890	0.6648 ; 0.7121
$w^-(7/8)$	0.7538	0.0112	0.0001	0.7540	0.7312 ; 0.7755

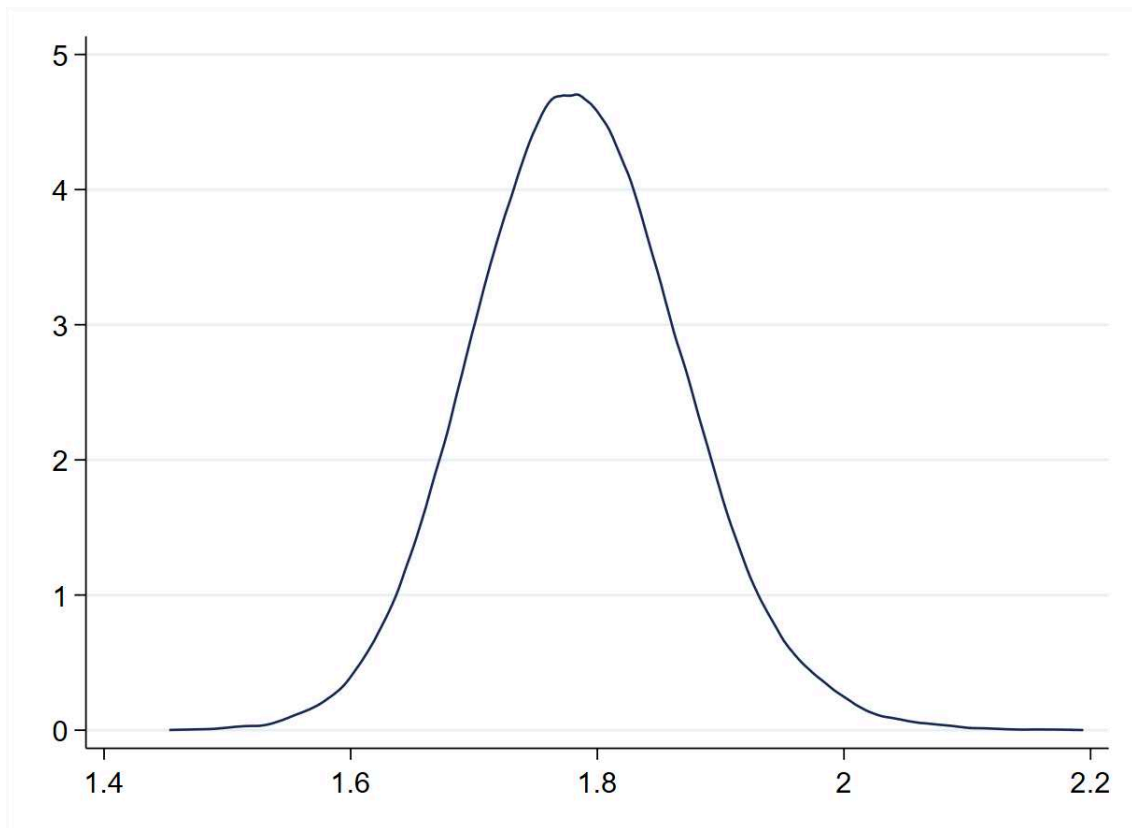
\* MCSE stands for Monte Carlo standard errors

### Loss aversion

Figure 1.D.4 shows the posterior distribution of the world-level loss aversion coefficient. The mean of the posterior distribution is 1.785, pointing to a substantial degree of loss aversion. The 95% credible interval of [1.6228, 1.9594] also rejects loss neutrality and points to  $\lambda > 1$ .



Figure 1.D.4: Posterior distribution of loss aversion (world-level)





## **Chapter 2**

# **Smoothing Spline Method for Measuring Prospect Theory Components**

This chapter is single-authored paper.

## Abstract

Prospect theory is today the main descriptive model for decision making under risk and uncertainty. Measurement methods of its components are key to many behavioral applications. This paper presents a smoothing spline method for measuring utility function, weighting function and loss aversion. The method is nonparametric and includes a penalty term to control the collinearity between the value and the weighting functions. It is applicable to both risk and uncertainty. We apply the method to individual data of [Tversky and Kahneman \(1992\)](#) and [Gonzalez and Wu \(1999\)](#). In line with original prospect theory, the probability weighting function is not sign-dependent. The value function is S-shaped with a loss aversion coefficient of 1.6.

**Keywords:** H prospect theory, risk attitudes elicitation, smoothing spline

**JEL codes:** D81, C91

## 2.1 Introduction

Empirical violations of expected utility theory (EUT; see [Starmer, 2000](#), for a review) explain the development of alternative theories of decision makings. Cumulative Prospect Theory (CPT; see [Tversky and Kahneman, 1992](#), henceforth TK92) emerged as the theory with more descriptive validity (e.g. [Blavatskyy, 2021](#); [Attema et al., 2013](#)).

Under CPT, Risk attitudes result simultaneously from the value and weighting functions. As result, several combinations of the shapes of the value and weighting functions can lead to the same level of risk-attitudes. A main challenge when measuring CPT is how to deal with the collinearity between the value and weighting functions (e.g. [Zeisberger et al., 2012](#); [Abdellaoui et al., 2011a](#)).

Measurement methods of CPT can be done under three approaches: parametric (with parametric specification of the utility and probability weighting functions)<sup>1</sup>, semi-parametric (with parametric specification of the utility function and parameter-free probability weighting function) and non-parametric (no parametric specification for either function).

Parametric (e.g. TK92) and semi-parametric ([Abdellaoui et al., 2008](#)) methods are more often used because their implementations are quick and easy. Yet, collinearity between the value and the weighting functions makes estimation results sensitive to parametric specifications (e.g. [Abdellaoui, 2000](#); [Abdellaoui et al., 2008](#)). A pragmatic and limited way to get rid of this collinearity is to assume a linear value function (e.g. [l'Haridon and Vieider, 2019](#)) in line with the dual theory of [Yaari \(1987\)](#).

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<sup>1</sup>For the utility function, Power and Exponential are popularly used and sometime a mixture of them called Expo-Power ([Saha, 1993](#); [Holt and Laury, 2002](#); [Abdellaoui et al., 2007a](#)). For the distortion of probability, one-parameter (e.g. TK92) and two-parameter ([Prelec, 1998](#); [Goldstein and Einhorn, 1987](#); [Chateauneuf et al., 2007](#); [Abdellaoui et al., 2010](#)) weighting functions (for a review, see table 4 of [Epper and Fehr-Duda, 2020](#)) are available.

The so-called tradeoff method of [Wakker and Deneffe \(1996\)](#) is an alternative. This method is non-parametric and the collinearity between utility and weighting functions does not play a role in the elicitation procedure. This explains why most non-parametric methods (e.g. [Abdellaoui, 2000](#); [Abdellaoui et al., 2007b, 2016](#); [Blavatsky, 2021](#)) are built upon the tradeoff method (see [Kpegli et al., 2023](#), for detailed discussions on elicitation methods). The nonparametric method of [Gonzalez and Wu \(1999\)](#), henceforth GW99 is a notable exception which does not rely on the tradeoff method.<sup>2</sup> However, the collinearity between utility and weighting function takes a stronger form in this method. Irrespective to the data under consideration, the method can lead to unrealistic concave value function and probability weights close to 1 (see footnote 4).

This paper establishes an alternative nonparametric method to the tradeoff-type methods. The proposed method approximates the value function with smoothing spline. The smooth parameter allows to control for the collinearity between the value and weighting functions by penalizing deviation from the linear value function. In contrast to the tradeoff-type methods, the proposed method accounts for response errors and rely on simple questions. The method remains applicable under uncertainty where probabilities of events are unknown. The method is applied on the two datasets of TK92 and GW99. Results indicate that the probability weighting function is not sign-dependent. The value function is S-shaped with a loss aversion coefficient of 1.6.

The rest of the paper is organized as follows. Section 2.2 presents the spline value function. Section 2.3 develops the smoothing spline method for eliciting cumulative prospect theory components. Section 2.4 presents the key features of the method. We illustrate the method in Section 2.5 using the data of TK92 and GW99. Sections 2.6 and 2.7 provide discussion and conclusion.

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<sup>2</sup>See the appendix of [Fehr-Duda and Epper \(2012\)](#) for a similar procedure.

## 2.2 Spline value function for CPT

### 2.2.1 Prospect theory for binary lottery

Consider a binary lottery  $L = (x, y; p, 1 - p)$  yielding outcome  $x$  with probability  $p$  and outcome  $y$  with probability  $1 - p$ , both outcomes being real numbers.<sup>3</sup> For notational convenience, let  $x > y \geq 0$  ( $x < y \leq 0$ ) for non-mixed prospects involving only gains (losses). For mixed prospects (*i.e.*, involving both gains and losses), outcomes are denoted with an asterisk and  $y^* < 0 < x^*$ .  $\succsim$  is a preference relation over prospects with  $\succ$  ( $\sim$ ) denoting strict preference (indifference). Preferences are represented by CPT with a probability weighting function  $w^i$  and a value function  $v$  as defined in equation (2.1) for non-mixed prospects and in equation (2.2) for the mixed ones:

$$CPT(L) = (v(x) - v(y)) w^i(p) + v(y) \quad (2.1)$$

$$CPT(L) = w^+(p)v(x) + w^-(1 - p)v(y) \quad (2.2)$$

where  $w^i$  and  $v$  are both continuous, strictly increasing and satisfying  $v(0) = 0$ ,  $w^i(0) = 0$  and  $w^i(1) = 1$ , and  $i = "+"$  ( $i = "-"$ ) stands for the gain (loss) domain. CPT makes no explicit link between weighting functions  $w^+(\cdot)$  and  $w^-(\cdot)$  which makes it more general than the original version of prospect theory (OPT, [Kahneman and Tversky, 1979](#)) in which  $w^+(p) = w^-(p)$ , or rank dependent utility theory (RDU, [Quiggin, 1982](#); [Gilboa, 1987](#); [Schmeidler, 1989](#)) that includes the duality condition  $w^+(p) = 1 - w^-(1 - p)$ .

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<sup>3</sup>This notation is related to decision under risk. In the case of decisions under uncertainty, one would simply replace  $p$  and  $1 - p$  by  $E$  and  $E^c$  respectively.  $E$  denotes an event in a state space  $\Omega$  and  $E^c$  denotes its complement in  $\Omega$ . In that case,  $L = (x, y; E, E^c)$  is a binary prospect that gives outcome  $x$  if  $E$  occurs, and  $y$  otherwise.

Following the seminal study by TK92 and the meta-analysis of [Brown et al. \(2021\)](#), the value function  $v(\cdot)$  is composed of the loss aversion index  $\lambda > 0$ , which reflects the exchange rate between gain and loss utility units, and the (basic) utility function  $u(\cdot)$  that reflects the intrinsic value of outcomes:

$$v(x) = \begin{cases} u_+(x) & \text{if } x \geq 0 \\ -\lambda u_-(-x) & \text{if } x < 0 \end{cases} \quad \text{and} \quad u(x) = \begin{cases} u_+(x) & \text{if } x \geq 0 \\ -u_-(-x) & \text{if } x < 0 \end{cases} \quad (2.3)$$

with  $u_+ : \mathcal{R}_+ \rightarrow \mathcal{R}_+$ ,  $u_- : \mathcal{R}_+ \rightarrow \mathcal{R}_+$  and  $u_+(0) = u_-(0) = 0$ . Let's assume that the basic utility function  $u$  is twice differentiable over  $\mathbb{R} - \{0\}$  and differentiable at 0. Assuming that the utility function is differentiable at 0 means that the loss aversion index in the relation 2.3 corresponds to the ratio of the left and right derivative of the value function as defined by [Köbberling and Wakker \(2005\)](#). Loss aversion (loss seeking) corresponds to  $\lambda > 1$  ( $\lambda < 1$ ), whereas  $\lambda = 1$  captures loss neutrality.

### 2.2.2 Spline value function

The spline approximation of the function  $u_i(\cdot)$  corresponds to (e.g., [Ahamada and Flachaire, 2010](#); [Ruppert, 2002](#); [Green and Silverman, 1993](#)):

$$u_i(z) = a_0^i + \sum_{j=1}^{J_i} a_j^i z^j + \sum_{t=1}^{Q_i} b_t^i (z - q_t^i)_+^{J_i} \quad \text{for} \quad z \geq 0 \quad \text{and} \quad i = +, - \quad (2.4)$$

with  $J_i \geq 1$  the order of the spline,  $Q_i$  the number of internal knots,  $q_1^i < q_2^i < \dots < q_T^i$  and

$$(z - q_t^i)_+^{J_i} = \begin{cases} (z - q_t^i)^{J_i} & \text{if } z \geq q_t^i \\ 0 & \text{otherwise} \end{cases}$$



To accommodate with  $u(0) = 0$  of Prospect Theory, the scaling  $a_0^i = 0$  is used. Without loss of generality, the scaling  $a_1^i = 1$  is used to allow identification of the loss aversion index à la [Köbberling and Wakker \(2005\)](#). This scaling means that the utility function is differentiable at 0, with  $u'(0) = 1$ .

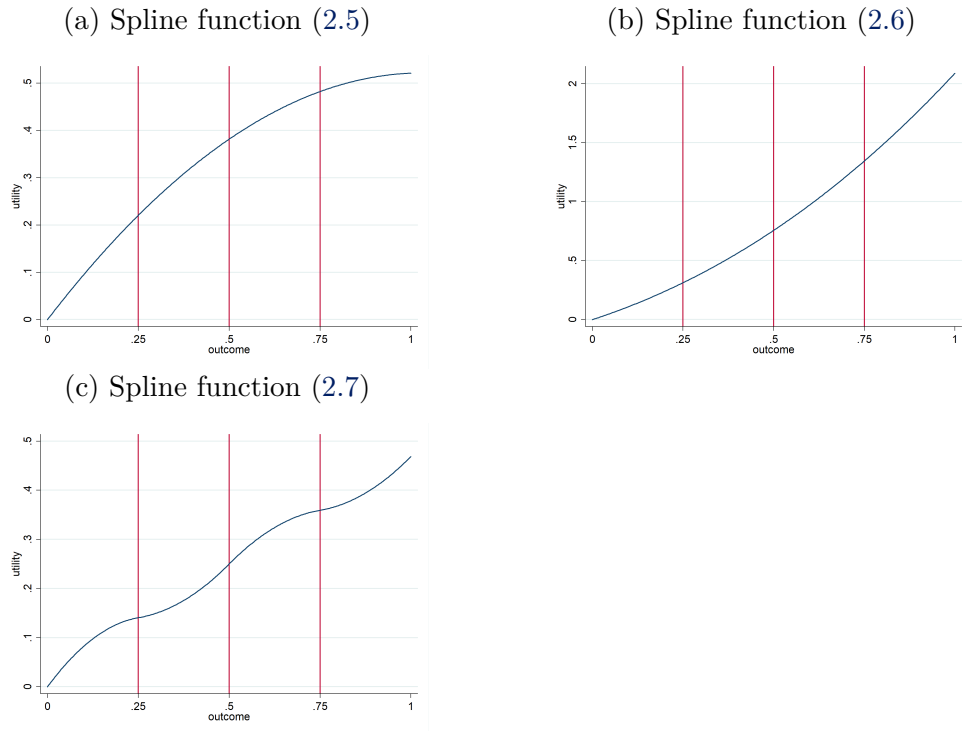
A main advantage of (2.4) is that the shape of the utility function is very flexible. The following three quadratic splines (2.5) - (2.7) illustrate this flexibility. The spline (2.5) leads to a concave utility function (Figure 2.2.1, panel (a)). The spline (2.6) leads to a convex utility function. The spline (2.7) leads to a concave utility function over two intervals  $[0, 0.25]$  and  $[0.5, 0.75]$ , and also leads to a convex utility over the two intervals  $[0.25, 0.50]$  and  $[0.75, 1]$ .

$$u_i(z) = z - 0.47z^2 - 0.01(z - 0.25)_+^2 - 0.01(z - 0.25)_+^2 - 0.01(z - 0.25)_+^2 \quad (2.5)$$

$$u_i(z) = z + z^2 + 0.1(z - 0.25)_+^2 + 0.1(z - 0.50)_+^2 + 0.1(z - 0.75)_+^2 \quad (2.6)$$

$$u_i(z) = z - 1.75z^2 + 3(z - 0.25)_+^2 - 2.5(z - 0.25)_+^2 + 2.5(z - 0.25)_+^2 \quad (2.7)$$

Figure 2.2.1: Spline: example of shapes



## 2.3 Elicitation method

### 2.3.1 Step 1: utility and weighting functions in the gain domain

In the gain domain, the method can be implemented by following three substeps. First, a set of probabilities  $\{p_k : k = 1, 2, \dots, K\}$  are selected, with  $p_k < p_{k+1}$ . Second, at least two certainty equivalents for each probability  $p_k$  are elicited:

$$ce_{j,k} \sim (x_{j,k}, y_{j,k}; p_k, 1 - p_k) \quad , \quad j = 1, 2, \dots, N_k^+ \quad \text{and} \quad N_k^+ \geq 2 \quad (2.8)$$

where  $N_k^+$  stands for the number of certainty equivalents for positive outcomes  $x_{j,k}$  and  $y_{j,k}$  such that  $x_{j,k} > y_{j,k} \geq 0$ . Thus, in total  $N^+ = \sum_{k=1}^K N_k^+ \geq$

$2 \times K$  certainty equivalents are elicited. Using (2.1) and (2.3), these certainty equivalents satisfy the following condition:

$$u_+(ce_{j,k}) = \left( u_+(x_{j,k}) - u_+(y_{j,k}) \right) w^+(p_k) + u_+(y_{j,k}) \quad (2.9)$$

Let  $\mathbf{ce}$ ,  $\mathbf{x}$  and  $\mathbf{y}$  be the column vectors containing all the realizations of  $ce_{j,k}$ ,  $x_{j,k}$  and  $y_{j,k}$ , respectively. Let also  $\mathbf{I}^k$  be a dummy variable set to 1 if the probability equals  $p_k$  and 0 otherwise. For  $k = 1, \dots, K$ , denote  $\delta_k^+ \equiv w^+(p_k) \in (0, 1)$ . Arranging the terms in equation (2.9) and taking the log leads to the following equation:

$$\log\left(u_+(ce_{j,k}) - u_+(y_{j,k})\right) = \log\left(u_+(x_{j,k}) - u_+(y_{j,k})\right) + \log\left(w^+(p_k)\right) \quad (2.10)$$

Adding an error term  $\mathbf{e}$  to the log-transformation (2.10) leads to the following empirical equation:<sup>4</sup>

$$\log\left(u_+(\mathbf{ce}_l) - u_+(\mathbf{y}_l)\right) = \log\left(u_+(\mathbf{x}_l) - u_+(\mathbf{y}_l)\right) + \log\left(\sum_{k=1}^K \delta_k^+ \mathbf{I}_l^k\right) + \mathbf{e}_l \quad (2.11)$$

---

<sup>4</sup>An alternative approach would be to introduce the response error term at the utility level (GW99, eq. 7):  $u(\mathbf{ce}_l) = (u(\mathbf{x}_l) - u(\mathbf{y}_l)) \sum_{k=1}^K \delta_k^+ \mathbf{I}_l^k + u(\mathbf{y}_l) + \mathbf{e}_l$ . However, defining the response error at the utility level is problematic when using certainty equivalents data because it produces solutions that are characterized by unrealistic concavity of the utility and probability weighting functions. To illustrate this point, suppose that we are interested in eliciting utility only over strictly positive outcomes with a power utility function  $u(z) = z^\alpha$ . For an extremely concave utility function (i.e.,  $\alpha > 0$  and  $\alpha \rightarrow 0$ ) and an extremely concave weighting function (i.e.,  $\delta_k^+ = 1$  for  $k = 1, 2, \dots, K$ ) along with the PT assumptions  $w^+(0) = 0$  and  $w^+(1) = 1$ , we have  $\mathbf{e}_l = 0$  for all  $l = 1, 2, \dots, N^+$ . For the non-parametric method of GW99 which aims at estimating  $u(z)$  for  $z \in A(z) \equiv \{\$25, \$50, \$75, \$100, \$150, \$200, \$400, \$800\}$  and the probability weights  $w(p)$  for  $p \in B(p) \equiv \{0.01, 0.05, 0.10, 0.25, 0.40, 0.50, 0.60, 0.75, 0.90, 0.95, 0.99\}$ , it follows that an extremely concave utility function (i.e.,  $u(z) = \text{constant} > 0$  for  $z \in A(z)$  and  $u(0) = 0$ ) and an extremely concave weighting function (i.e.,  $w(p) = 1$  for  $p \in B(p)$  and  $w(0) = 1 - w(p) = 0$ ) are solutions of the optimization problem (Kpegli et al., 2023).

where  $l$  is the  $l^{\text{th}}$  line in  $\mathbf{ce}$ ,  $\mathbf{x}$ ,  $\mathbf{y}$ ,  $\mathbf{I}^k$  and  $\mathbf{e}$ . Denote by  $\theta^+$  the vector of parameters  $(\{a_j^+\}_j^{J_+}, \{b_t^+\}_{t=1}^{Q_+})$  associated with the smooth approximation of the utility function  $u_+(\cdot)$ . Minimizing the following penalized sum of squared error allows to estimate the utility function and the probability weights as follows:<sup>5</sup>

$$\min_{\theta^+, \delta_1^+, \dots, \delta_K^+} \sum_{l=1}^{N^+} \mathbf{e}_l^2 + \rho^+ \int_0^{\bar{x}} [u_+''(z)]^2 dz \quad (2.12)$$

where  $\rho^+ \geq 0$  is the smooth parameter,  $u_+''(\cdot)$  the concavity (second derivative) of the utility function and  $[0, \bar{x}]$  the range over which the utility function is elicited. Each level of the smooth parameter  $\rho^+$  corresponds to a specific combination of utility curvature and probability weighting function. For example, when subject exhibits risk-aversion, the case  $\rho^+ \rightarrow +\infty$  corresponds to the linear utility function and the less elevated probability weighting function that will result from an estimation based on the dual theory of [Yaari \(1987\)](#). Then, the smooth parameter allows to chose the combination of shapes of the utility and weighting functions by penalizing deviation from the linear utility function.

Following the literature (e.g. [Ahamada and Flachaire, 2010](#); [Green and Silverman, 1993](#)), the optimal values of the smooth parameter  $\rho^+$  and the order of the spline  $Q_+$  corresponds to the ones that minimize the leave-one cross-validation (CV). Formally, the optimal  $\rho^+$  and  $Q_+$  provide the smallest value for:

$$CV = \frac{1}{N^+} \sum_{l=1}^{N^+} |\widehat{\mathbf{ce}}_{-l} - \mathbf{ce}_l| \quad (2.13)$$

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<sup>5</sup>Note that we do not require monotonicity of the utility and weighting functions as is commonly done in the literature (see e.g. [GW99](#), p. 147).

where  $\widehat{ce}_{-l}$  is the predicted value of  $ce_l$  based on data without the  $l^{th}$  observation.<sup>6</sup>

The following measure of utility curvature over  $[0, \bar{x}]$  in the gain domain (see [Kpegli et al., 2023](#); [Abdellaoui et al., 2016](#)) is used to classify the utility function as concave or convex:

$$\alpha = \frac{1}{\bar{x}u_+(\bar{x})} \int_0^{\bar{x}} u_+(t)dt \quad (2.14)$$

The utility function  $u_+(\cdot)$  is considered to be concave, linear and convex on the interval  $[0, \bar{x}]$  when  $\alpha > 0.5$ ,  $\alpha = 0.5$  and  $\alpha < 0.5$  respectively.

### 2.3.2 Step 2: utility and weighting functions in the loss domain

This step is similar to the first step. At least two certainty equivalents for each probability  $p_k$  are elicited:

$$ce_{j,k} \sim (x_{j,k}, y_{j,k}; p_k, 1 - p_k) \quad , \quad j = 1, 2, \dots, N_k^- \quad \text{and} \quad N_k^- \geq 2 \quad (2.15)$$

where  $N_k^-$  stands for the number of certainty equivalents for negative outcomes  $x_{j,k}$  and  $y_{j,k}$  such that  $x_{j,k} < y_{j,k} \leq 0$ . Thus, in total  $N^- = \sum_{k=1}^K N_k^- \geq 2 \times K$  certainty equivalents are elicited.

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<sup>6</sup>Denote by  $\widehat{u}_+(\cdot)$  and  $\widehat{\delta}_k^+$  ( $k = 1, 2, \dots, K$ ) the estimated utility function and decision weights. The predicted certainty equivalent  $\widehat{ce}_l$  is the solution to the equation  $\widehat{u}_+(\widehat{ce}_l) = (\widehat{u}_+(\mathbf{x}_l) - \widehat{u}_+(\mathbf{y}_l)) \sum_{k=1}^K \widehat{\delta}_k^+ \mathbf{I}_l^k + \widehat{u}_+(\mathbf{y}_l)$ .

Consider the following log-transformation of prospect theory functional form with an additive error term:

$$\begin{aligned} \log\left(u_{-}(-\mathbf{c}e_l) - u_{-}(-\mathbf{y}_l)\right) = & \log\left(u_{-}(-\mathbf{x}_l) - u_{-}(-\mathbf{y}_l)\right) + \\ & \log\left(\sum_{k=1}^K \delta_k^- \mathbf{I}_l^k\right) + \mathbf{e}_l \end{aligned} \quad (2.16)$$

where  $l$  is the  $l^{\text{th}}$  line in  $\mathbf{c}e$ ,  $\mathbf{x}$ ,  $\mathbf{y}$ ,  $\mathbf{I}^k$  and  $\mathbf{e}$ . Denote by  $\theta^-$  the vector of parameters  $(\{a_j^-\}_{j=1}^{J_-}, \{b_t^-\}_{t=1}^{Q_-})$  associated with the smooth approximation of the utility function  $u_{-}(\cdot)$ . Minimizing the following penalized sum of squared error provides the estimate of the utility function and the probability weights:<sup>7</sup>

$$\min_{\theta^-, \delta_1^-, \dots, \delta_K^-} \sum_{l=1}^{N^-} \mathbf{e}_l^2 + \rho^- \int_0^{-\bar{x}} [u_{-}''(z)]^2 dz \quad (2.17)$$

where  $\rho^- \geq 0$  is a (fixed) smooth parameter,  $u_{-}''(\cdot)$  the concavity (second derivative) of the utility function and  $[\bar{x}, 0]$  the range on which the utility function is elicited. As in the gain domain, the smooth parameter controls the concavity of the utility function by penalizing deviation from linear utility function or the dual theory of Yaari (1987).

As in the gain domain, the optimal values of the smooth parameter  $\rho^-$  and the order of the spline  $Q_-$  correspond to the ones that minimize the leave-one cross-validation (CV):

$$CV = \frac{1}{N^-} \sum_{l=1}^{N^-} |\widehat{\mathbf{c}e}_{-l} - \mathbf{c}e_l| \quad (2.18)$$

---

<sup>7</sup>As in gain domain, the method does not require monotonicity of the utility and weighting functions as is commonly done in the literature (see e.g. GW99, p. 147).

where  $\widehat{ce}_{-l}$  is the predicted value of  $ce_l$  based on data without the  $l^{th}$  observation.<sup>8</sup>

As in the gain domain, the following measure of utility curvature over the loss interval  $[\underline{x}, 0]$  is used to classify the utility function as concave or convex (see [Kpegli et al., 2023](#); [Abdellaoui et al., 2016](#)):

$$\beta = \frac{1}{xu_{-}(\underline{x})} \int_{\underline{x}}^0 u_{-}(t) dt \quad (2.19)$$

The utility function  $u_{-}(\cdot)$  is considered to be concave, linear and convex on the interval when  $\beta > -0.5$ ,  $\beta = -0.5$  and  $\beta < -0.5$  respectively.

### 2.3.3 Step 3: measuring loss aversion

The third step allows to measure the loss aversion index  $\lambda$  as defined in (2.3). Following [Abdellaoui et al. \(2007b\)](#), the estimation of the loss aversion index can be done using a set of  $K$  indifference relationships that involve mixed binary prospects:

$$ce_k \sim (x_k, y_k, p_k, 1 - p_k), \quad k = 1, 2, \dots, K \quad (2.20)$$

with  $y_k < 0 < x_k$ . Under CPT these indifferences imply that:

$$\left(1_{(ce_k \geq 0)} + \lambda 1_{(ce_k < 0)}\right) u(ce_k) = w^{+}(p_k)u(x_k) + \lambda w^{-}(1 - p_k)u(y_k) \quad (2.21)$$

where  $1_{(\cdot)}$  refers to the indicator function. Denote by  $\mathbf{D}^{+}$  a dummy variable that takes the value 1 if the certainty equivalent is positive (or zero) and 0 otherwise. Similarly,  $\mathbf{D}^{-}$  is a dummy variable that takes value 1 if the certainty equivalent

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<sup>8</sup>Denote by  $\widehat{u}_{-}(\cdot)$  and  $\widehat{\delta}_k^{-}$  ( $k = 1, 2, \dots, K$ ) the estimated utility function and decision weights. The predicted certainty equivalent  $\widehat{ce}_l$  is solution to the equation  $\widehat{u}_{-}(-\widehat{ce}_l) = (\widehat{u}_{-}(-\mathbf{x}_l) - \widehat{u}_{-}(-\mathbf{y}_l)) \sum_{k=1}^K \widehat{\delta}_k^{-} \mathbf{I}_l^k + \widehat{u}_{-}(-\mathbf{y}_l)$ .

is negative and 0 otherwise. Assuming additive error at the basic utility scale ( $\mathbf{e}_k$ ), the empirical counterpart of equation (2.21) then becomes:

$$\left(\mathbf{D}_k^+ + \lambda \mathbf{D}_k^-\right) \hat{u}(\mathbf{c}\mathbf{e}_k) = \hat{\delta}_k^+ \hat{u}(\mathbf{x}_k) + \lambda \hat{\delta}_k^- \hat{u}(\mathbf{y}_k) + \mathbf{e}_k \quad (2.22)$$

with  $\hat{u}$ ,  $\hat{\delta}_k^+$  and  $\hat{\delta}_k^-$  the estimates of the utility function  $\hat{u}$ , the probability weights in the gain domain  $w^+(p_k)$  and the probability weights in the loss domain  $w^-(1 - p_k)$  from steps 1 and 2.

Estimate of loss aversion index  $\lambda$  of [Köbberling and Wakker \(2005\)](#) is given by the minimization of the sum of squared error:

$$\min_{\lambda} \sum_{k=1}^K \mathbf{e}_k^2 \quad (2.23)$$

## 2.4 Key features of the method

This section highlights six features of the method.

***Robust to collinearity.*** The method controls for the collinearity between utility and weighting functions (e.g. [Zeisberger et al., 2012](#)) with smooth parameters. Indeed, these smooth parameters allow to choose optimal combination of curvatures of utility and weighting functions in the gain and loss domains.

***Applicability to unknown probabilities.*** The use of fixed effects for estimating decision weights is taken from [Kpegli et al. \(2023\)](#). The method is then directly applicable to cases of uncertainty where probabilities are unknown. The probability dummy variables can then be replaced by the event dummy variables in equations (2.11) and (2.16). It does not require setting any specific conditions



on the event space, and hence can be applied to real-life uncertainty situations (Baillon et al., 2018).<sup>9</sup>

**Error-robust.** In contrast to the tradeoff method (Wakker and Deneffe, 1996), the smoothing spline method considers that subjects can make error in their responses. Estimations of prospect theory components result from a minimization of (penalized) sum of squared response errors.

**Easy (not cognitively demanding).** The method is a certainty equivalent method. As such, it uses simple questions that involves the lowest possible number of outcomes (i.e., 3): comparisons of certain outcomes and binary lotteries. Hence, the method is less cognitively demanding than the tradeoff method that rely on comparison of two non-degenerate lotteries (e.g. Abdellaoui et al., 2008).

**Tractable.** The method can be implemented by using optimization programs available in standard statistical software. For example, the ML routine for Stata popularized by Harrison and Rutström (2008) and Moffatt (2015) for parametric risk elicitation can be used to implement the smoothing spline method.

**Data-inefficient.** The method builds upon the smoothing spline literature. Application of the method is more data consuming than parametric methods (e.g. Ahmada and Flachaire, 2010; Green and Silverman, 1993). This method should thus be used in two main cases. First, behavioral studies often elicit few observations per subjects. In such case, the method can be used to derive estimates at the aggregate level by pooling subjects as in TK92. The dataset include 25 subjects. For each subject, only 28 observations are available to derive estimates of utility and weighting function in each domain. The pooled data with 700 ( $= 25 \times 28$ ) observations per domain can then be used to derive

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<sup>9</sup>Previous methods require that the universal event is an interval of real numbers (e.g. temperature in a town) which is most suitable to deal with artificial uncertainty situations that can be created in the laboratory (Van De Kuilen and Wakker, 2011).

estimate at the aggregate level. Second, the method can be performed at the individual level if the number of observations per subjects is sufficiently large as in GW99. For each subject, the dataset include 165 observations to measure utility and weighting functions in the gain domain.

## 2.5 Application

This section applies the smoothing spline method on the data of TK92 and GW99.

### 2.5.1 Data

#### 2.5.1.1 Data of TK92

**Subjects:** TK92 run a computerized experiment with 25 graduate students from Berkeley and Stanford with no particular training in decision theory. Each subject participated in three separate one-hour sessions organized over several days, and received \$25 for participation.

**Procedure:** the data are generated via the switching outcome procedure in which an indifference value is inferred through a list of equally spaced certain outcomes, ranging from the admissible maximum indifference value to the admissible minimum indifference value. Internal consistency of the responses to each prospect is monitored by a computer software to reduce response errors.

**Data for the first and second steps:** all outcomes are expressed in US dollars. For each subject, there are 28 values of certainty equivalents for binary lotteries that involve 7 pairs of positive monetary outcomes (0, 50), (0, 100), (0, 200), (0, 400), (50, 100), (50, 150) and (100, 200), and 9 probabilities of getting the higher

outcome: 0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95 and 0.99. Also, there are, for each subject, 28 values of certainty equivalents for binary lotteries that involve 7 pairs of negative monetary outcomes (0, -50), (0, -100), (0, -200), (0, -400), (-50, -100), (-50, -150) and (-100, -200), and the same list of 9 probabilities as in the gain domain. These probabilities are now associated to losing the higher outcome.

**Data for the third step:** for mixed prospects, individual data are not available. We then use the median values reported in Table 6 of TK92. We use the four indifferences on mixed prospects that consist in eliciting the values of gains  $x$  to make subjects indifferent between the mixed prospects  $(x, y; 0.5, 0.5)$  and 0. The values of  $y$  are -25, -50, -100 and -150.

#### 2.5.1.2 Data of GW99

**Subjects and procedure:** GW99 run a computerized experiment with 10 graduate students in psychology. They also use the switching outcome procedure for eliciting certainty equivalents.

**Data for the first step (only gain):** Each subject has 165 certainty equivalents. The 165 values of certainty equivalents correspond to binary lotteries that involve 15 pairs of positive monetary outcomes (0, 25), (0, 50), (0, 75), (0, 100), (0, 150), (0, 200), (0, 400), (0, 800), (25, 50), (50, 75), (50, 100), (50, 150), (100, 150), (100, 200) and (150, 200) and 11 probabilities of obtaining the higher outcome: 0.01, 0.05, 0.1, 0.25, 0.4, 0.5, 0.6, 0.75, 0.9, 0.95 and 0.99.

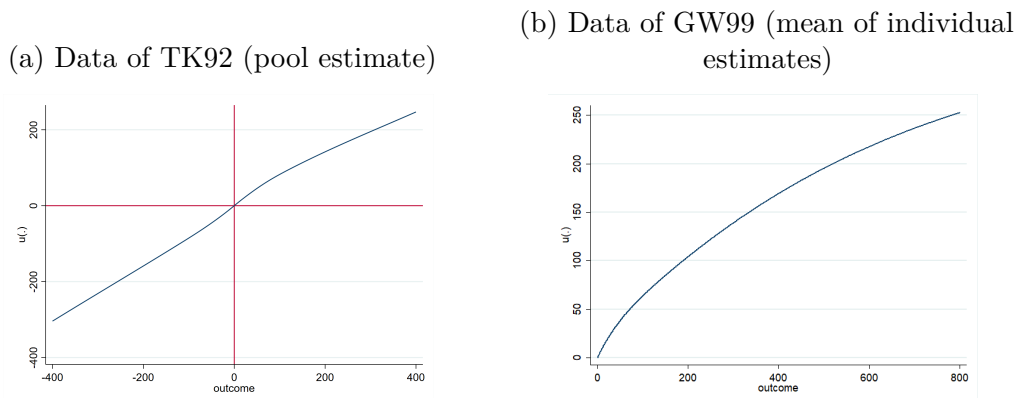
## 2.5.2 Results

### 2.5.2.1 Utility function

Figure 2.5.1 provides the estimated utility functions on both datasets.<sup>10</sup> The pool estimate on the data of TK92 leads to a concave (resp. convex) utility in the gain (resp. loss) domain. The utility curvature in gain domain is  $\alpha = 0.554$  and is significantly different from linearity ( $p - value = 0.0011$ )<sup>11</sup>, which corresponds to  $\alpha = 0.5$ . In the loss domain, the mean of utility curvature in the gain domain is  $\beta = -0.517$  and is significantly different from linearity ( $p - value = 0.0036$ ) where  $\beta = -0.5$ . Furthermore, partial reflection is rejected ( $H_0 : \alpha + \beta = 0, p - values = 0.0355$ ).

For the data of GW, the mean of individual utility function in the gain domain is also concave.<sup>12</sup> The utility curvature is  $\alpha = 0.623$  and is significantly different from linearity ( $p - value < 0.0001$ ).

Figure 2.5.1: Utility function



<sup>10</sup>Appendixes 4.A and 4.B provides detailed informations about estimates.

<sup>11</sup>All p-values are computed on the basis of Bootstrap with 1000 replications.

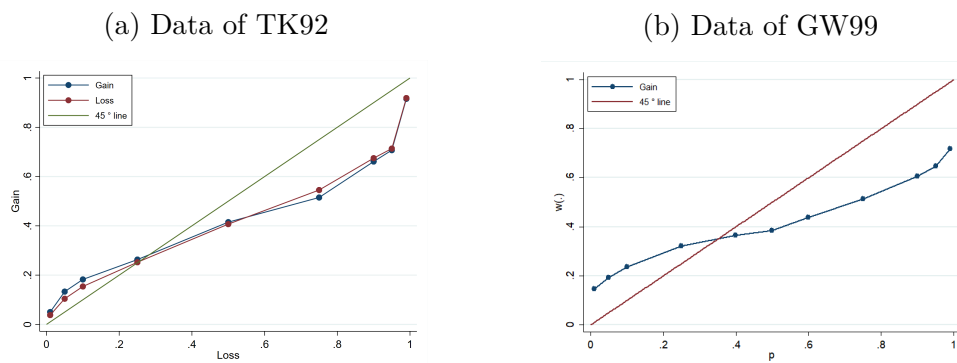
<sup>12</sup>see appendix for detailed results at the individual level

### 2.5.2.2 Weighting function

Figure 2.5.2 provides the estimated probability functions. For the data of TK92, probabilistic risk neutrality in the gain domain  $w^+(p) = p$  is rejected for most probabilities (all  $p$ -values  $< 0.0004$ ), except for 0.25 ( $p$ -value = 0.3978). Similar patterns emerge in the loss domain. Probabilistic risk neutrality  $w^-(p) = p$  is rejected for most probabilities (all  $p$ -values  $< 0.0014$ ), except for 0.25 ( $p$ -value = 0.8598). Hence, the weighting function in both domains is inverse S-shaped with overweighting for  $p \in (0, 0.25]$  and underweighting for  $p \in (0.25, 1)$ . The data of GW99 in the gain domain also leads to a crossing point at  $p = 0.25$  ( $p$ -value = 0.6189). For the data of GW99, probabilistic risk neutrality in the gain domain  $w^+(p) = p$  is rejected for most probabilities (all  $p$ -values  $< 0.0127$ ), except for 0.40 ( $p$ -value = 0.3710).

Over the 9 probabilities in the data of TK92, the hypothesis of identical probability weights across domains ( $w^+(p_k) = w^-(p_k)$ ) of OPT cannot be rejected for all probabilities (all  $p$ -values  $> 0.0514$ ). In contrast, the hypothesis of duality ( $w^+(p_k) = 1 - w^-(1 - p_k)$ ) of RDU is rejected for all probabilities (all  $p$ -values  $< 0.0327$ ).

Figure 2.5.2: Probability weighting function)



### 2.5.2.3 Loss aversion

The estimated value of loss aversion is  $\lambda = 1.636$  and is significantly different from loss neutrality ( $p - value < 0.0001$ ). Hence, subjects exhibit loss aversion.

## 2.6 Discussion

The estimation result of concave utility function in the gain domain is a very common finding in the literature, irrespective to the approach: parametric (e.g. [l'Haridon and Vieider, 2019](#), TK92), semi-parametric (e.g. [Abdellaoui et al., 2008, 2011a](#); [Kpegli et al., 2023](#)) and non-parametric (e.g. [Wakker and Deneffe, 1996](#); [Abdellaoui et al., 2016](#); [Blavatsky, 2021](#), GW99).

In the loss domain, the finding of convex utility function corroborates the original parametric estimates of TK92. Though, the evidences about utility curvature in loss domain are mixed in the literature. Results based on non-parametric methods (e.g. [Abdellaoui et al., 2011b](#); [Attema et al., 2018](#); [Abdellaoui et al., 2016](#); [Blavatsky, 2021](#); [Hajimoladarvish, 2017](#)) tend to provide evidences in favor of a convex utility function. In contrast, results based on semi-parametric methods (e.g. [Abdellaoui et al., 2008](#); [Attema et al., 2013, 2016](#); [Kpegli et al., 2023](#)) tend to provide evidences in favor of a concave utility function.

The methods also leads to the rejection of partial reflection ( $\alpha + \beta = 0$ ). Empirical evidences on partial reflection in the literature is mixed. The rejection of partial reflection is consistent with some studies ([Abdellaoui et al., 2013, 2016](#); [Attema et al., 2013, 2016](#), ABL), but not with others (e.g. [Abdellaoui, 2000](#); [Andersen et al., 2006](#); [Abdellaoui et al., 2007b](#); [Booij and Van de Kuilen, 2009](#); [Harrison and Rutström, 2009](#); [Booij et al., 2010](#)).

The estimation results provide support for identical probability weighting function across domains of OPT and reject the duality condition of RDU.

Tests of identical probability weightings and duality are scarce in the literature. [Abdellaoui \(2000\)](#) and [Kpegli et al. \(2023\)](#) reject both duality and identical probability weighting functions across domains under risk. [Abdellaoui et al. \(2005\)](#) do not reject duality under uncertainty although they reject identical weighting functions across domains. The observation of identical probability weights and the rejection of duality provide support for OPT.

The method confirms loss aversion, with a loss aversion index of  $\lambda = 1.636$ . This estimate is less than the 2.25 reported by TK92. Our estimate is close to the estimated value of 1.6 that was elicited in both [Booij et al. \(2010\)](#) who use structural estimation techniques, and [Abdellaoui et al. \(2008\)](#) for pooled data. It is also close to the estimates of  $\lambda = 1.8$  reported by [Pennings and Smidts \(2003\)](#). The evidence of loss aversion is a very common finding in the literature as only few studies find evidences for loss seeking (e.g. [Abdellaoui et al., 2013](#); [Nilsson et al., 2011](#)).

## 2.7 Conclusion

In sum, this paper introduces a smoothing spline method to elicit the utility function, the weighting function and the loss aversion. The method allows to control for the collinearity between utility and weighting function and can be applied under both risk and uncertainty. Its application on experimental data provides reliable results.

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## 2.A Appendix Data of TK92

Table 2.A.1 provides detailed results on the data of TK92. We use three internal knots that correspond to quartile of the certainty equivalent (e.g. [Ahamada and Flachaire, 2010](#)).

Table 2.A.1: Individual estimates: data of TK92

Domain	Gain ( $i = +$ )	Loss ( $i = -$ )
Utility function		
$a_2^i$	-0.00207	-0.00220
$a_3^i$	0.00000662	0.00000898
$b_1^i$	-0.0000120	-0.00000555
$b_2^i$	0.0000152	0.00000192
$b_3^i$	-0.00000901	-0.00000510
Probability weights		
$w^i(0.01)$	0.0501	0.0378
$w^i(0.05)$	0.133	0.104
$w^i(0.10)$	0.183	0.154
$w^i(0.25)$	0.263	0.252
$w^i(0.50)$	0.415	0.407
$w^i(0.75)$	0.515	0.545
$w^i(0.90)$	0.661	0.675
$w^i(0.95)$	0.707	0.714
$w^i(0.99)$	0.916	0.919
Order of the spline and smooth parameter		
$Q_+$	3	3
$\rho^+$	9500	9000
$CV$	12.42	11.49
$N$	700	700

## 2.B Appendix Data of GW99

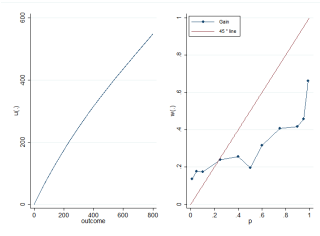
Table 2.B.1 provides detailed results for the 10 subjects in the data of GW99. We use three internal knots that correspond to quartile of the certainty equivalent (e.g. [Ahamada and Flachaire, 2010](#)).

Table 2.B.1: Individual estimates: data of GW99

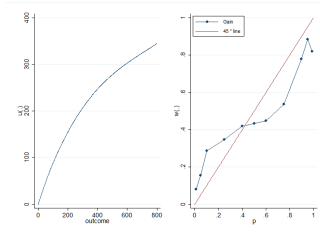
Subject	1	2	3	4	5	6	7	8	9	10
Utility function										
$a_2^+$	-0.0005	-0.0007	-0.0006	-0.0045	-0.0219	-0.0008	-0.0067	-0.0067	-0.0053	-0.0085
$a_3^+$	$-5 \times 10^{-6}$	$-7 \times 10^{-4}$								
$b_1^+$	$7 \times 10^{-6}$	$4 \times 10^{-6}$	$-1.1 \times 10^{-4}$	$-1.3 \times 10^{-7}$	0.0205	$-3.4 \times 10^{-4}$	$9.5 \times 10^{-4}$	$2.2 \times 10^{-4}$	0.0013	0.0038
$b_2^+$	$-6 \times 10^{-7}$	$6.3 \times 10^{-6}$	$1.3 \times 10^{-4}$	$5.25 \times 10^{-5}$	0.0008	-0.0001	0.0041	0.0022	0.0020	0.0035
$b_3^+$	$-1.2 \times 10^{-6}$	$-3 \times 10^{-6}$	0.0004	0.0040	0.0006	0.0009	0.0015	0.0040	0.0020	0.0012
Probability weights										
$w^+(0.01)$	0.137	0.0801	0.340	0.101	0.233	0.0682	0.127	0.162	0.0282	0.196
$w^+(0.05)$	0.177	0.155	0.334	0.175	0.281	0.113	0.237	0.171	0.0689	0.225
$w^+(0.10)$	0.175	0.286	0.428	0.130	0.365	0.133	0.230	0.187	0.121	0.301
$w^+(0.25)$	0.240	0.347	0.485	0.220	0.451	0.280	0.256	0.283	0.245	0.404
$w^+(0.40)$	0.255	0.420	0.507	0.154	0.517	0.440	0.281	0.242	0.359	0.489
$w^+(0.50)$	0.195	0.434	0.523	0.183	0.535	0.542	0.246	0.221	0.442	0.523
$w^+(0.60)$	0.315	0.448	0.489	0.178	0.574	0.623	0.319	0.355	0.492	0.595
$w^+(0.75)$	0.406	0.537	0.563	0.217	0.597	0.795	0.352	0.396	0.687	0.576
$w^+(0.90)$	0.415	0.779	0.640	0.238	0.681	0.931	0.443	0.434	0.799	0.699
$w^+(0.95)$	0.458	0.885	0.612	0.255	0.730	0.960	0.466	0.469	0.896	0.737
$w^+(0.99)$	0.661	0.819	0.738	0.362	0.850	0.968	0.530	0.620	0.769	0.866
Order of the spline and smooth parameter										
$Q_+$	3	3	2	2	2	2	2	2	2	2
$\rho^+$	10000	9000	5100	1700	1	3000	600	3500	500	400
$CV$	14.00	14.02	18.63	7.23	14.49	6.24	8.31	11.86	11.68	14.01
$N$	165	165	165	165	165	165	165	165	165	165

Figure 2.B.1: Individual estimates: data of GW99

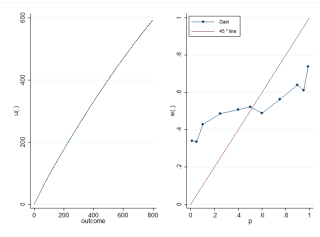
(a) Subject 1



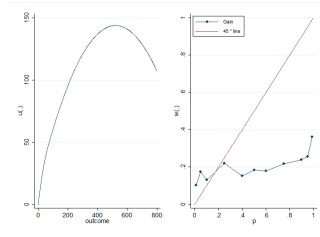
(b) Subject 2



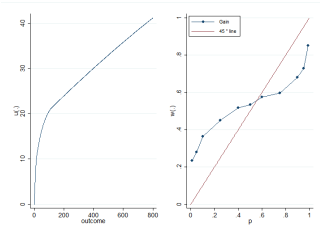
(c) Subject 3



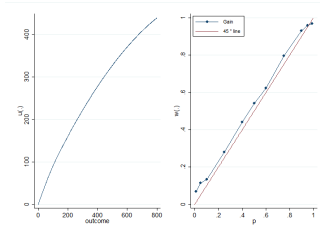
(d) Subject 4



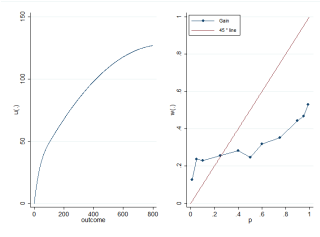
(e) Subject 5



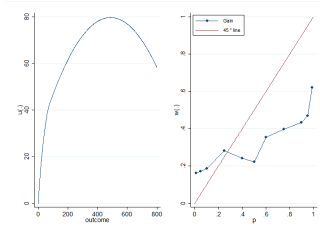
(f) Subject 6



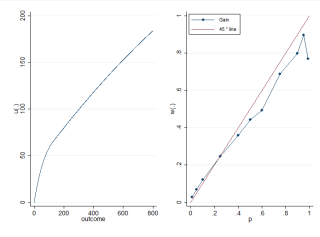
(g) Subject 7



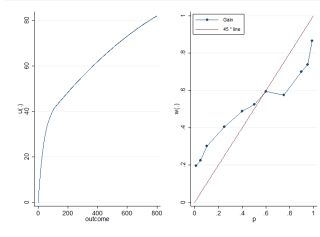
(h) Subject 8



(i) Subject 9



(j) Subject 10



## **Chapter 3**

# **Measuring Beliefs and Ambiguity Attitudes Towards Discrete Sources of Uncertainty**

This chapter is based on a paper co-authored with Maria Alejandra Erazo Diaz.

## Abstract

This chapter proposes a new method to measure beliefs and ambiguity attitudes towards events that are not necessarily equally likely and belong to a discrete set (i.e., discrete sources of uncertainty). Our method increases robustness to misspecification and allows flexibility in parametric choices compared to previous methods. We implement our method experimentally to both equal and different sources of uncertainty in two contexts: trust and coordination games. We find two main results. First, for equal sources of uncertainty, our method successfully reveals that subjects have context-independent beliefs on events, but context-dependent utility and weighting functions. This result indicates that comparing different sources of uncertainty requires a complete measurement of the utility and weighting functions. Second, different sources of uncertainty where the events are not equally likely lead to an increase in likelihood insensitivity, which indicates that the beliefs formation process of unknown events is cognitively demanding.

**Keywords:** Subjective beliefs, ambiguity attitudes, sources of uncertainty, trust game, coordination game.

**JEL codes:** D81, C91



## 3.1 Introduction

Ambiguous situations are pervasive in human decisions. These decisions vary from choosing a place to work to important investment decisions. Subjects decide under ambiguous situations when the objective probabilities of the possible events are unknown (Knight, 1921). In contrast, subjects make decisions under risk when the objective probabilities are known.

The standard theory under ambiguity – Subjective Expected Utility (SEU) – considers that subjects (i) form subjective probabilities or beliefs on events, (ii) have the same utility function under ambiguity as under risk, and (iii) value lotteries as expected utility over outcomes in which the weights are the beliefs. Ellsberg (1961)’s paradox showed that people deviate from SEU by exhibiting *ambiguity attitudes* (aversion or even seeking). Consequently, several models (e.g. Gilboa, 1987; Schmeidler, 1989; Tversky and Kahneman, 1992; Klibanoff et al., 2005) have been proposed to account for ambiguity attitudes by allowing events weighting function and a difference in utility between risk and ambiguity.

The estimation of the utility and weighting functions – as a measure of ambiguity attitudes – has been focused on *continuous-valued sources of uncertainty*, meaning that the universal event is an interval of real numbers (Abdellaoui et al., 2021b; Van De Kuilen and Wakker, 2011). The main advantage of *continuous-valued sources of uncertainty* is that the concept of *exchangeability of events*, introduced by Baillon (2008), can be used to build elicitation methods (see subsection 3.2.2). Two events are exchangeable for a decision maker when she is indifferent towards permutations of their outcomes. Exchangeability allows to iteratively partition the universal event in equally likely events. Then, with a set of exchangeable events for which the subjective probabilities are known, elicitation methods can provide a measurement of the utility and weighting functions.

In our daily life, situations of *continuous-valued sources of uncertainty* are not common compared to situations that involve *discrete sources of uncertainty*. A *Discrete source of uncertainty* refers to any source of uncertainty that takes their values in a discrete set of events, which are not necessarily equally likely. The universal event is no longer an interval of real numbers. As such, it excludes the possibility of building *exchangeable events*. [Baillon et al. \(2018a,b\)](#) shed light on this regard by proposing two methods that do not require exchangeable events; therefore, the two methods can be used for discrete sources of uncertainty. However, these methods rely on restricted parametric assumptions (source independent utility function and the neo-additive weighting function of [Chateauneuf et al. \(2007\)](#)), which makes them prone to misspecification issues.

The objective of this chapter is to develop a method to completely estimate utility function, weighting function and beliefs for discrete sources of uncertainty. Examples of discrete sources of uncertainty are present in almost all fields of economics. Some of the experimental from game theory include trust, ultimatum, and public good games. In the trust game (e.g. [Bohnet et al., 2008](#)), for instance, the universal event of the Trustor is often the union of two unequally likely events; either the Trustee reciprocates or betrays. Also, in the ultimatum game (e.g. [Slonim and Roth, 1998](#)), the universal event for the first mover is the union of two unequally likely events; either the second mover accepts or rejects the money sent by the first mover. Similarly, in a public good game with two players (e.g. [Kosfeld et al., 2009](#)), the universal event of each player is the union of two unequally likely events; either the other player contributes or the other player does not contribute.

Further examples of discrete sources of uncertainty can be found in health economics. For instance, the universal event of someone that consumes harmful products (e.g., tobacco, alcohol, unhealthy diets) can be represented as the union

of two unequally likely events: either the development of a non-communicable disease or stay healthy (e.g. Bloom et al., 2020; Mane et al., 2019). This example can also be extended to communicable diseases like AIDS or COVID-19, where people do not know the exact probability of getting sick and they decide whether or not to wear condoms or masks (e.g. Cuddington, 1993; Rieger et al., 2020). Additionally, transport economics (e.g. Guarda et al., 2016) and taxation economics (e.g. Dhami and Al-Nowaihi, 2007; Dhami and Hajimoladarvish, 2020) exemplified these situations. For instance, subjects who do not pay for the transport tickets face the union of two unequally likely events; being checked or not by controllers. Similarly, subjects who avoid taxes can be caught or not.

To measure these types of discrete sources of uncertainty, we propose a two-stage method in which the parametric assumptions of the utility function and the weighting function are made sequentially. The method allows for source-dependent utility function and any two-parameter weighting function (e.g. Goldstein and Einhorn, 1987; Prelec, 1998; Chateauneuf et al., 2007). Using simulations, we show that the two-stage structure of the method favors robustness to misspecification issues (see subsection 3.D).

We combine our method and the empirical data from an experiment conducted based on the trust and coordination game, in which subjects make decisions under different sources of uncertainty. Our data allows us to confront the method with two validity tests on (i) symmetric events and (ii) stability of beliefs for unequally likely events of the same sources of uncertainty involved in different decision contexts. Our method successfully passes validity tests, which supports the reliability of the results derived from it.

We provide three main results. First, we identify which sources of uncertainty are captured by likelihood insensitivity or pessimism. We find that several forms of uncertainty attitudes operate through variations in the likelihood insensitivity

component, the main driver of the inverse S-shaped weighting function in the literature (e.g. Wakker, 2010; Åstebro et al., 2015; Abdellaoui et al., 2011a). Subjects exhibit more likelihood insensitivity towards sources of uncertainty involving not symmetric events, which indicates that the beliefs formation process of unknown events is cognitively demanding. Second, empirical evidence supports theories that model ambiguity attitudes with the weighting function rather than with the utility function. Finally, our method reveals that subjects exhibit two additional behaviors which are not related to attitudes toward the source of uncertainty: *payoff dependence aversion* and *variety of payoffs seeking*. *Payoff dependence aversion* refers to the fact that subjects dislike that their own payoffs depend on the preferences of others, this behavior is captured by a more concave utility function. *Variety of payoffs seeking* means that subjects prefer a greater number of possible payoffs, when such possible payoffs depend on the preference of others, this is captured by a decrease in pessimism.

The remainder of this chapter proceeds as follows. Section 3.2 presents different theoretical approaches to model ambiguity attitudes and existing measurement methods. Section 4.3 presents our elicitation method. Section 4.4 provides a review of related literature about attitudes towards sources of uncertainty in the coordination and trust game. Section 3.5 presents the experimental design. Section 3.6 provides the results. We discuss the results in section 3.7 and, conclude in section 3.8.

## 3.2 Theoretical background

This section presents a general theoretical framework of ambiguity attitudes. Also, we present existing methods of measuring ambiguity attitudes and beliefs and, the explanation of their limits.

### 3.2.1 Biseparable preferences model

Denote by  $L = (x, y; E, E^c)$  a binary lottery that gives the outcome  $x$  if the event  $E$  occurs and  $y$  otherwise.  $E$  denotes an event of the state space  $\Omega$  and  $E^c$  denotes the complement of  $E$  in  $\Omega$ . Outcomes are real numbers. For notational convenience, we assume that  $x > y \geq 0$ . We denote  $\succsim$  as the preference relation of the decision-maker over prospects. The relations  $\succ$  and  $\sim$  denote strict preference and indifference, respectively. The preference relation of the decision-maker is represented by the following model that values the prospect  $L = (x, y; E, E^c)$  as

$$V(L) = W(P(E))(U(x) - U(y)) + U(y) \quad (3.1)$$

where  $W(\cdot)$  is the weighting function or source function for uncertainty ([Abdellaoui et al., 2011a](#)),  $P(E)$  is the subjective probability or beliefs of  $E$  occurring, and  $U(\cdot)$  the utility function that captures the attitude toward outcomes. Both  $W(\cdot)$  and  $U(\cdot)$  are strictly increasing functions.

Model (3.1) corresponds to the biseparable preferences model of [Ghirardato and Marinacci \(2001\)](#), with the assumption that the decision maker can assign subjective probabilities to events, even when she does not maximize SEU (e.g. [Ellsberg, 1961](#), p. 659). The biseparable preference model is a very general ambiguity model (e.g., [Attema et al., 2018](#); [Abdellaoui et al., 2021a](#)) because it contains many of the ambiguity models (e.g. [Gilboa, 1987](#); [Schmeidler, 1989](#); [Gilboa and Schmeidler, 1989](#); [Tversky and Kahneman, 1992](#)) that have been proposed to explain Ellsberg's paradox as special cases.

For decisions under risk, the objective probabilities of events are known. Denote by  $L = (x, y; p, 1 - p)$  a binary lottery that gives outcome  $x$  with probability  $p$  and  $y$  otherwise. The preference relation of the decision-maker is

represented by the following model that values the prospect  $L = (x, y; p, 1 - p)$  as

$$V(L) = w(p)(u(x) - u(y)) + u(y) \quad (3.2)$$

with  $w(\cdot)$  as the weighting function or source function for risk and  $u(\cdot)$  the utility function that captures the attitude toward the outcomes. Both  $w(\cdot)$  and  $u(\cdot)$  are strictly increasing functions.

Source-dependent Utility (SDU) models assume identical weighting functions between risk and uncertainty, *i.e.*  $W(\cdot) = w(\cdot)$ . Source-dependent weighting (SDW) models assume identical utility functions between risk and uncertainty, *i.e.*  $U(\cdot) = u(\cdot)$ .

## 3.2.2 Existing methods

### 3.2.2.1 Elicitation methods based on exchangeability of events

The main difficulty for measuring the ambiguity model (3.1) resides in how to disentangle the weighting function  $W(\cdot)$  from the beliefs  $P(\cdot)$  (e.g. [Li et al., 2020](#)) (LW, hereafter). The solution proposed in the literature is based on the concept of *exchangeability of events* ([Baillon, 2008](#)). Two events are exchangeable for a decision-maker when she is indifferent towards permutations of their outcomes. Formally, two events  $E_1$  and  $E_2$  are exchangeable if  $(x, E_1, y) \sim (x, E_2, y)$ , which implies that such events are equally likely or symmetric:  $P(E_1) = P(E_2)$ . If these events are complementary, then the subjective probability associated with each event should be  $\frac{1}{2}$ , assuming the additivity of  $P(\cdot)$ .

Based on this concept of exchangeability of events, several methods have been proposed (e.g. [Abdellaoui et al., 2011a](#); [Van De Kuilen and Wakker, 2011](#); [Abdellaoui et al., 2021a](#); [Gutierrez and Kemel, 2021](#)). The common idea underlying these methods is to start by splitting the universal event into two

exchangeable events  $E_1$  and  $E_2$ , such that  $P(E_1) = P(E_2) = \frac{1}{2}$ . The following steps of these methods consist of splitting  $E_1$  and  $E_2$  into exchangeable events that will result in  $\frac{1}{4}$  as the subjective probability. Repeating the procedure allows to construct iteratively a series of exchangeable events that have a subjective probability of  $\frac{1}{2^i}$ , with  $i = 1, 2, \dots, n$ . With the set of exchangeable events for which one knows the subjective probability, these methods can provide a measurement for  $W(\cdot)$  and  $U(\cdot)$ .

The construction of these exchangeable events are only possible for *continuous-valued sources of uncertainty*, which means that the universal event is an interval of real numbers (Abdellaoui et al., 2021b; Van De Kuilen and Wakker, 2011). For instance, when the source of uncertainty is the temperature in a town or the stock market index.

### 3.2.2.2 Elicitation method not based on exchangeable events

Oppositely, a *discrete source of uncertainty* comes from a source of uncertainty that takes their values in a discrete set of events which are not necessarily equally likely. Consequently, the universal event is no longer an interval of real numbers, therefore, it is not longer possible to build *exchangeable events*. In the next subsection, we introduce the indexes of Baillon et al. (2018b) (BW, hereafter), which are applicable to measure ambiguity towards *discrete sources of uncertainty*.

#### Belief hedges method of BW

For *discrete sources of uncertainty*, BW introduced the *belief hedges method* that consists of evaluating ambiguity attitudes through two indexes. BW assume a minimal degree of richness of the state space  $\Omega$ , meaning that there should be three nonnull events  $E_1 = A$ ,  $E_2 = B$  and  $E_3 = C$  that are mutually exclusive

and exhaustive:  $E_1 \cup E_2 \cup E_3 = \Omega$  and  $E_i \cap E_j = \emptyset$  for  $i \neq j$ . Denote by  $E_{ij}$  the union  $E_i \cup E_j$  of two events. We call  $E_i$  a single event and  $E_{ij}$  a composite event. Denote by  $\Omega_1^* = \{E_1, E_2, E_3\} = \{A, B, C\}$  the set of single events and by  $\Omega_2^* = \{E_{12}, E_{13}, E_{23}\}$  the set of the composite events.

BW propose their two indexes in the framework of SDW. The difference in the weighting functions under ambiguity and risk is measured by the *ambiguity function*  $f(\cdot) = w^{-1}[W(\cdot)]$ . The matching probability  $m_E$  of an event  $E$  is the probability that ensures the following indifference  $(x, y; E, E^c) \sim (x, y; m_E, 1 - m_E)$ . Under SDW, the *ambiguity function* corresponds to the *matching probability* (Dimmock et al., 2016, Theorem 3.1):

$$m_E = f[P(E)] \quad (3.3)$$

The two indexes of the ambiguity function of BW are given by:

$$b = 1 - (m_1 + m_2)$$

$$a = 3 \left[ \frac{1}{3} - (m_2 - m_1) \right]$$

with  $m_1 = \frac{1}{3}[m_A + m_B + m_C]$  and  $m_2 = \frac{1}{3}[m_{AB} + m_{AC} + m_{BC}]$  being the averages matching probability for the single and composite events.

The quantity  $b$ , called *ambiguity aversion index*, approximates the elevation of the decision maker's ambiguity function. Ambiguity neutrality (*i.e.*  $w(\cdot) = W(\cdot)$ ) implies  $b = 0$ . A higher value of  $b$  is associated with more ambiguity aversion from the pessimism component of the weighting function. The quantity  $a$ , called *ambiguity-generated insensitivity* (a-insensitivity), approximates the flatness of the ambiguity function in the middle region. Ambiguity-neutrality implies  $a = 0$ . A higher value of  $a$  is associated with more ambiguity aversion from the likelihood insensitivity component of the weighting function.



The main purpose of the two indexes of BW is to compare a risky situation with an ambiguous situation. Although, it can be tempting to use these two indexes to compare two different sources of uncertainty, our main point (formulated in Proposition 1) is to stress the fact that this second use of the two indexes could be misleading.

**Proposition 1.** Consider two different sources of uncertainty 1 and 2 involving each three mutually exclusive and exhaustive events  $E_i$ ,  $i = 1, 2, 3$ . Denote by  $W_j(\cdot)$  and  $P_j(\cdot)$  the weighting and belief functions for the source of uncertainty  $j$ , with  $j = 1, 2$ . Assume that subjects have:

(A1) the same non-linear weighting functions for the two sources of uncertainty  
:  $W_1(\cdot) = W_2(\cdot) \equiv W(\cdot)$

(A2) different beliefs for events :  $P_1(\cdot) \neq P_2(\cdot)$ .

Assumptions (A1) and (A2) imply that  $a_1 \neq a_2$  and  $b_1 \neq b_2$

**Proof**

Under (A1), we have the same ambiguity function  $f_1(\cdot) = f_2(\cdot) = w^{-1}[W(\cdot)] \equiv f(\cdot)$ , with  $w(\cdot)$  being the probability weighting function for risk. So, there is no difference in ambiguity attitudes in the sense of SDW. The two indexes of BW for the two sources of uncertainty are given by

$$b_i = 1 - \frac{1}{3} \left( \sum_{E \in \Omega_1^*} f[P_i(E)] + \sum_{E \in \Omega_2^*} f[P_i(E)] \right) \quad i = 1, 2$$

$$a_i = 1 - \left( \sum_{E \in \Omega_2^*} f[P_i(E)] - \sum_{E \in \Omega_1^*} f[P_i(E)] \right) \quad i = 1, 2$$

Since the ambiguity function  $f(\cdot)$  is bijective and  $P_1(\cdot) \neq P_2(\cdot)$ , there is no reason, a priori, to expect that  $b_1 = b_2$  and  $a_1 = a_2$ . To illustrate, let's consider the following numerical example. For the source of uncertainty 1, assume that  $E_1$ ,  $E_2$ , and  $E_3$  are symmetric:  $P_1(E_1) = P_1(E_2) = P_1(E_3) = \frac{1}{3}$ . For the source 2, assume  $P_2(E_1) = \frac{1}{10}$ ,  $P_2(E_2) = \frac{1}{10}$  and  $P_3(E_3) = \frac{8}{10}$ . Also, assume  $w(p) = p$  for risk and the non-linear [Prelec \(1998\)](#) compound invariance family  $W(z) = (\exp(-(-\ln(z))^\alpha))^\beta$  with  $\alpha = 0.65$  and  $\beta = 1.05$  ([Wakker, 2010](#), pg. 270) for both treatments 1 and 2. With these values, we have  $b_1 = 0.11 \neq 0.06 = b_2$  and  $a_1 = 0.31 \neq 0.19 = a_2$ . QED.

The Proposition 1 shows that the indexes of BW may be misleading to learn about the differences in ambiguity functions related to different sources of uncertainty when the distributions of beliefs differ markedly between these sources. Note that the only case where the indexes of BW work perfectly, is when the ambiguity function is linear ([Baillon et al., 2021](#), Theorem 16). This happens when the weighting functions  $w(\cdot)$  and  $W(\cdot)$  are the specification of [Chateauneuf et al. \(2007\)](#).

Our point applies in particular to LW, who compare the indexes of BW between uncertainty generated by nature with uncertainty generated by a second player in the trust game. In this case, events are symmetric for nature (e.g [Abdellaoui et al., 2011a](#)), while they are asymmetric for the trust game. Hence, the results found by LW might be driven by the beliefs. A second drawback is that the indexes are proposed under the framework of SDW and this does not allow for ambiguity attitudes to be captured by the utility function.

### Neo-additive method

[Baillon et al. \(2018a\)](#) proposed a method which releases the assumption of identical utility functions across sources or, in particular, between risk and

uncertainty. This method allows to elicit the utility function, the neo-additive weighting function  $W(P(E)) = sP(E) + c$  proposed by [Chateauneuf et al. \(2007\)](#), and the beliefs do not require exchangeable events.<sup>1</sup> The method consists of using certainty equivalent data of binary lotteries that involve three mutually exclusive and exhaustive events  $(E_1, E_2, E_3)$  and, one composite event (say  $E_{12}$ ). The neo-additive weighting function and the parametric utility function (e.g. power utility  $x^\alpha$ ) are specified. The certainty equivalent data can be used in three-stages or one-stage procedure to estimate the utility, the neo-additive weighting function, and the beliefs of each  $P(E_i)$ ,  $i = 1, 2, 3$ .

In the three-stages procedure, parametric assumptions are made sequentially. In the one-stage, the certainty equivalent data associated to one event (say  $E_1$ ) is used to estimate the utility function parameter (say  $\alpha$ ) and the one event weight (say  $W(P(E_1))$ ), according to the method of [Abdellaoui et al. \(2008\)](#). In the second stage, the certainty equivalent data related to the three remaining events ( $E_2, E_3$  and  $E_{12}$ ) are used to compute, in a deterministic way, the three event weights  $W(P(E_2))$ ,  $W(P(E_3))$  and  $W(P(E_{12}))$ , according to [Abdellaoui et al. \(2011b\)](#). In the third stage, the four event weights from the first and second stage allow to estimate the two-parameter of the neo-additive weighting function and the three beliefs as follows

$$c = W(P(E_1)) + W(P(E_2)) - W(P(E_{12})) \quad (3.4)$$

$$s = \sum_{i=1}^3 W(P(E_i)) - 3(W(P(E_1)) + W(P(E_2)) - W(P(E_{12}))) \quad (3.5)$$

$$P(E_i) = \frac{W(P(E_i)) - c}{s} \quad \text{for} \quad i = 1, 2, 3 \quad (3.6)$$

---

<sup>1</sup>Similar procedure is proposed by [Gutierrez and Kemel \(2021, study C\)](#), but they keep the assumption of same utility for all sources of uncertainty.

In the one-stage procedure, the parametric assumption of the utility and the weighting functions are not made sequentially, but simultaneously. Then, the certainty equivalent data is used in a single step to estimate the utility function parameter (say  $\alpha$ ), the two-parameters ( $s$  and  $c$ ) of the neo-additive weighting function, and the two beliefs  $P(E_1)$  and  $P(E_2)$ , knowing that  $P(E_3) = 1 - P(E_1) - P(E_2)$ .

Even though the one-stage and three-stages neo-additive methods allow for source-dependent utility function, they might suffer from two drawbacks. The first drawback applies to both methods. This drawback relies on the fact that the assumption of the neo-additive weighting function may be restrictive to fit the data (e.g. [Li et al., 2018](#)), probably due to misspecification issues ([Kpegli et al., 2022](#)). Second, in the case of the three-stages approach, the certainty equivalents that are used to compute the event weights in a deterministic way during the second stage contain with response errors. These response errors are not controlled and, then they could bias the future estimates of the event weights in the second stage, as well as generate additional bias in the beliefs of the third stage ([Etchart-Vincent, 2004](#), pg. 221).

### 3.3 Elicitation Method

In this section, we extend the multistage neo-additive method of [Baillon et al. \(2018a\)](#) to any two-parameter weighting function to elicit beliefs  $P(\cdot)$ , utility function  $U(\cdot)$ , and weighting function  $W(\cdot)$  for discrete sources of uncertainty. In addition, we show that the two-stage method is more robust to misspecification than the one-stage method. We keep the same notations as in section 3.2.

### 3.3.1 Stage 1: Elicitation of utility function and willingness to bet

This stage is based on the *all at once method* of [Kpegli et al. \(2022\)](#). The researcher starts by considering a set of  $m = 3$  mutually exclusive and exhaustive nonnull events  $\Omega_1^* = \{E_1, E_2, E_3\}$ .<sup>2</sup> The resulting set of composite events is given by  $\Omega_2^* = \{E_{12}, E_{13}, E_{23}\}$ . Further, the researcher will pick a composite event in  $\Omega_2^*$ , say  $E_{12}$  (see also [Baillon et al., 2018a](#)). Subsequently, the researcher elicits in an experiment, at least two certainty equivalents for each single event and the chosen composite event  $E \in \Omega_1^* \cup E_{12}$

$$ce_k^h \sim (x_E^h, y_E^h; E, E^c), \quad h = 1, 2, \dots, N_E \quad \text{and} \quad N_E \geq 2 \quad (3.7)$$

with  $N_E$  being the number of certainty equivalents that involve the event  $E$ .  $x_E^h$  and  $y_E^h$  refer to the outcomes such that  $x_E^h > y_E^h$ . In total, the number of certainty equivalents elicited is  $N = \sum_{E \in \Omega_1^* \cup E_{12}} N_E \geq 2(m + 1) = 8$ .

Now, we denote by  $\mathbf{ce}$ ,  $\mathbf{x}$ , and  $\mathbf{y}$  the variables that collect the values  $ce_E^h$ ,  $x_E^h$ , and  $y_E^h$ , respectively. Also, we denote by  $\mathbf{I}^E$  a dummy variable that takes the value 1 if the event  $E$  occurs and 0 otherwise. Denote  $\delta_E \equiv W(P(E))$  for  $E \in \Omega_1^* \cup E_{12}$ . We call  $\delta_E$  the *willingness to bet* on the event  $E$  ([Ghirardato and Marinacci, 2001](#); [Abdellaoui et al., 2011a](#)). Also, we assume that the certainty equivalents are observed with additive response error terms  $\mathbf{e}$ . Assuming that  $U$  is invertible, it turns out

$$\mathbf{ce}_l = U^{-1} \left[ (U(\mathbf{x}_l) - U(\mathbf{y}_l)) \left( \sum_{E \in \Omega_1^* \cup E_{12}} \delta_E \mathbf{I}_l^E \right) + U(\mathbf{y}_l) \right] + \mathbf{e}_l \quad (3.8)$$

---

<sup>2</sup>We cover the cases of  $m \neq 3$  in the subsection 3.3.2.

where  $l$  is the  $l^{th}$  line in  $\mathbf{ce}$ ,  $\mathbf{x}$ , and  $\mathbf{y}$ . Finally, the Eq. (3.8) is estimated by nonlinear least squares, by giving an explicit functional form for  $U$  (and thus for  $U^{-1}$ ). The two-popular utility function are power (eq. 3.16) and exponential (eq. 3.17).

From the estimations results, one gets the parameter(s) of the utility function  $U(\cdot)$  and the willingness to bet  $\delta_E$  on the event  $E \in \Omega_1^* \cup E_{12}$ . These willingness to bet correspond to the compound function  $W(P(\cdot))$  evaluated at each single and composite events in the set  $\Omega_1^* \cup E_{12}$ .

This stage allows to reject subjective expected utility theory (that is  $W(z) = z$ ), if any of the following two equalities is not satisfied

$$\sum_{E \in \Omega_1^*} \hat{\delta}_E = 1 \quad \text{and} \quad \hat{\delta}_{E_{12}} = \hat{\delta}_{E_1} + \hat{\delta}_{E_2} \quad (3.9)$$

The following stage allows to break down the willingness to bet in terms of weighting function  $W(\cdot)$ , and beliefs  $P(E)$  for  $E \in \Omega_1^* \cup E_{12}$ .

### 3.3.2 Stage 2: Elicitation of weighting function and beliefs

Following [Gonzalez and Wu \(1999\)](#), we assume that the weighting function  $W(\cdot)$  is characterized by two parameters  $\eta$  and  $\gamma$ , which correspond to the *insensitivity* of the decision-maker to likelihood information, and the decision-maker's *pessimism/optimism*, respectively. To make explicit the dependence of the weighting function on  $\eta$  and  $\gamma$ , we write  $W(\cdot) \equiv W_{\eta,\gamma}(\cdot)$ .

With  $m = 3$  single events, we have the following system of 5 equations:

$$W_{\eta,\gamma}(P(E_i)) = \hat{\delta}_{E_i} \quad , \quad i = 1, 2, \dots, m = 3 \quad (3.10)$$

$$W_{\eta,\gamma}(P(E_1) + P(E_2)) = \hat{\delta}_{E_{12}} \quad (3.11)$$

$$\sum_{i=1}^m P(E_i) = 1 \quad (3.12)$$

The system of equations (3.10)-(3.12) contains exactly 5 unknown elements:  $P(E_1)$ ,  $P(E_2)$ ,  $P(E_3)$ ,  $\eta$ , and  $\gamma$ . The first three equations in (3.10) come from Eq. (3.8). The fourth Eq. in (3.11) comes from Eq. (3.8) and, the fact that the events  $E_1$  and  $E_2$  are mutually exclusive. The last Eq. in (3.12) comes from the fact that the events  $E_1, E_2$ , and  $E_3$  are exhaustive. Any two-parameter weighting functions can be specified (see [Epper and Fehr-Duda, 2020](#), for a review) in the system of equations (3.10)-(3.12). The three popular weighting functions in the ambiguity literature are the specifications<sup>3</sup> of GE87 (eq. 3.18), P98 (eq. 3.19) and CEG7 (eq. 3.20).

When the estimated decision weights satisfy strict monotonicity<sup>4</sup> in the sense that  $\delta_{E_{12}} > \delta_{E_1}$  and  $\delta_{E_{12}} > \delta_{E_2}$ , the system of equations (3.10) - (3.12) could be solved (numerically) to estimate the strictly increasing two-parameter weighting function (*i.e.*  $\eta$  and  $\gamma$ ) and the beliefs  $P(E_1)$ ,  $P(E_2)$ , and  $P(E_3)$ .

It is noteworthy to talk about our method when the number  $m$  of single events is different from 3. When the number of single events is more than 3, the procedure to apply our method remains unchanged. The beliefs of additional single events can be estimated by using the corresponding number  $m$  of the single events in equations (3.10) and (3.12). When the number of single events is  $m = 2$ , the Eq. (3.11) collapses from the method because  $W(1) = 1$  by assumption. In this case, our method does not allow to identify two-parameters weighting

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<sup>3</sup>We refer to [Goldstein and Einhorn \(1987\)](#) as GE87.

<sup>4</sup>Monotonicity at the aggregate level (e.g. pooled data, mean data and median data) will naturally hold. But, at the individual level this condition might not be satisfied.

function. Instead, it allows to identify one-parameter weighting function (e.g. [Tversky and Kahneman, 1992](#); [Prelec, 1998](#)).

Despite the fact that we focus on the presentation of our method on discrete source of uncertainty, it can also apply to continuous-valued sources of uncertainty (see [Appendix 3.A](#) for details). In this context, using the subjective probabilities of the three exclusive and exhaustive events  $E_1, E_2, E_3 \subset \mathcal{R}$  allows to completely estimate continuous two-parameter distribution like the beta distribution ([Abdellaoui et al., 2021a](#)). Consequently, our method covers all types of sources of uncertainty.

Also, the method accommodates both SDU and SDW since we do not require equality of utility or weighting functions between risk and uncertainty. Then, the data allows to discriminate between SDU and SDW.<sup>5</sup>

## 3.4 Related literature on uncertainty attitudes in experiments

The reminder of the chapter shows how our method can be used to measure beliefs and disentangle crucial forms of uncertainty in trust and coordination games. In this section, we present some of the related literature.

### 3.4.1 Crucial forms of uncertainty in trust and coordination games

In economic experiments, subjects playing the traditional trust game, face two sources of uncertainty: *strategic uncertainty* and *social ambiguity*. First, subjects

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<sup>5</sup>In [Appendix 3.D](#) we present the parameter recovery and misspecification exercises (e.g. [Gao et al., 2020](#); [Kpegli et al., 2022](#); [Nilsson et al., 2011](#)) with the aim of comparing our multi-stage approach with the one-stage approach.



face *strategic uncertainty* when the actions of others are uncertain in strategic interactions. Strategic uncertainty confronts individuals with the delicate task of forming beliefs about other individuals' decisions (Renou and Schlag, 2010). Second, decision-makers face *social ambiguity*, when the uncertainty comes from the non-strategic decisions of other individuals. Social ambiguity refers to the fact that subjects treat acts by humans, even in the absence of strategic interactions, differently from acts of nature, which do not involve human agency (LW). Hence, behind any strategic uncertainty, there is also social ambiguity, which might play a role in the decision-making process.

Additionally, social preferences play a role in trust games since players are aware that their actions impact not only their payoffs, but also the payoffs of others (Bohnet et al., 2008) (BZ, hereafter). Also, in a modified version of the trust game, Trustors can interact with nature instead of another person, in which case, they face *nature ambiguity*. This means that the ambiguous outcomes are determined by a non-human source.

Besides social ambiguity, strategic uncertainty, and social preferences (all present in strategic interactions), a key component that differentiates the trust game from other games that comprise strategic interactions in game theory (e.g., beauty contest, and coordination games) is *betrayal aversion*. Betrayal aversion represents a cost for the Trustor when trust is violated (BZ). This cost is viewed by BZ as a dis-utility that enters into the utility function alongside the utility towards one's own payoffs and social preferences. It becomes clear that strategic uncertainty, social ambiguity and betrayal aversion can play a major role in strategic interactions and trust decisions.

### 3.4.2 Social ambiguity, strategic uncertainty and betrayal aversion

Under SDU, *strategic uncertainty*, *social ambiguity* and *betrayal aversion* would be captured by the utility function. Contrary, under SDW, they would be captured by the weighting function. The weighting function captures such ambiguous attitudes into two components: optimism/pessimism and likelihood insensitivity (Gonzalez and Wu, 1999). Optimism/pessimism reflects the extent to which subjects overweight/underweight the beliefs regarding whether the resulting outcome will be beneficial for them. On the other hand, likelihood insensitivity refers to subjects' cognitive ability to distinguish between several levels of subjective probabilities or beliefs (e.g. Choi et al., 2022). Wakker (2010) refers to optimism/pessimism as a motivational component and, to likelihood insensitivity as a cognitive component in the decision-making process.

BZ develop an experiment, using a version of the trust game, to identify betrayal aversion through the Minimum Acceptable Probability (MAP) related to the utility function. The MAP is the probability for which the Trustor is indifferent between trust and distrust. BZ identify betrayal aversion as the difference in MAP between two treatments: the trust game and the risky dictator game (RDG). In the trust game treatment, if the Trustor decides to trust, the final payoffs for both Trustor and Trustee are determined by the Trustee. Contrary, in the RDG, if the Trustor trusts, the payoffs for both players are determined by nature. The possible payoffs under both treatments are the same. Their results show that subjects state higher MAPs in the trust game compared to the RDG, which means that subjects are betrayal averse. Quercia (2016) provides an improvement of MAP design and confirm betrayal aversion.

LW show that the MAP design of BZ does not hold under SDW. The difference in MAP across treatments can be explained by the weighting function

and beliefs instead of the utility. The authors use the two indexes of pessimism and likelihood insensitivity provided by BW to disentangle social ambiguity and strategic uncertainty in the trust game. They find that pessimism is lower when subjects face social ambiguity than when they face nature ambiguity. Also, they find that strategic uncertainty and betrayal attitudes only have cognitive implications by making subjects more likelihood insensitive in the trust game compared to nature ambiguity. The fact that social ambiguity is captured by the pessimism component of the weighting function in the trust game, suggests that social ambiguity plays a major role in strategic uncertain situations. Therefore, it is important to control for social ambiguity when studying strategic uncertainty. Nevertheless, a vast majority of previous studies (e.g., [Heinemann et al., 2009](#); [Ivanov, 2011](#); [Bruttel et al., 2022](#)), do not control for social ambiguity when they investigate strategic uncertainty. In this chapter, we also aim to identify which components of the utility function and the weighting function (pessimism and likelihood insensitivity) capture the effect of social ambiguity, strategic uncertainty, and betrayal aversion.

### 3.5 Experimental Design

We recruit 174 students to participate in a computerized experiment, which is conducted online. Subjects are invited through the subjects pool of GATE-Lab. Subjects are told that the experiment could last up to 45 minutes, that they would receive €1.5 as a participation fee and, they could additionally earn a variable amount up to €20. Such additional payment corresponds to a randomly selected outcome of one of the decisions made during the experiment. The mean age of subjects is 21 years and 56.9% are female. Our experiment follows a within-subjects design.

The experiment consists of 5 experimental conditions. Four out of these conditions have two stages, the remaining condition consists only of the second stage. In the first stage, we implement experimental treatments based on the coordination game and the trust game. In the second stage, we apply a binary decisions task between a safe option and a lottery to elicit beliefs, ambiguity attitudes, and utility functions.<sup>6</sup> The order in which subjects play the five experimental conditions is randomized.

We refer to the blocks containing one or two stages as experimental conditions and to the task implemented in each of the stages as experimental treatments. The goal of the conditions and treatments is to implement our method experimentally and combine it with empirical data. Each of the experimental conditions allows to elicit ambiguity attitudes linked to different crucial forms of uncertainty.

### 3.5.1 First stage

We use a within-subjects design along the experiment. In four out of the five conditions of the experiment, the first stage contains the following experimental treatments: *social ambiguity – coordination game (social ambiguity - cg)*, *strategic uncertainty - coordination game (strategic uncertainty - cg)*, *social ambiguity – trust game (social ambiguity - tg)*, and *betrayal ambiguity*. In these conditions, 89 subjects play the role of Player 1 and, 85 subjects take the role of Player 2. Subjects keep their role along the whole experiment. For each condition, new couples formed by Player 1 and Player 2 are randomly re-matched. Subjects are informed that they do not play against the same partner more than once and, they do not receive feedback about the decisions of their counterparts until the end of the experiment.

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<sup>6</sup>The complete instructions can be found in the Appendix 3.C

At the beginning of each condition, Player 1s are informed whether the condition contains one or two stages, specific instructions for each stage are given at the beginning of each stage. Our implemented procedure for incentives allows to avoid hedging issues and it is established as follows. Player 1 received the payoff of one randomly selected decision in either one of the two stages of the four conditions, or one of the decisions made in the remaining treatment (*nature*). Also, one out of the four decisions done by Player 2, is randomly selected for payoff.

With the *social ambiguity - cg* treatment, we measure ambiguity attitudes and social ambiguity. Player 1s make a strategic decision between Left (L), Right (R), and Middle (M). On the other hand, Player 2s receive €5 and, their task is to answer where they would prefer to spend this money between an Amazon voucher, a Google Play voucher, and an Apple Store voucher. Player 2s do not know the payoff matrix. As such, Player 2s decide between three possible options that represent their own preferences and are independent of Player 1s' decisions. Therefore, Player 1s should not base their decisions on a strategic interaction. However, decisions of Player 2s directly affect Player 1s' payoff, which is why Player 1s face social ambiguity. The structure of the payments<sup>7</sup> for this treatment is displayed in Table 3.5.1.

Table 3.5.1: Social ambiguity - coordination game treatment.

		Player 2		
		Amazon	Google Play	Apple Store
Player 1	Left	15, 5	10, 5	8, 5
	Right	8, 5	15, 5	10, 5
	Middle	10, 5	8, 5	15, 5

To measure strategic uncertainty, we implement the *strategic uncertainty - cg* treatment. The matrix of the game, which follows a traditional coordination

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<sup>7</sup>The exchange rate is such that 1 ECU = 1 euro.

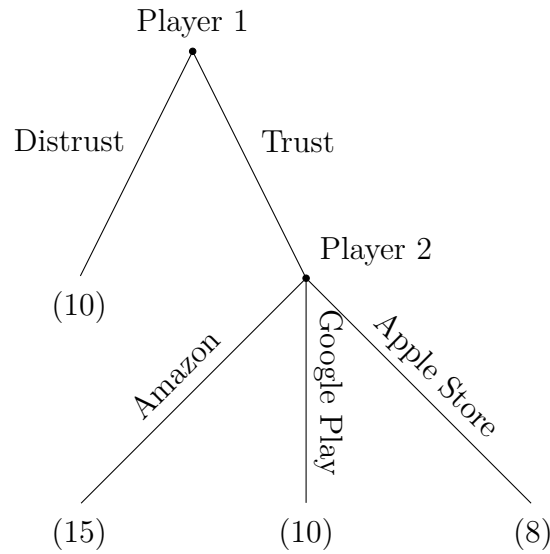
game, and is known by both Player 1 and Player 2, is shown in Table 3.5.2. Both Players 1 and 2 make a strategic decision between alternatives  $L$ ,  $R$ , or  $M$ . Hence, subjects make their decisions under ambiguity attitudes, strategic uncertainty, and social ambiguity. Contrary to the choice alternatives presented to Player 2 in the *social ambiguity - cg* treatment, in the *strategic uncertainty - cg* treatment, we use the frame  $L$ ,  $R$ , and  $M$  in order to keep a neutral language unrelated with preferences.

Table 3.5.2: Strategic uncertainty - coordination game treatment.

		Player 2		
		Left	Right	Middle
Player 1	Left	15, 15	10, 18	8, 22
	Right	8, 22	15, 15	10, 18
	Middle	10, 18	8, 22	15, 15

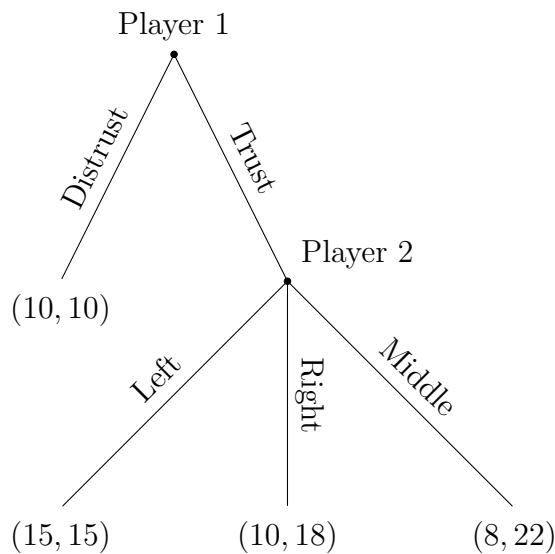
Treatments *social ambiguity - tg* and *betrayal ambiguity* are based on the experimental design of LW. In the *social ambiguity - tg* treatment (see Figure 4.4.3), Player 1 decides between distrust (D) or trust (T). If Player 1 decides D, she receives a payoff of 10 ECU with certainty. On the other hand, if Player 1 decides T, the payment is determined based on the preferences of Player 2. Player 2s receive €5 and are asked to decide where they would prefer to spend this money between an Amazon voucher, a Google Play voucher, or an Apple Store voucher. In this treatment, as in the *social ambiguity - cg*, Player 1s make their decisions facing ambiguity attitudes and social ambiguity.

Figure 3.5.1: Social ambiguity - trust game treatment



Finally, we study ambiguity attitudes, social ambiguity, strategic uncertainty, betrayal aversion, and social preferences in the *betrayal aversion* treatment. Player 1 decides between the safe option D and the ambiguous option T. In case Player 1 chooses D, both Players 1 and 2 receive 10 ECU and no further decisions are made. Differently, if Player 1 decides T, Player 2's decision between L, R, or M, determines the final payoffs for both players. Player 2's decisions L, R, and M represent reciprocation, no hurt, and betrayal, respectively. The structure of the game and payments are shown in Figure 3.5.2. In this treatment, Player 1 faces ambiguity regarding the strategic decision made by Player 2, which also leads to the possibility for Player 1 to be betrayed by Player 2.

Figure 3.5.2: Betrayal aversion treatment



### 3.5.2 Second stage: elicitation of beliefs, ambiguity attitudes, and utility function

Only Player 1s perform the second stage of each condition and the remaining condition. The first stage in every condition is followed by the second stage. Therefore, Player 1 perform the second stage of each condition immediately after each of the treatments and, only when the task of the second stage is completed, Player 1 moves to the next condition. We elicit Player 1s' certainty equivalents through the switching outcome technique (Gonzalez and Wu, 1999; Tversky and Kahneman, 1992) for a list of 12 binary lotteries  $L = (x, y; E, E^c)$  that involved Player 2s' decisions as events. Such events can be either L, R, and M, or Amazon, Google Play, and Apple Store vouchers, depending on the immediately latest treatment performed by the participant. To infer the certainty equivalent of each lottery  $L = (x, y; E, E^c)$ , Player 1s are asked to make a series of binary



decisions between a lottery and a list of equally spaced safe payoffs, ranged from the maximum value  $x$  to the minimum value  $y$  of the lottery.

Table 3.5.3 displays an example of the lotteries corresponding to the second stage of the conditions containing the treatments *strategic uncertainty - cg* and *betrayal aversion*, where the decisions done by Player 2s correspond to the options  $L$ ,  $R$ , or  $M$ . Consider for example, lottery number 1 in the first set of lotteries in Table 3.5.3. In this case, Player 1 is asked to make eight decisions between a safe outcome and a lottery. Payoffs for the safe option vary from 15 ECU to 8 ECU, while the lottery remains constant.

Table 3.5.3: Binary lotteries

No. of lottery	x	y	$E$	$E^c$	Midpoint of outcome lotteries
First set of lotteries					
1	15 ECU	8 ECU	$E_1 = L$	$E_1^c = R \cup M$	11.5 ECU
2	15 ECU	8 ECU	$E_1 = R$	$E_1^c = L \cup M$	11.5 ECU
3	15 ECU	8 ECU	$E_1 = M$	$E_1^c = L \cup R$	11.5 ECU
4	15 ECU	8 ECU	$E_1 = L \cup R$	$E_1^c = M$	11.5 ECU
Second set of lotteries					
5	10 ECU	0 ECU	$E_1 = L$	$E_1^c = R \cup M$	5 ECU
6	10 ECU	0 ECU	$E_1 = R$	$E_1^c = L \cup M$	5 ECU
7	10 ECU	0 ECU	$E_1 = M$	$E_1^c = L \cup R$	5 ECU
8	10 ECU	0 ECU	$E_1 = L \cup R$	$E_1^c = M$	5 ECU
Third set of lotteries					
9	15 ECU	0 ECU	$E_1 = L$	$E_1^c = R \cup M$	7.5 ECU
10	15 ECU	0 ECU	$E_1 = R$	$E_1^c = L \cup M$	7.5 ECU
11	15 ECU	0 ECU	$E_1 = M$	$E_1^c = L \cup R$	7.5 ECU
12	15 ECU	0 ECU	$E_1 = L \cup R$	$E_1^c = M$	7.5 ECU

Finally, Player 1s complete another set of binary decisions which are not linked with any treatment performed before by the participant. Such an additional set of binary decisions is the experimental condition called *nature ambiguity*. In this task, Player 1s also decide between a safe outcome or a lottery. However, in this case, the outcome of the lottery is determined by nature, which is a randomly equally likely selection between L, R, or M made by the computer. Therefore, this condition allows us to measure only ambiguity attitudes. Figure 3.5.3 shows

a screen shot of some of the binary decisions contained in the *nature ambiguity* task.<sup>8</sup>

Figure 3.5.3: Nature ambiguity.

Safe payments for alternative A:	Alternative A	Alternative B	Variable payments for alternative B:
15 ECU	A1	B1	You get 15 ECU if the computer randomly chooses Left or 8 ECU if the computer randomly chooses Right or Middle.
14 ECU	A2	B2	
13 ECU	A3	B3	
12 ECU	A4	B4	
11 ECU	A5	B5	
10 ECU	A6	B6	
9 ECU	A7	B7	
8 ECU	A8	B8	

Example of one of the screens of the task in the nature ambiguity treatment.

Our experimental design allows us to disregard social preferences in this part of the experiment. Therefore, at the stage of elicitation of certainty equivalents, social preferences collapse for Player 1s' decision-making process. We use the data of certainty equivalents as input to elicit the utility function, weighting function, and beliefs with our method presented in Section 4.3.

### 3.5.2.1 Comparison between treatments and hypotheses

We perform a series of comparisons based on the decisions done by Player 1 in the second stage of the conditions previously presented. The aim of these comparisons between the five treatments is to isolate and capture the effect of social ambiguity, strategic uncertainty, and betrayal aversion. The following are our conjectures.

1. **Comparison between *social ambiguity - cg* and *strategic uncertainty - cg*:** the condition *social ambiguity - cg* measures ambiguity attitudes and social ambiguity. The *strategic uncertainty - cg* condition,

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<sup>8</sup>The image is presented in English for illustration purposes. However, the experiment was conducted in French.

measures ambiguity attitudes, social ambiguity, and strategic uncertainty.<sup>9</sup> Hence, with the comparison between these two conditions, we are able to capture the effect of strategic uncertainty.

2. **Comparison between *nature ambiguity* and *social ambiguity - cg*:** the *nature ambiguity* condition captures only ambiguity attitudes and, the *social ambiguity - cg* condition captures both ambiguity attitudes and social ambiguity. Consequently, the comparison of these two conditions, allows us to capture the effect of social ambiguity under the context of the coordination game.
3. **Comparison between *nature ambiguity* and *social ambiguity - tg*:** *nature ambiguity* condition measures ambiguity attitudes and, *social ambiguity - tg* measures both ambiguity attitudes and social ambiguity. Hence, through the comparison of these conditions, we are able to capture the effect of social ambiguity in the context of the trust game.
4. **Comparison between *social ambiguity - tg* and *betrayal aversion*:** the condition *social ambiguity - tg* measures ambiguity attitudes and social ambiguity. The *betrayal aversion* condition, captures ambiguity attitudes, social ambiguity, strategic uncertainty, and betrayal aversion. Through the comparison of these two treatments we can capture the combined effect of strategic uncertainty and betrayal aversion. In addition, we are able to disentangle the effect of strategic uncertainty and betrayal aversion by controlling for the isolated effect of strategic uncertainty obtained from

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<sup>9</sup>Following Li et al. (2020), social preferences collapse in the second stage of the conditions. Therefore, social preferences are not considered in these comparisons.

comparison 1.<sup>10</sup> Consequently, comparing *social ambiguity - tg* and *betrayal aversion*, allows to measure the effect of betrayal aversion.

5. **Comparison between *social ambiguity - cg* and *social ambiguity - tg*:** these two conditions have the same source of uncertainty, but differ in two aspects. First, in the *social ambiguity - cg* treatment, Player 1 does not have the possibility to make her payoffs independent from the preferences of Player 2. Contrary, the *social ambiguity - tg* offers this possibility. We call such difference *dependence payoff attitudes*. Second, in the *social ambiguity - cg*, Player 1 has multiple options of payoffs (8, 10, and 15) associated to each preference (*i.e.* Amazon, Google Play and Apple Store) of Player 2. Opposite, the *social ambiguity - tg* treatment does not offer such variety of payoff to Player 1 associated to each preference of Player 2. We call this second difference *variety of payoff attitudes*.

Based on the previous comparisons, we aim to test the following predictions.<sup>11</sup>

**Hypothesis 1:** social ambiguity is captured by pessimism.

**Hypothesis 2:** strategic uncertainty is captured by likelihood insensitivity.

**Hypothesis 3:** betrayal aversion is captured by the utility function.

## 3.6 Results

All statistical tests are two-sided  $z$ -test computed from median regressions, unless otherwise stated. Inline with the simulation results (see Appendix 3.D), we perform our multi-stage method by assuming sequentially power utility function (Eq. 3.16) in the first stage and the weighting function of GE87 (Eq. 3.18) in

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<sup>10</sup>Comparison 1 refers to the difference found between the treatments *social ambiguity - cg* and *strategic uncertainty - cg*.

<sup>11</sup>This design and behavioral conjectures have been pre-register at AsPredicted (#71020).

the second stage. First, we estimate the utility and willingness to bet on the events. Second, we estimate beliefs, likelihood insensitivity, and pessimism. The details of individual estimates are provided in Appendix 3.B.

### 3.6.1 First stage: utility and event weights

In the first stage, we estimate at the individual level, the utility and willingness to bet on the events.

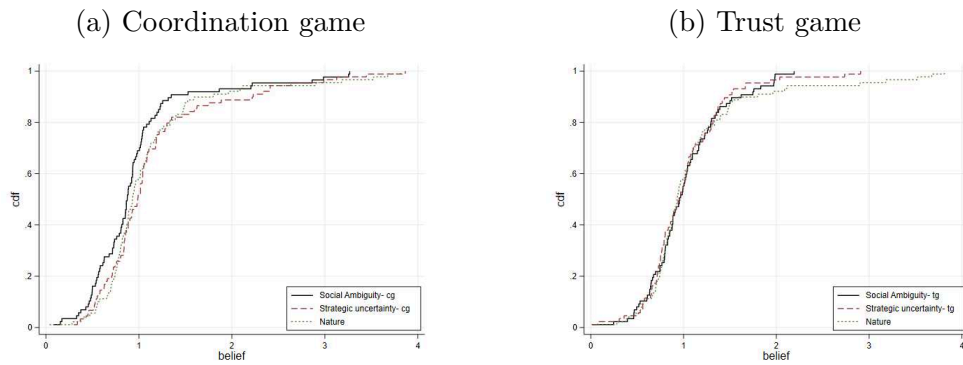
**Utility curvature:** Figure 3.6.1 displays the cumulative distributions of the utility curvature and Table 3.6.1 provides the summary of the estimated values. The median utility curvatures are 0.930, 0.876, 0.988, 0.968 and 0.968 for *nature ambiguity*, *social ambiguity - cg*, *strategic uncertainty - cg*, *social ambiguity - tg*, and *betrayal aversion*, respectively. These values are less than 1, the utility functions are concave in all treatments. Also, the utility curvature in the *social ambiguity -cg* is significantly different from linear ( $p - values < 0.0001$ ). Contrary, for the other treatments, we cannot reject null hypothesis of linear utility (all  $p - values > 0.0733$ ).

Table 3.6.1: Utility function

	Nature	Social ambiguity- cg	Strategic uncertainty	Social ambiguity- tg	Betrayal aversion
Median ( $\alpha$ )	0.930	0.876	0.988	0.968	0.968
IQR	[0.771, 1.196]	[0.625, 1.042]	[0.760, 1.194]	[0.790,1.259]	[0.750 ,1.248]

IQR: interquartile range

Figure 3.6.1: Cumulative distribution of utility curvature



**Events weights:** Figure 3.6.2 provides the cumulative distribution of the event weights and Table 3.6.2 provides the summary of the estimated values. SEU is true if we cannot reject both that (i) the weights of three mutually exclusive events sum 1 and, (ii) the weight of the composite event is equal to the sum of the weights of the two single events involved in the composition (Eq. 3.9). Condition (i) cannot be rejected for *social ambiguity -cg* ( $p - value = 0.7642$ ) and it is rejected in all the other treatments (all  $p - values < 0.0002$ ). Condition (ii) is systematically rejected in all the treatments ( $p - values < 0.0045$ ). Also, a joint test of conditions (i) and (ii) leads to a strong rejection in all treatment (all  $p - values < 0.0001$ ). Then, subjects violate SEU.

Figure 3.6.2: Cumulative distribution of event weights

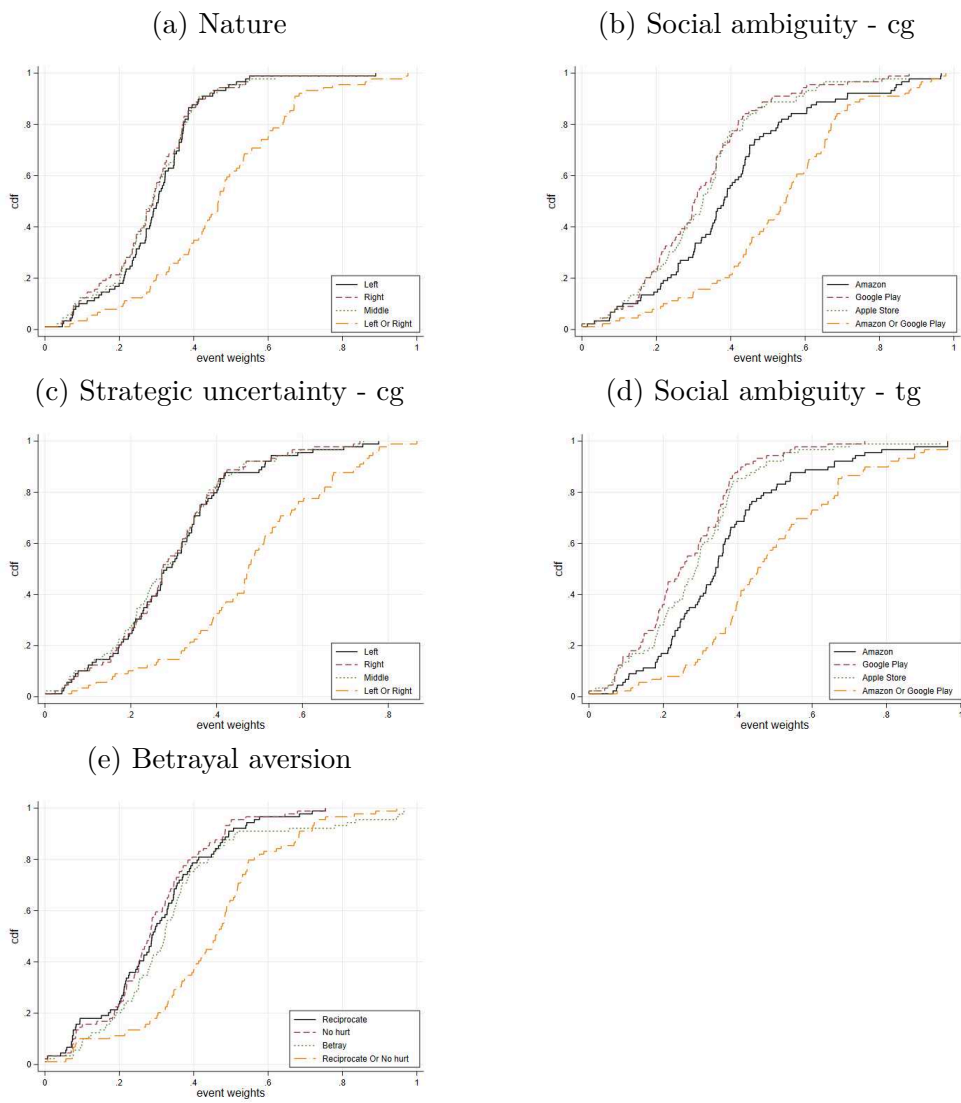


Table 3.6.2: Median of event weights or willingness to bet

	Nature	Social ambiguity- cg	Strategic uncertainty- cg	Social ambiguity- tg	Betrayal aversion
$W(P(L))$	0.305 [0.235 , 0.369]	0.382 [0.258, 0.478]	0.284 [0.203, 0.364]	0.341 [0.231, 0.432]	0.288 [0.204, 0.383]
$W(P(R))$	0.292 [0.212, 0.292]	0.303 [0.206, 0.399]	0.274 [0.202, 0.361]	0.247 [0.158, 0.354]	0.282 [0.211, 0.361]
$W(P(M))$	0.291 [0.212 , 0.364]	0.325 [0.219 , 0.392]	0.273 [0.187 , 0.369]	0.289 [0.185 , 0.370]	0.323 [0.235 , 0.390]
$W(P(L \cup R))$	0.467 [0.337 , 0.600]	0.549 [0.421 , 0.660]	0.474 [0.363 , 0.586]	0.454 [0.367 , 0.625]	0.459 [0.335 , 0.540]

Interquartile ranges are in [.]

$L$ ,  $R$  and  $M$  mean Amazon, Google Play and Apple Store in social ambiguity- cg and social ambiguity- tg

$L$ ,  $R$  and  $M$  mean Reciprocate, No hurt strategy and Betray in Betrayal aversion

$L$ ,  $R$  and  $M$  mean Left, Right and Middle in nature and strategic uncertainty- cg

### 3.6.2 Second stage: beliefs and weighting function

In the second stage, we used the weights of single and composite events from the first stage (see Figure 3.6.2) to estimate the beliefs ( $P(\cdot)$ ), likelihood sensitivity ( $\gamma$ ), and the pessimism ( $\eta$ ) at the individual level.

#### Beliefs

Figure 3.6.3 displays the cumulative distributions of beliefs and Figure 3.6.4 plots the mean of the estimated values.

The null hypothesis of equally likely events cannot be rejected for the *nature* ( $p - value = 0.6656$ ) and *strategic uncertainty - cg* treatments ( $p - value = 0.2974$ ). A priori, symmetry of events is expected for the treatment *nature*. Similarly, symmetry of events for the *strategic uncertainty - cg* treatment can be expected, since the coordination game does not have any dominated strategy. These results provide a first successful validity test of our method.

On the other hand, symmetry of events is rejected for the *social ambiguity - cg* ( $p - value = 0.0061$ ) and *social ambiguity - tg* ( $p - value = 0.0001$ ). In these two conditions, the cumulative distribution function of the beliefs of Player 1



about Player 2 choosing an Amazon voucher first order stochastically dominates the Player 1's beliefs about Player 2 choosing a Google Play and an Apple Store voucher. In the *social ambiguity - cg* treatment, Player 1 thinks that Player 2 chooses to spend money in Amazon, Google Play and Apple Store vouchers with probability 40.6%, 28.1% and 31.3%, respectively. In the treatment *social ambiguity - tg*, Player 1 believes that Player 2 chooses to spend money in Amazon, Google Play and Apple Store vouchers with probability 43.4%, 25.7% and 30.9%, respectively. Joint test leads to the conclusion that the distribution of beliefs are the same in these two social ambiguity treatments ( $p - value = 0.7106$ ). This result provides a second successful validity test of our method. In fact, these two social ambiguity treatments involve the same events. Therefore, the beliefs in these two different ambiguity situations should remain the same.

Symmetry of events is also rejected for *betrayal aversion* (p-value = 0.0051). The cumulative distribution function of the beliefs about the fact that the Trustee will follow the "betray" strategy first order stochastically dominates the strategies of "no hurt" and "reciprocate". We find that Player 1 (Trustor) thinks that Player 2 (Trustee) reciprocates, adopts a no hurt strategy, and betrays with probability 29.3%, 29.7% and 41.0%, respectively.

Figure 3.6.3: Cumulative distribution of subjective probability (beliefs)

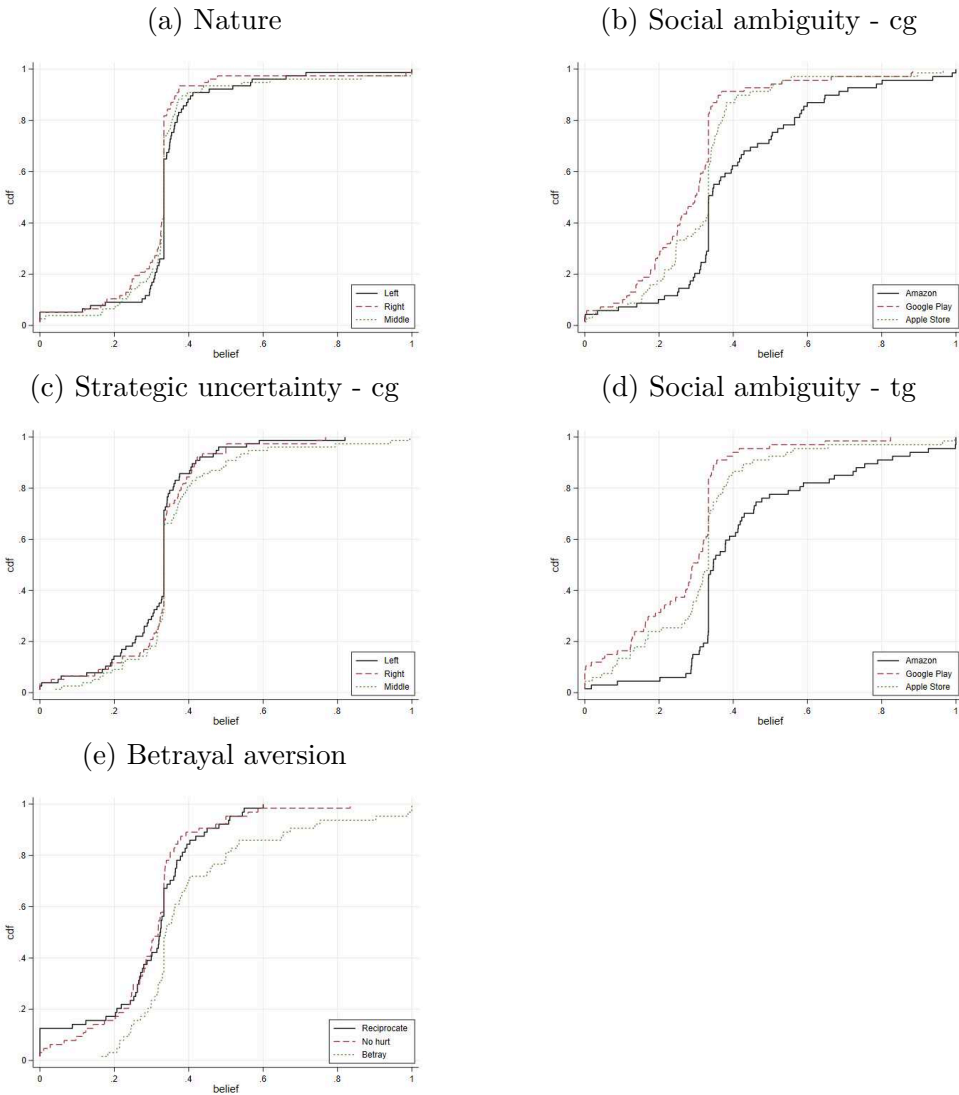
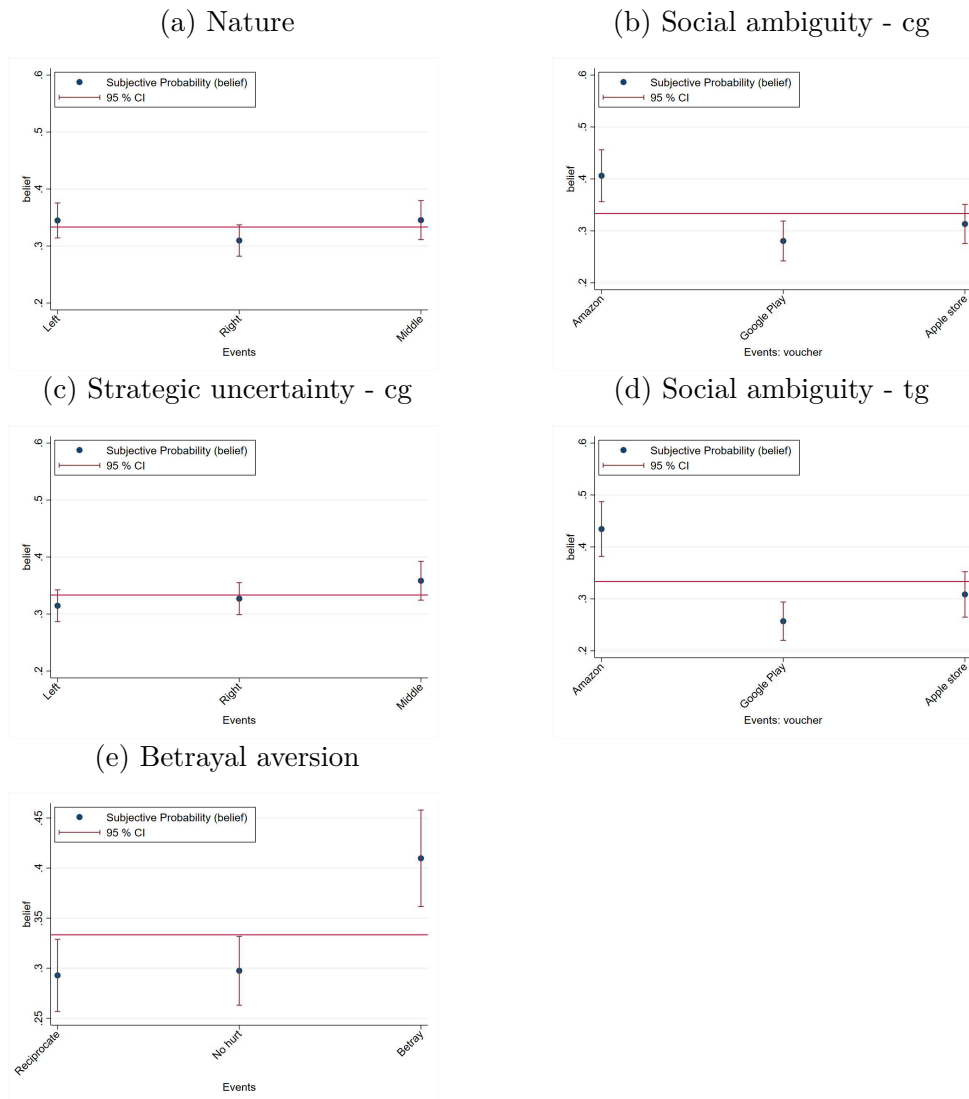


Figure 3.6.4: Mean of subjective probability (beliefs)



### Weighting function

Figures 3.6.5 and 3.6.6 provide the cumulative distributions of pessimism ( $\eta$ ) and likelihood insensitivity ( $\gamma$ ).<sup>12</sup> Figure 3.6.7 displays the plots of the weighting functions based on the median estimates of  $\eta$  and  $\gamma$ . Table 3.6.3 summarizes the

<sup>12</sup>The smaller  $\eta$  is, the higher is the level of pessimism. The smaller  $\gamma$  is, the higher is the level of likelihood insensitivity.

results of the weighting function: pessimism ( $\eta$ ) and likelihood insensitivity ( $\gamma$ ). The usual pattern of over-weighting of small likelihoods and under-weighting intermediate and high likelihoods is reproduced. The cross-over points are 0.210, 0.345, 0.193, 0.266, and 0.264 in the treatments *nature*, *social ambiguity - cg*, *strategic uncertainty - cg*, *social ambiguity - tg*, and *betrayal aversion*, respectively.

Table 3.6.3: Median weighting function by treatment

	Nature	Social ambiguity- cg	Strategic uncertainty- cg	Social ambiguity- tg	Betrayal aversion
Median ( $\eta$ )	0.615	0.736	0.570	0.611	0.613
IQR	[0.450, 0.973]	[0.472, 1.071]	[0.408, 0.802]	[0.438, 1.018]	[0.508, 0.888]
Median ( $\gamma$ )	0.633	0.534	0.607	0.513	0.524
IQR	[0.425, 0.837]	[0.361, 0.797]	[0.327, 0.922]	[0.272, 0.861]	[0.291, 0.931]

Pessimism and insensitivity correspond to small values of  $\eta$  and  $\gamma$  respectively

IQR: Interquartile ranges are presented in [.]

Figure 3.6.5: Cumulative distribution of pessimism ( $\eta$ )

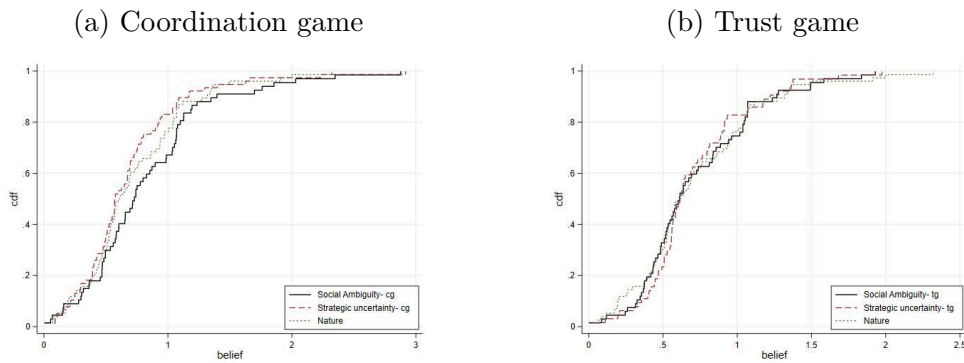


Figure 3.6.6: Cumulative distribution of likelihood insensitivity ( $\gamma$ )

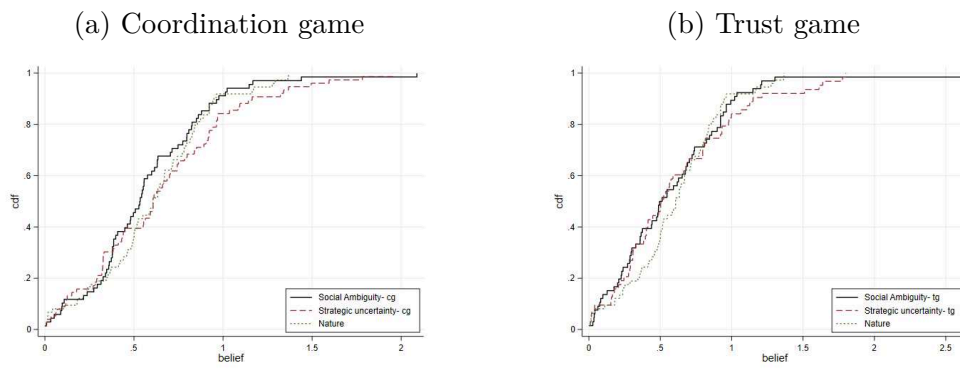
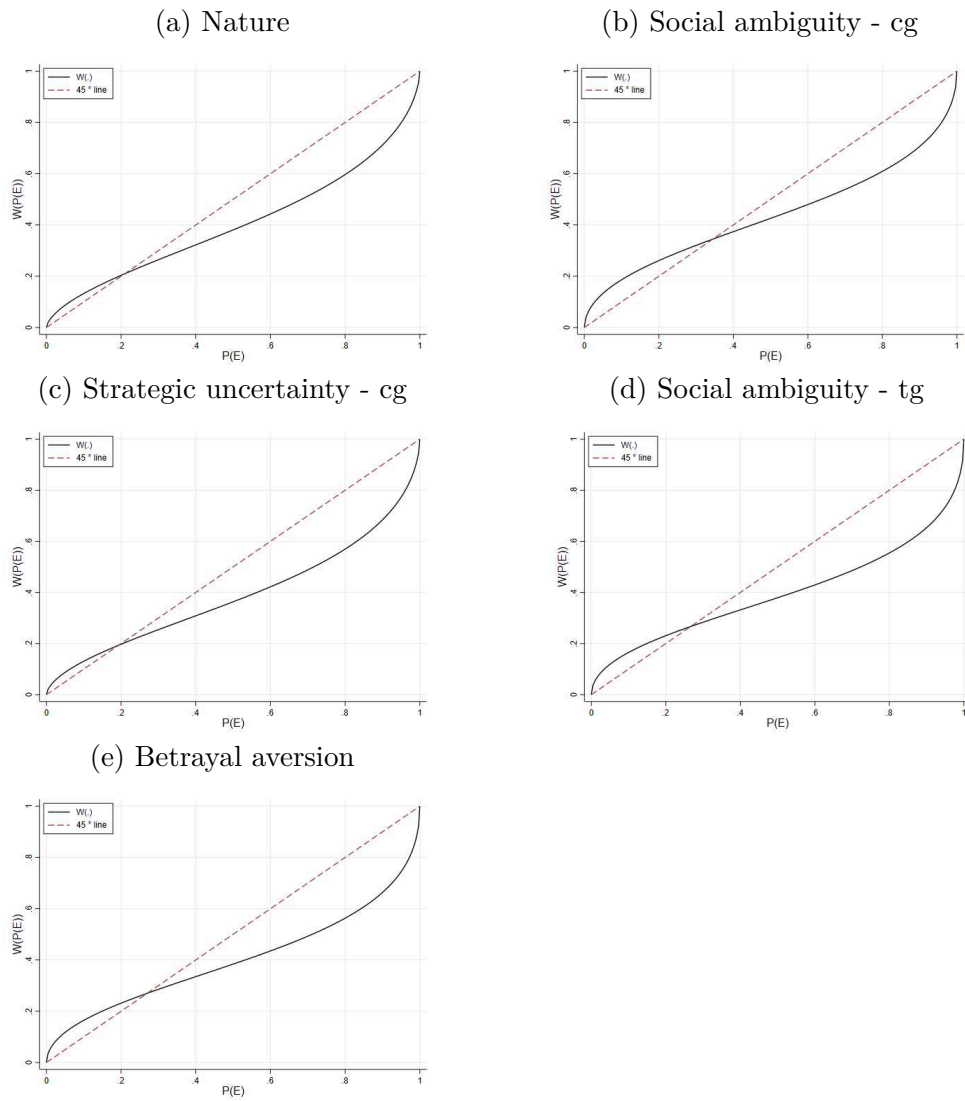


Figure 3.6.7: weighting function based median of individual estimates



### 3.6.2.1 Social ambiguity, strategic uncertainty, and betrayal aversion

Now we turn into the main purpose of the application of this chapter: the identification of social ambiguity, strategic uncertainty and betrayal aversion through pessimism, likelihood insensitivity and utility curvature. Table 3.6.4

presents the results of the estimation of the utility curvature ( $\alpha$ ), pessimism ( $\eta$ ) and likelihood insensitivity ( $\gamma$ ).

Table 3.6.4: Ambiguity attitudes by treatments

	Nature	Social ambiguity - cg	Strategic uncertainty- cg	Social ambiguity - tg	Betrayal aversion
Utility function					
curvature ( $\alpha$ )	0.930 [0.771, 1.196]	0.876 [0.625, 1.042]	0.988 [0.760, 1.194]	0.968 [0.790, 1.259]	0.968 [0.750, 1.248]
Weighting function					
Pessimism ( $\eta$ )	0.615 [0.450, 0.973]	0.736 [0.472, 1.071]	0.570 [0.408, 0.802]	0.611 [0.438, 1.018]	0.613 [0.508, 0.888]
Insensitivity ( $\gamma$ )	0.633 [0.425, 0.837]	0.534 [0.361, 0.797]	0.607 [0.327, 0.922]	0.513 [0.272, 0.861]	0.524 [0.291, 0.931]

Pessimism and insensitivity correspond to small values of  $\eta$  and  $\gamma$  respectively

Interquartile ranges are presented in [.]

### 1. Social ambiguity

The difference between treatments 0 (*nature*) and 1 (*social ambiguity - cg*), as well as the difference between the treatments 0 (*nature*) and 3 (*social ambiguity - tg*) corresponds to what [Li et al. \(2020\)](#) called social ambiguity.

**Utility curvature ( $\alpha$ ):** the estimates of the CRRA parameter for treatments 0, 1 and 3 are 0.93, 0.876, and 0.968, respectively. The difference in the utility parameters between treatments 0 and 1 is not significant ( $p - value=0.332$ , two sided sign test). This is also the case for the difference between the treatments 0 and 3 ( $p - value= 1$ , two sided sign test).

**Pessimism ( $\eta$ ):** the estimates of pessimism for treatments 0, 1, and 3 are 0.615, 0.736, and 0.611, respectively. Pessimism is lower in treatment 1 in treatment 0 ( $p - value= 0.0030$ ). Pessimism is the same in treatment 3 and in treatment 0 ( $p - value= 0.9245$ ).

**Likelihood insensitivity ( $\gamma$ ):** the estimates of the likelihood insensitivity for treatments 0, 1 and 3 are 0.633, 0.534, and 0.513, respectively. Likelihood insensitivity is lower in treatment 0 than 1 ( $p$ -value= 0.0001). Also, the likelihood insensitivity is lower in treatment 0 than in 3 ( $p$ -value = 0.0037).

Consequently, we conclude that social ambiguity is captured by an increase in likelihood insensitivity. Also, social ambiguity can operate through a decrease in pessimism (treatments 0 vs 1). This partially confirms our Hypothesis 1: social ambiguity is capture by pessimism.

## 2. Strategic uncertainty

The difference between treatments 1 (*social ambiguity - cg*) and 2 (*strategic uncertainty - cg*) corresponds to strategic uncertainty.

**Utility curvature ( $\alpha$ ):** the estimate of CRRA parameter for treatments 1 and 2 are 0.876 and 0.988, respectively. The difference in the utility parameters between treatment 1 and 2 is not significant ( $p$ -value= 0.5900, two sided sign test).

**Pessimism ( $\eta$ ):** the estimate of pessimism for treatments 1 and 2 are 0.736 and 0.570, respectively. Pessimism is lower in treatment 1 than in treatment 2 ( $p$ -value < 0.0001).

**Likelihood insensitivity ( $\gamma$ ):** the estimates of likelihood insensitivity for treatments 1 and 2 are 0.534 and 0.607, respectively. The likelihood insensitivity in treatment 1 is larger than in treatment 2 ( $p$ -value= 0.0037).

Consequently, we conclude that strategic uncertainty is captured by a decrease in likelihood insensitivity and by an increase in pessimism. This



partially confirms our Hypothesis 2: strategic uncertainty is captured by likelihood insensitivity.

### 3. Betrayal aversion

The difference between treatments 3 (*social ambiguity - tg*) and 4 (*betrayal aversion*) corresponds to the mixture of strategic uncertainty and what BZ called betrayal aversion.

**Utility curvature ( $\alpha$ ):** the estimate of CRRA parameter for treatments 3 and 4 are both 0.968. The difference in the utility parameters between treatment 3 and 4 is not significant ( $p - value = 0.5203$ , two sided sign test).

**Pessimism ( $\eta$ ):** the estimate of pessimism for treatments 3 and 4 are 0.611 and 0.613, respectively. The difference in pessimism between these treatments is not significant ( $p - value = 0.9343$ ).

**Likelihood insensitivity ( $\gamma$ ):** the estimate of likelihood insensitivity for treatments 3 and 4 are 0.513 and 0.524, respectively. The difference in the likelihood insensitivity between treatments 3 and 4 is not significant ( $p - value = 0.8122$ ).

In the previously presented results from strategic uncertainty (treatment 1 versus 2), we show that strategic uncertainty decreases likelihood insensitivity. Additionally, the analysis of betrayal aversion shows a non-significant difference of the likelihood insensitivity between treatments 3 and 4. Nevertheless, given that the comparison between treatments 3 and 4 contains the effect of strategic uncertainty, we should find different likelihood insensitivities. This opposite result is due to the fact that the effect of strategic uncertainty offsets the betrayal aversion effect, leading to a lack of difference in likelihood insensitivity between treatments 3 and 4. In

other words, betrayal aversion and strategic uncertainty are captured by likelihood insensitivity in two opposites directions: strategic uncertainty is captured by a decrease in likelihood insensitivity, while betrayal aversion is captured by an increase in likelihood insensitivity. Consequently, we conclude that betrayal aversion is captured by an increase in likelihood insensitivity. This rejects our Hypothesis 3: betrayal aversion is captured by the utility function.

### 3.6.3 Dependence payoff aversion and variety of payoff seeking

Besides the previously presented results, we find that subjects exhibit two additional behaviors which are not related to attitudes toward the source of uncertainty. In this section, we present these findings. Treatments 1 (*social ambiguity - cg*) and 3 (*social ambiguity - tg*) have the same source of uncertainty (*i.e.*, preferences of Player 2, which constitutes social ambiguity). Hence, any differences in the utilities and the weighting functions between these two conditions is not due to attitudes toward the underlying source of uncertainty. Instead, the difference between treatments 1 (*social ambiguity - cg*) and 3 (*social ambiguity - tg*) corresponds to the mixture of dependence payoff aversion and the variety of payoff attitudes.

**Utility curvature ( $\alpha$ ):** the estimates of CRRA parameter for treatments 1 and 3 are 0.876 and 0.968, respectively. The difference in the utility parameters between treatments 1 and 3 is significant ( $p - value = 0.0165$ , two sided sign test). Hence, utility is more concave in treatment 1 than in treatment 3.

**Pessimism ( $\eta$ ):** the estimate of pessimism for treatments 1 and 3 are 0.736 and 0.611. The difference between these treatments is significant ( $p - value = 0.0001$ ). Therefore, pessimism is lower in treatment 1 than in treatment 3.

**Likelihood insensitivity** ( $\gamma$ ): the estimates of the likelihood insensitivity for treatments 1 and 3 are 0.534 and 0.513. The difference in the insensitivity between treatments 3 and 4 is not significant ( $p - value = 0.5884$ ).

We conclude that the greater concavity of the utility function in treatment 1 compared to treatment 3, represents a payoff dependence aversion. Also, the higher pessimism in treatment 1 compared to treatment 3 constitutes variety of payoff seeking.

## 3.7 Discussion

### 3.7.1 Experimental discussion

Our method allows to replicate some well known results. First, we confirm that the weighting function, in the case of uncertainty, is not an identity function. Consequently, subjects distort beliefs and then violate the traditional SEU theory (e.g. Abdellaoui et al., 2005, 2011a, 2016, 2021a; Attema et al., 2018; Li et al., 2019, 2020; Tversky and Fox, 1995; Camerer and Ho, 1994; Bruttel et al., 2022; Bleichrodt et al., 2018; Fehr-Duda and Epper, 2012; l'Haridon and Vieider, 2019). Typically, subjects overweight small subjective probability and underweight intermediate and high subjective probability. Also, we find that only the weighting function differs across different sources of ambiguity, but not the utility function. This provides support for ambiguity theories based on the weighting function (e.g. Schmeidler, 1989), but not for ambiguity theories based on the utility function (e.g. Klibanoff et al., 2005). These results are consistent with previous studies (e.g. Abdellaoui et al., 2016; Attema et al., 2018; Abdellaoui et al., 2022; Bruttel et al., 2022).

We make two internal validity tests for our method. First, the treatments *social ambiguity - cg* and *social ambiguity - tg* involve the same events. Therefore,

the distributions of beliefs in these two conditions should be the same. Our method successfully produces this results. Second, the events in the *nature* treatment are a priori symmetric; as well as the beliefs in the *strategic uncertainty* - *cg* treatment, which does not have any dominated strategy. Our method also successfully satisfies the symmetry test for both *nature* and *strategic uncertainty* - *cg* treatments. Replicating well known results and successfully passing validity tests provide support for our method (Abdellaoui et al., 2008).

We apply our method to measure beliefs towards different discrete sources of uncertainty. One of the remarkable findings in this regard concerns the beliefs about trustworthiness. When subjects trust, they put themselves in a vulnerable situation based upon the belief the other will respond in a positive way (Özer and Zheng, 2017). As Arrow (1972) wrote "virtually every commercial transaction has within itself an element of trust". Because decisions of trust play a major role in social and economic interactions, it becomes important to be able to measure beliefs about trustworthiness, considering that the trustor distorts her own formation of beliefs (weighting functions). We find that the cumulative distribution function of the beliefs about trustworthiness is first order stochastically dominated by being betrayed. Most subjects believe that trust is not reciprocated with a mean of subjective beliefs of people being trustworthy equal to 29%.

Regarding our empirical aim of identifying the role of social ambiguity, strategic uncertainty and betrayal attitudes, our method provides the following contributions.

First, we find that social ambiguity operates mainly through an increase in the likelihood insensitivity. Therefore, subjects prefer social ambiguity over nature ambiguity when there is a small probability of winning, and prefer nature ambiguity over social ambiguity when there is a high probability of winning. The

increase in likelihood insensitivity suggests that subjects find social ambiguity more cognitively demanding compared to nature ambiguity (e.g. Wakker, 2010; Choi et al., 2022). Social ambiguity can also operate through a decrease in pessimism compared to nature ambiguity. The fact that subjects are less pessimistic towards ambiguity caused by other humans than ambiguity coming from nature, was pointed out by other studies (e.g. Li et al., 2020; Bolton et al., 2016; Chark and Chew, 2015). The decrease in pessimism due to social ambiguity could be explained by the competence hypothesis (Li et al., 2020; Heath and Tversky, 1991; Fox and Weber, 2002). Fox and Tversky (1995) propose under the competence hypothesis that, subjects' confidence is undermined when they contrast their limited knowledge about an event with their superior knowledge about another event. They argue that this contrast between states of knowledge is the predominant source of ambiguity aversion. Subjects' perception of their own knowledge about other humans' choices could be higher than their knowledge perception about choices done by nature.

Second, strategic uncertainty also operates, as social ambiguity, through likelihood insensitivity and pessimism, but in opposite directions. Contrary to social ambiguity, strategic uncertainty leads to a decrease in likelihood insensitivity and an increase in pessimism. The difference of likelihood insensitivity supports that subjects prefer social ambiguity over strategic uncertainty for small probabilities of winning and, prefer strategic uncertainty over social ambiguity for high probabilities of winning. These two opposite effects offset. Accordingly, we did not find a difference of likelihood insensitivity between the treatments *nature* and *strategic uncertainty - cg*. This result suggests that subjects tend to exhibit a similar level of likelihood insensitivity towards sources of uncertainty in which events are symmetric (e.g. *strategic uncertainty - cg* and *nature* treatments). In contrast, subjects tend to exhibit a high likelihood insensitivity when events are

asymmetric, like in our two conditions of social ambiguity (*social ambiguity - cg* and *social ambiguity - tg*). This corroborates that beliefs formation process is cognitively demanding.

Third, betrayal aversion also operates through the likelihood insensitivity. Betrayal aversion increases likelihood insensitivity. We find that subjects prefer betrayal and social ambiguities over nature ambiguity for small probabilities of winning and prefer nature ambiguity over betrayal and social ambiguities for a high probabilities of winning. [Li et al. \(2020\)](#) do not make a distinction between betrayal aversion and strategic uncertainty. The authors find that the overall effect of betrayal aversion and strategic uncertainty increases likelihood insensitivity, suggesting that the effect of betrayal aversion is larger than the effect of strategic uncertainty. However, according to our Proposition 1, we should be cautious with the possibility of having a greater effect of betrayal aversion. Indeed, the fact that events are symmetric under nature ambiguity while they are highly asymmetric in the *betrayal aversion* treatment, can mislead to a difference in likelihood insensitivity measured with the method of [Baillon et al. \(2018b\)](#).

Finally, we identify two main behaviors which are not related to attitudes towards sources of uncertainty. First, the behaviour we call *dependence payoff aversion*, which represents the fact that subjects dislike situations in which their possible payoffs depend on the preferences of others. This behaviour operates by increasing the concavity of the utility function. Second, the behavior we call *variety of payoffs seeking*, which proposes that subjects prefer to have more options of possible payoffs, when these payoffs depend on others. The *variety of payoffs seeking* is captured by a decrease in pessimism for situations that contain more possible payoffs (e.g. social ambiguity - cg) compared to situation containing a lower amount of possible payoffs (e.g. social ambiguity -tg).

### 3.7.2 Methodological discussion

Our method allows to completely measure the utility function, it is more robust to misspecification issues, it is easy, and error-robust. Below we discuss these features.

**Complete measurement of utility function.** Throughout the combination of our method with experimental data, we show the importance of measuring the utility function, which contrasts with previous methods, in which the utility function is not measured (e.g. [Baillon et al., 2018b](#); [Gutierrez and Kemel, 2021](#); [Abdellaoui et al., 2021a](#)). We show that the utility function can capture additional behaviors (e.g. *payoff dependence aversion*), unrelated to the source of uncertainty. This implies that not measuring the utility function makes more difficult to have a clean empirical measurement of ambiguity attitudes from the existing methods that do not allow the estimation of utility function (e.g. [Baillon et al., 2018b](#); [Gutierrez and Kemel, 2021](#); [Abdellaoui et al., 2021a](#)).

**More robust to misspecification.** We propose a multistage method instead of one-stage method ([Gutierrez and Kemel, 2021](#)). In the first stage, we only specify utility and estimate events weights non-parametrically. Based on event weights from the first stage, the method allows to estimate the parameters of any weighting function. Our method thus allows for more flexibility in the parametric choices of weighting function in comparison to existing methods (e.g. [Baillon et al., 2018b, 2021, 2018a](#)) that rely on the neo-additive weighting function of ([Chateauneuf et al., 2007](#)).

**Easy and error-robust.** Our method is based on simple choices that involve the lowest possible number of outcomes (i.e., three). As such, this method is not cognitively demanding - easy - for subjects, compared to methods that are based on *exchangeable events* or *matching probabilities* (e.g. [Baillon et al., 2018b](#); [Gutierrez and Kemel, 2021](#); [Abdellaoui et al., 2021a](#)), in which each choice

involves four outcomes (Kpegli et al., 2022; Abdellaoui et al., 2008). Finally, contrary to previous methods (e.g. Baillon et al., 2018b,a), our method account for response errors that are pervasive in experimental data (Kpegli et al., 2022).

### 3.8 Conclusion

We proposed a two-stage method that clearly measures beliefs and ambiguity attitudes towards discrete sources of uncertainty. Subjects make decisions under these types of uncertain situations in a daily life basis. The method successfully passes validity tests and provides plausible results for trust and coordination games, showing the reliability of the results derived from it. In this chapter, we implement our method to discrete sources of uncertainty; nevertheless, it also applies to continuous-valued sources of uncertainty. Therefore, this method allows to measure beliefs and ambiguity attitudes related to several fields in Economics.



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### 3.A Applicability of the method for continuous-valued sources of uncertainty

This appendix aims to show the validity of our method for continuous-valued sources of uncertainty. Consider the case in which an experimenter aims to measure the distribution of beliefs that a subject holds about a source of uncertainty  $S$  that takes its values in an interval  $\mathcal{I} = [s_0, s_3] \subset \mathcal{R}$ . The experimenter can proceed through the following three stages.

**First stage: utility and event weights.** In this step, the experimenter needs to arbitrarily split the universal event  $\mathcal{I}$  in three exclusive and exhaustive events  $E_1 = [s_0, s_1]$ ,  $E_2 = (s_1, s_2]$  and  $E_3 = (s_2, s_3]$  with  $s_0 < s_1 < s_2 < s_3$ . Hence, we have the composite event  $E_{12} = [s_0, s_2]$ . Applying the stage 1 of our method, presented in section 4.3 allows us to estimate the utility function and the four event weights:  $\hat{\delta}_E$  for  $E = E_1, E_2, E_3, E_{12}$ .

**Second stage: weighting and beliefs of single events.** Applying the second stage presented in section 4.3 allows us to break down the estimated events weights  $\hat{\delta}_E$  into the weighting function (*i.e.*  $\hat{\delta}, \hat{\gamma}$ ) and the beliefs of the single events  $P(\widehat{[s_0, s_1]})$ ,  $P(\widehat{[s_1, s_2]})$ , and  $P(\widehat{[s_2, s_3]})$ .

**Third stage: density and cumulative distribution over the range  $[0, 1]$ .** This stage complements the two stages presented in section 4.3 because  $S$  is a continuous-valued sources of uncertainty. The interval  $\mathcal{I}$  can be re-scaled to be in the range  $\tilde{\mathcal{I}} = [0, 1]$ :  $\tilde{s} = \frac{s-s_0}{s_3-s_0} \in [0, 1]$  for  $s \in \mathcal{I} = [s_0, s_3]$ .

At this stage, a two-parameter specification of the distribution is needed. A common and flexible distribution is the beta distribution  $\mathcal{B}(a, b)$  with param-

eters  $a, b$ . Denote by  $F_{a,b}(\cdot)$  the cumulative distribution function of the beta distribution. We then have the following three equations

$$F_{a,b}(\tilde{s}_i) - F_{a,b}(\tilde{s}_{i-1}) = P(\widehat{[\tilde{s}_{i-1}, \tilde{s}_i]}) , \quad i = 1, 2, 3 \quad (3.13)$$

with  $F_{a,b}(\tilde{s}_0) = 0$  and  $F_{a,b}(\tilde{s}_3) = 1$ . These three equations in (3.13) are summarized in the following two equations

$$F_{a,b}(\tilde{s}_2) = P(\widehat{[\tilde{s}_0, \tilde{s}_1]}) + P(\widehat{[\tilde{s}_1, \tilde{s}_2]}) \quad (3.14)$$

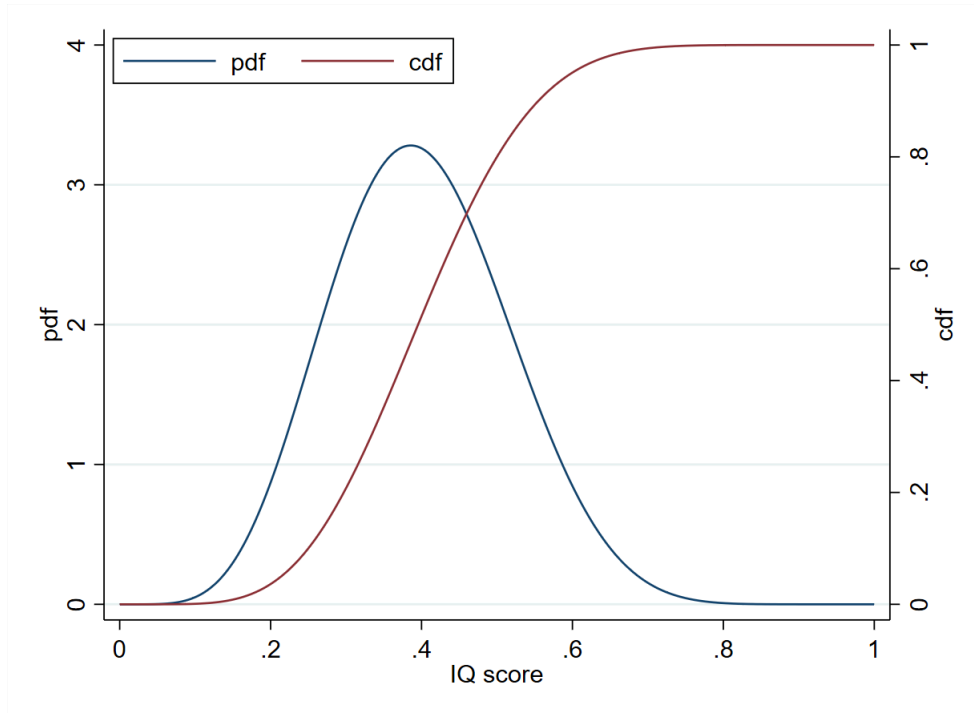
$$1 - F_{a,b}(\tilde{s}_1) = P(\widehat{[\tilde{s}_1, \tilde{s}_2]}) + P(\widehat{[\tilde{s}_2, \tilde{s}_3]}) \quad (3.15)$$

Solving (numerically) the system of the two equations (3.14) and (3.15) provides the estimation of the distribution of beliefs (*i.e.*  $a, b$ ).

For illustration purposes, lets consider that an experimenter aims to elicit the beliefs of a subject  $A$  about the IQ score of a subject  $B$ . The IQ score belongs to  $[0, 1]$ , with high values meaning a high IQ score. After applying stages 1 and 2 with  $E_1 = [0, 0.25]$ ,  $E_2 = [0.25, 0.50]$  and  $E_3 = [0.5, 1]$ , the experimenter finds the following:  $P(\widehat{[0, 0.25]}) = 0.1$ ,  $P(\widehat{[0.25, 0.5]}) = 0.7$  and  $P(\widehat{[0.5, 1]}) = 0.2$ . Then, the equations (3.14) and (3.15) of the third stage corresponds to  $F_{a,b}(\frac{2}{3}) = 0.8$  and  $1 - F_{a,b}(\frac{1}{3}) = 0.9$ . Solving these two equations, provides  $\hat{a} = 6.62$  and  $\hat{b} = 9.95$ . The density and cumulative functions are provided in figure 3.A.1.



Figure 3.A.1: beliefs of subject A about the IQ score of subject B: probability density (pdf) and cumulative density (cdf) functions.



### 3.B Individual estimates

Tables 3.B.1 - 3.B.9 give results of our first stage ( $\alpha$  and  $W(P(\cdot))$ ) and second stage ( $\eta$ ,  $\gamma$  and  $P(\cdot)$ ). Dots in tables mean monotonicity violation and then  $\eta$ ,  $\gamma$  and  $P(\cdot)$  cannot be estimated.

Table 3.B.1: Individual estimate: nature

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
1	0.549	0.494	0.447	0.491	0.643	1.319	0.525	0.361	0.283	0.356
2	0.754	0.386	0.365	0.365	0.672	1.086	0.874	0.348	0.326	0.326
3	1.399	0.235	0.235	0.235	0.337	0.395	0.365	0.333	0.333	0.333
4	0.821	0.385	0.385	0.385	0.601	0.973	0.633	0.333	0.333	0.333
5	3.180	0.113	0.113	0.206	0.113	.	.	.	.	.
6	0.554	0.369	0.369	0.415	0.553	0.937	0.584	0.309	0.309	0.382

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Table 3.B.2 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
7	2.088	0.153	0.134	0.141	0.153	0.172	0.006	1	0	0
8	0.891	0.229	0.229	0.229	0.483	0.527	0.828	0.333	0.333	0.333
9	0.768	0.243	0.317	0.288	0.358	0.476	0.253	0.176	0.478	0.346
10	1.589	0.174	0.151	0.209	0.197	0.254	0.216	0.294	0.164	0.542
11	0.729	0.305	0.327	0.259	0.327	.	.	.	.	.
12	0.580	0.540	0.540	0.540	0.774	2.002	0.772	0.333	0.333	0.333
13	1.392	0.299	0.270	0.309	0.299	0.437	0.013	0.136	0	0.864
14	1.471	0.200	0.220	0.184	0.282	0.297	0.237	0.322	0.441	0.237
15	0.912	0.324	0.308	0.308	0.515	0.687	0.592	0.352	0.324	0.324
16	0.867	0.368	0.368	0.368	0.650	1.038	0.837	0.333	0.333	0.333
17	1.524	0.371	0.467	0.393	0.467	0.753	0.010	0	1	0
18	1.129	0.348	0.295	0.361	0.388	0.599	0.237	0.380	0.180	0.440
19	3.523	0.145	0.098	0.020	0.230	.	.	.	.	.
20	0.713	0.410	0.431	0.463	0.683	1.364	0.825	0.306	0.329	0.364
21	3.675	0	0	0.032	0.001	0.006	3.379	0.114	0.267	0.618
22	0.744	0.306	0.374	0.374	0.580	0.907	0.743	0.275	0.363	0.363
23	1.064	0.256	0.296	0.296	0.533	0.692	0.815	0.298	0.351	0.351
24	1.478	0.050	0.067	0.058	0.067	0.067	0.018	0	0.984	0.016
25	0.654	0.291	0.317	0.317	0.613	0.857	0.943	0.314	0.343	0.343
26	1.493	0.323	0.323	0.323	0.458	0.635	0.413	0.333	0.333	0.333
27	1.196	0.284	0.235	0.214	0.289	.	.	.	.	.
28	0.772	0.424	0.406	0.406	0.702	1.268	0.857	0.347	0.327	0.327
29	0.695	0.319	0.273	0.273	0.363	0.463	0.182	0.519	0.241	0.241
30	1.108	0.269	0.246	0.246	0.640	0.762	1.164	0.349	0.325	0.325
31	1.490	0.133	0.113	0.094	0.284	0.203	0.671	0.398	0.333	0.269
32	0.532	0.412	0.412	0.442	0.580	1.046	0.517	0.316	0.316	0.368
33	0.858	0.293	0.293	0.293	0.447	0.578	0.483	0.333	0.333	0.333
34	1.269	0.235	0.217	0.261	0.292	0.382	0.288	0.320	0.247	0.433
35	0.809	0.287	0.297	0.269	0.413	0.509	0.355	0.340	0.373	0.286
36	0.783	0.238	0.238	0.238	0.485	0.542	0.797	0.333	0.333	0.333
37	1.228	0.070	0.070	0.070	0.334	0.194	1.364	0.333	0.333	0.333
38	1.122	0.214	0.201	0.201	0.214	.	.	.	.	.
39	0.667	0.285	0.236	0.236	0.471	0.525	0.635	0.394	0.303	0.303
40	0.934	0.316	0.300	0.300	0.534	0.701	0.673	0.350	0.325	0.325
41	0.537	0.550	0.550	0.550	0.749	1.911	0.644	0.333	0.333	0.333
42	0.775	0.373	0.373	0.377	0.373	.	.	.	.	.
43	0.790	0.076	0.076	0.076	0.076	.	.	.	.	.
44	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333

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Table 3.B.2 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
45	0.832	0.354	0.326	0.326	0.644	0.936	0.890	0.354	0.323	0.323
46	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
47	0.411	0.455	0.546	0.464	0.861	2.320	1.276	0.310	0.374	0.316
48	1.962	0.307	0.142	0.129	0.482	0.371	0.671	0.566	0.231	0.203
49	0.472	0.369	0.369	0.369	0.634	1.005	0.783	0.333	0.333	0.333
50	0.742	0.254	0.207	0.207	0.391	0.409	0.517	0.411	0.294	0.294
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	1.101	0.272	0.248	0.248	0.419	0.488	0.505	0.370	0.315	0.315
53	1.080	0.322	0.322	0.322	0.443	0.615	0.371	0.333	0.333	0.333
54	0.992	0.246	0.044	0.203	0.878	1.353	3.052	0.385	0.248	0.367
55	1.158	0.313	0.313	0.294	0.600	0.791	0.839	0.341	0.341	0.318
56	0.799	0.386	0.394	0.385	0.394	.	.	.	.	.
57	2.902	0.077	0.077	0.077	0.141	0.117	0.489	0.333	0.333	0.333
58	1.334	0.212	0.212	0.212	0.422	0.444	0.719	0.333	0.333	0.333
59	1.334	0.188	0.164	0.164	0.262	0.264	0.343	0.405	0.298	0.298
60	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
61	0.871	0.306	0.292	0.163	0.335	.	.	.	.	.
62	0.281	0.486	0.524	0.620	0.524	1.338	0.016	0	0	1
63	0.699	0.348	0.205	0.394	0.659	1.120	1.294	0.360	0.243	0.396
64	0.843	0.377	0.444	0.350	0.582	0.864	0.425	0.301	0.453	0.246
65	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
66	0.379	0.515	0.414	0.414	0.556	0.941	0.180	0.662	0.169	0.169
67	3.812	0.210	0.146	0.402	0.210	0.423	0.043	0	0	1
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	0.930	0.216	0.258	0.258	0.430	0.512	0.666	0.284	0.358	0.358
70	1.081	0.349	0.349	0.349	0.503	0.735	0.459	0.333	0.333	0.333
71	2.117	0.092	0.092	0.092	0.274	0.195	0.949	0.333	0.333	0.333
72	0.891	0.372	0.372	0.291	0.426	.	.	.	.	.
73	1.204	0.218	0.243	0.243	0.386	0.450	0.550	0.296	0.352	0.352
74	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
75	0.802	0.074	0.074	0.074	0.965	1.492	4.225	0.333	0.333	0.333
76	1.172	0.451	0.176	0.201	0.533	0.536	0.463	0.715	0.121	0.164
77	0.929	0.281	0.281	0.281	0.536	0.672	0.781	0.333	0.333	0.333
78	0.963	0.373	0.333	0.333	0.400	0.577	0.111	0.571	0.215	0.215
79	0.926	0.346	0.286	0.346	0.471	0.686	0.500	0.373	0.255	0.373
80	1.799	0.083	0.083	0.044	0.437	0.188	1.368	0.369	0.369	0.262
81	0.821	0.385	0.385	0.385	0.601	0.973	0.633	0.333	0.333	0.333
82	0.949	0.323	0.266	0.217	0.497	0.523	0.501	0.455	0.325	0.220

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**Table 3.B.2 – continued from previous page**

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
83	0.039	0.889	0.889	0.889	0.976	18.021	1.170	0.333	0.333	0.333
84	0.941	0.291	0.291	0.291	0.430	0.556	0.441	0.333	0.333	0.333
85	0.702	0.396	0.368	0.270	0.481	.	.	.	.	.
86	0.762	0.246	0.246	0.246	0.468	0.535	0.716	0.333	0.333	0.333
87	1.074	0.300	0.300	0.364	0.300	.	.	.	.	.
88	0.952	0.332	0.310	0.310	0.489	0.656	0.496	0.363	0.318	0.318
89	0.967	0.047	0.047	0.047	0.117	0.081	0.710	0.333	0.333	0.333

Table 3.B.3: Individual estimate: social ambiguity- cg

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
1	1.316	0.440	0.168	0.168	0.643	0.604	0.826	0.579	0.210	0.210
2	0.739	0.465	0.379	0.362	0.654	1.035	0.615	0.429	0.298	0.273
3	0.172	0.845	0.807	0.784	0.908	5.999	0.449	0.446	0.308	0.246
4	0.718	0.831	0.350	0.288	0.885	1.761	0.379	0.938	0.042	0.020
5	0.466	0.617	0.594	0.637	0.759	2.349	0.547	0.334	0.296	0.370
6	1.212	0.158	0.509	0.105	0.653	0.470	0.398	0.091	0.879	0.030
7	0.479	0.605	0.605	0.630	0.605	.	.	.	.	.
8	0.857	0.303	0.283	0.283	0.456	0.575	0.497	0.363	0.319	0.319
9	1.084	0.211	0.160	0.250	0.211	0.299	0.033	0.034	0	0.966
10	0.966	0.346	0.332	0.273	0.346	.	.	.	.	.
11	0.563	0.438	0.409	0.452	0.540	0.984	0.361	0.344	0.275	0.381
12	0.680	0.438	0.295	0.392	0.686	1.186	0.977	0.395	0.256	0.349
13	0.976	0.434	0.346	0.360	0.434	.	.	.	.	.
14	0.808	0.391	0.449	0.431	0.501	0.872	0.237	0.215	0.429	0.356
15	0.732	0.333	0.361	0.379	0.498	0.777	0.479	0.284	0.340	0.376
16	0.932	0.605	0.146	0.397	0.747	1.396	1.147	0.520	0.138	0.342
17	0.910	0.631	0.419	0.338	0.631	.	.	.	.	.
18	1.194	0.259	0.208	0.225	0.259	0.318	0.010	1	0	0
19	2.219	0.159	0.139	0.159	0.410	0.363	1.013	0.345	0.309	0.345
20	1.017	0.230	0.164	0.374	0.363	0.584	0.774	0.296	0.196	0.507
21	0.376	0.298	0.298	0.108	0.298	.	.	.	.	.
22	0.613	0.526	0.311	0.436	0.610	1.100	0.528	0.505	0.156	0.339
23	0.541	0.860	0.484	0.443	0.912	2.877	0.543	0.801	0.113	0.086
24	0.330	0.563	0.563	0.603	0.731	2.031	0.576	0.312	0.312	0.376
25	0.816	0.360	0.360	0.360	0.549	0.828	0.556	0.333	0.333	0.333
26	3.255	0.089	0.089	0.089	0.189	0.151	0.630	0.333	0.333	0.333
27	0.932	0.451	0.267	0.301	0.498	0.653	0.294	0.685	0.120	0.195
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.429	0.522	0.485	0.651	0.608	1.698	0.409	0.253	0.191	0.556
30	1.131	0.374	0.224	0.361	0.565	0.855	0.861	0.397	0.221	0.381
31	0.865	0.451	0.297	0.325	0.534	0.742	0.386	0.566	0.189	0.245
32	1.348	0.150	0.209	0.185	0.520	0.496	1.168	0.292	0.369	0.339
33	2.204	0.015	0.055	0.049	0.055	0.055	0.095	0	0.664	0.336
34	0.875	0.304	0.303	0.321	0.530	0.731	0.704	0.326	0.324	0.350
35	0.922	0.219	0.219	0.219	0.219	0.280	0	0.002	0.104	0.894
36	0.533	0.412	0.361	0.353	0.441	0.656	0.108	0.645	0.202	0.152
37	0.352	0.537	0.512	0.598	0.698	1.855	0.599	0.313	0.278	0.409
38	1.529	0.384	0.184	0.151	0.569	0.483	0.631	0.600	0.231	0.169

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Table 3.B.4 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
39	0.806	0.259	0.214	0.153	0.553	0.472	0.850	0.412	0.344	0.244
40	0.934	0.357	0.277	0.300	0.442	0.582	0.359	0.466	0.236	0.298
41	0.498	0.966	0.244	0.131	0.979	.	.	.	.	.
42	0.890	0.488	0.418	0.359	0.488	.	.	.	.	.
43	0.790	0.076	0.076	0.076	0.076	.	.	.	.	.
44	0.854	0.391	0.372	0.372	0.662	1.078	0.823	0.348	0.326	0.326
45	0.625	0.254	0.254	0.254	0.478	0.559	0.714	0.333	0.333	0.333
46	3.267	0.880	0.880	0.880	0.880	.	.	.	.	.
47	0.455	0.713	0.592	0.497	0.713	.	.	.	.	.
48	2.863	0.074	0.151	0.126	0.151	0.160	0.053	0	0.884	0.116
49	0.488	0.529	0.439	0.433	0.625	1.128	0.347	0.496	0.258	0.245
50	0.922	0.320	0.170	0.170	0.517	0.468	0.747	0.502	0.249	0.249
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	0.828	0.478	0.311	0.339	0.555	0.799	0.373	0.590	0.177	0.233
53	1.865	0.265	0.265	0.265	0.406	0.496	0.463	0.333	0.333	0.333
54	0.154	0.714	0.714	0.872	0.714	.	.	.	.	.
55	0.876	0.364	0.364	0.364	0.660	1.054	0.879	0.333	0.333	0.333
56	166.3	0.002	0	0	0.002	0	0.390	1	0	0
57	0.547	0.259	0.399	0.472	0.558	1.063	0.797	0.198	0.356	0.446
58	1.256	0.555	0.206	0.169	0.578	.	.	.	.	.
59	1.023	0.300	0.242	0.268	0.606	0.752	1.023	0.366	0.302	0.332
60	0.828	0.964	0.069	0.069	0.964	.	.	.	.	.
61	0.937	0.404	0.157	0.350	0.404	0.605	0.089	0.786	0	0.214
62	0.079	0.094	0.824	0.576	0.940	4.604	2.088	0.140	0.502	0.358
63	0.865	0.382	0.252	0.231	0.396	.	.	.	.	.
64	0.496	0.681	0.355	0.318	0.681	.	.	.	.	.
65	0.865	0.451	0.297	0.325	0.534	0.742	0.386	0.566	0.189	0.245
66	0.500	0.432	0.432	0.432	0.563	0.988	0.380	0.333	0.333	0.333
67	2.985	0.381	0.316	0.282	0.381	.	.	.	.	.
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	0.985	0.240	0.154	0.326	0.299	0.454	0.508	0.328	0.141	0.531
70	1.173	0.450	0.402	0.491	0.597	1.195	0.552	0.334	0.261	0.404
71	1.227	0.212	0.212	0.212	0.449	0.469	0.797	0.333	0.333	0.333
72	0.568	0.392	0.392	0.392	0.664	1.127	0.808	0.333	0.333	0.333
73	0.762	0.428	0.320	0.320	0.428	.	.	.	.	.
74	1.006	0.193	0.193	0.233	0.233	0.304	0.217	0.250	0.250	0.500
75	23.08	0.034	0	0	0.425	0.001	3.733	0.709	0.137	0.154
76	0.935	0.508	0.468	0.468	0.673	1.347	0.535	0.378	0.311	0.311

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Table 3.B.4 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
77	0.853	0.305	0.295	0.326	0.471	0.657	0.557	0.326	0.307	0.367
78	1.034	0.350	0.305	0.270	0.350	.	.	.	.	.
79	0.584	0.352	0.397	0.397	0.550	0.897	0.533	0.281	0.360	0.360
80	1.112	0.204	0.204	0.204	0.653	0.694	1.440	0.333	0.333	0.333
81	0.949	0.463	0.378	0.378	0.652	1.068	0.635	0.417	0.292	0.292
82	1.235	0.433	0.296	0.276	0.572	0.714	0.482	0.535	0.250	0.215
83	0.627	0.110	0.110	0.110	0.163	0.156	0.327	0.333	0.333	0.333
84	0.717	0.399	0.420	0.379	0.457	0.716	0.097	0.309	0.531	0.159
85	1.050	0.286	0.155	0.234	0.305	0.366	0.275	0.584	0.076	0.340
86	0.578	0.322	0.293	0.258	0.452	0.536	0.378	0.422	0.336	0.242
87	0.729	0.421	0.421	0.576	0.421	.	.	.	.	.
88	1.027	0.841	0.188	0.188	0.869	1.235	0.315	0.990	0.005	0.005
89	1.038	0.076	0.038	0.038	0.102	0.067	0.341	0.647	0.176	0.176

Table 3.B.5: Individual estimate: strategic uncertainty

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
1	0.929	0.230	0.230	0.230	0.470	0.515	0.784	0.333	0.333	0.333
2	0.842	0.364	0.350	0.350	0.719	1.174	1.094	0.341	0.329	0.329
3	0.452	0.505	0.462	0.462	0.755	1.629	0.839	0.364	0.318	0.318
4	0.512	0.393	0.393	0.393	0.393	0.649	0	0.005	0	0.995
5	0.369	0.696	0.734	0.697	0.734	.	.	.	.	.
6	0.886	0.159	0.159	0.541	0.325	0.754	0.970	0.193	0.193	0.613
7	0.849	0.342	0.328	0.214	0.438	.	.	.	.	.
8	0.723	0.261	0.261	0.330	0.510	0.715	0.851	0.304	0.304	0.391
9	1.051	0.194	0.194	0.194	0.260	0.291	0.271	0.333	0.333	0.333
10	0.582	0.514	0.539	0.539	0.539	1.168	0.010	0	0.500	0.500
11	0.542	0.407	0.376	0.376	0.407	.	.	.	.	.
12	1.331	0.238	0.263	0.213	0.473	0.493	0.661	0.333	0.380	0.287
13	2.634	0.077	0.077	0.066	0.077	.	.	.	.	.
14	0.857	0.262	0.283	0.303	0.474	0.627	0.667	0.300	0.334	0.367
15	0.925	0.320	0.317	0.303	0.511	0.674	0.565	0.345	0.340	0.315
16	2.989	0.178	0.178	0.116	0.316	0.246	0.383	0.419	0.419	0.162
17	0.661	0.512	0.565	0.451	0.672	1.298	0.291	0.326	0.502	0.172
18	0.838	0.318	0.338	0.338	0.338	0.510	0.007	0	0.500	0.500
19	1.351	0.404	0.467	0.369	0.513	0.784	0.106	0.199	0.742	0.059
20	1.301	0.229	0.167	0.316	0.574	0.790	1.368	0.328	0.269	0.403
21	1.597	0.063	0.055	0.055	0.063	.	.	.	.	.

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Table 3.B.6 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
22	0.798	0.284	0.309	0.351	0.470	0.692	0.593	0.280	0.323	0.397
23	0.868	0.624	0.624	0.434	0.866	2.232	0.750	0.403	0.403	0.194
24	2.340	0.046	0.046	0.046	0.146	0.091	0.905	0.333	0.333	0.333
25	1.184	0.249	0.249	0.249	0.481	0.553	0.743	0.333	0.333	0.333
26	1.187	0.331	0.331	0.331	0.530	0.747	0.592	0.333	0.333	0.333
27	0.841	0.309	0.354	0.334	0.475	0.673	0.434	0.280	0.384	0.336
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.991	0.171	0.276	0.171	0.572	0.525	1.036	0.289	0.423	0.289
30	1.108	0.269	0.246	0.246	0.640	0.762	1.164	0.349	0.325	0.325
31	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
32	0.804	0.303	0.303	0.303	0.549	0.727	0.742	0.333	0.333	0.333
33	0.522	0.380	0.287	0.374	0.380	0.605	0.034	0.590	0	0.410
34	1.279	0.208	0.202	0.202	0.391	0.403	0.651	0.342	0.329	0.329
35	1.541	0.171	0.171	0.206	0.194	0.250	0.151	0.220	0.220	0.561
36	0.462	0.527	0.375	0.596	0.652	1.662	0.686	0.358	0.185	0.457
37	1.041	0.101	0.184	0.223	0.348	0.391	0.972	0.217	0.362	0.421
38	1.091	0.248	0.274	0.292	0.445	0.576	0.627	0.291	0.338	0.371
39	0.985	0.173	0.181	0.113	0.411	0.298	0.705	0.376	0.394	0.230
40	0.725	0.307	0.417	0.382	0.547	0.864	0.554	0.231	0.415	0.354
41	3.864	0.040	0.040	0.040	0.206	0.103	1.322	0.333	0.333	0.333
42	0.760	0.499	0.468	0.468	0.499	.	.	.	.	.
43	0.627	0.110	0.110	0.110	0.163	0.156	0.327	0.333	0.333	0.333
44	0.744	0.417	0.417	0.417	0.530	0.899	0.327	0.333	0.333	0.333
45	0.529	0.203	0.203	0.243	0.603	0.698	1.340	0.320	0.320	0.359
46	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
47	0.302	0.741	0.526	0.742	0.747	2.917	0.280	0.480	0.031	0.489
48	3.127	0.119	0.059	0.166	0.119	0.164	0.068	0.057	0	0.943
49	0.641	0.277	0.212	0.172	0.583	0.539	0.941	0.410	0.324	0.267
50	0.903	0.197	0.154	0.154	0.500	0.427	1.084	0.374	0.313	0.313
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	1.086	0.342	0.239	0.252	0.356	0.432	0.121	0.820	0.067	0.113
53	0.848	0.420	0.383	0.420	0.538	0.918	0.412	0.360	0.279	0.360
54	2.404	0.208	0.246	0.002	0.764	.	.	.	.	.
55	1.625	0.269	0.269	0.260	0.393	0.476	0.394	0.342	0.342	0.315
56	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
57	3.447	0.068	0.068	0.068	0.102	0.091	0.319	0.333	0.333	0.333
58	1.056	0.343	0.343	0.343	0.383	0.570	0.125	0.333	0.333	0.333
59	1.035	0.225	0.265	0.331	0.315	0.477	0.323	0.177	0.295	0.528

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Table 3.B.6 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
60	1.189	0.224	0.024	0.139	0.415	0.338	1.495	0.474	0.147	0.379
61	1.886	0.044	0.104	0.058	0.421	0.212	1.595	0.277	0.408	0.316
62	1.746	0.151	0.156	0.134	0.742	0.667	1.955	0.337	0.342	0.321
63	0.708	0.336	0.424	0.093	0.779	.	.	.	.	.
64	1.178	0.347	0.347	0.374	0.448	0.697	0.332	0.307	0.307	0.386
65	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
66	0.580	0.527	0.576	0.576	0.590	1.399	0.118	0.126	0.437	0.437
67	2.412	0.238	0.238	0.211	0.238	.	.	.	.	.
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	1.084	0.211	0.211	0.211	0.488	0.506	0.917	0.333	0.333	0.333
70	2.229	0.099	0.158	0.158	0.318	0.296	0.893	0.249	0.376	0.376
71	1.466	0.051	0.078	0.051	0.464	0.217	1.782	0.315	0.370	0.315
72	0.552	0.401	0.401	0.401	0.638	1.086	0.700	0.333	0.333	0.333
73	1.194	0.183	0.221	0.284	0.264	0.377	0.324	0.168	0.292	0.540
74	1.018	0.273	0.273	0.273	0.465	0.571	0.607	0.333	0.333	0.333
75	1.297	0.071	0.135	0.453	0.157	0.393	0.552	0.049	0.157	0.794
76	0.431	0.778	0.719	0.728	0.778	.	.	.	.	.
77	0.832	0.589	0.398	0.187	0.725	.	.	.	.	.
78	1.218	0.296	0.215	0.215	0.363	0.394	0.293	0.556	0.222	0.222
79	1.041	0.206	0.259	0.232	0.356	0.409	0.431	0.258	0.409	0.332
80	0.922	0.409	0.320	0.320	0.651	0.938	0.798	0.406	0.297	0.297
81	0.952	0.377	0.377	0.377	0.586	0.926	0.613	0.333	0.333	0.333
82	0.842	0.320	0.292	0.184	0.525	0.499	0.440	0.466	0.393	0.141
83	2.218	0.001	0.001	0.001	0.054	0.007	3.119	0.333	0.333	0.333
84	0.980	0.318	0.318	0.318	0.337	0.487	0.061	0.333	0.333	0.333
85	0.988	0.298	0.405	0.239	0.490	0.550	0.178	0.190	0.768	0.041
86	0.625	0.408	0.318	0.185	0.800	0.953	1.142	0.430	0.349	0.221
87	1.094	0.389	0.239	0.239	0.389	.	.	.	.	.
88	0.715	0.362	0.403	0.403	0.488	0.802	0.327	0.256	0.372	0.372
89	0.340	0.331	0.331	0.331	0.480	0.676	0.451	0.333	0.333	0.333

Table 3.B.7: Individual estimate: social ambiguity- tg

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
1	1.757	0.270	0.079	0.018	0.391	.	.	.	.	.
2	1.266	0.245	0.203	0.203	0.597	0.615	1.149	0.365	0.318	0.318
3	0.806	0.397	0.302	0.302	0.619	0.838	0.741	0.419	0.291	0.291
4	28.42	0	0	0	0	0	0.506	1	0	0
5	0.745	0.643	0.643	0.701	0.643	.	.	.	.	.
6	1.296	0.092	0.092	0.525	0.113	0.375	0.327	0.018	0.018	0.965
7	1.620	0.219	0.203	0.191	0.540	0.527	1.037	0.353	0.331	0.316
8	0.677	0.379	0.379	0.379	0.530	0.831	0.442	0.333	0.333	0.333
9	1.972	0.098	0.052	0.052	0.118	0.085	0.240	0.732	0.134	0.134
10	1.259	0.299	0.386	0.286	0.386	.	.	.	.	.
11	0.604	0.367	0.367	0.298	0.367	.	.	.	.	.
12	0.909	0.365	0.285	0.332	0.402	0.577	0.226	0.498	0.163	0.339
13	0.394	0.315	0.300	0.300	0.315	.	.	.	.	.
14	1.353	0.245	0.263	0.289	0.396	0.516	0.513	0.288	0.327	0.385
15	0.876	0.296	0.321	0.321	0.528	0.726	0.676	0.308	0.346	0.346
16	1.231	0.504	0.212	0.293	0.504	0.649	0.042	1	0	0
17	1.516	0.431	0.247	0.175	0.431	.	.	.	.	.
18	0.746	0.376	0.376	0.376	0.376	0.602	0	0.286	0.286	0.428
19	0.986	0.392	0.392	0.384	0.558	0.887	0.474	0.339	0.339	0.323
20	1.832	0.146	0.042	0.378	0.251	0.451	1.211	0.310	0.128	0.561
21	0.644	0.107	0.134	0.107	0.134	.	.	.	.	.
22	0.902	0.417	0.239	0.311	0.417	0.569	0.035	0.999	0	0.001
23	0.968	0.661	0.205	0.205	0.810	1.047	0.861	0.673	0.164	0.164
24	0.468	0.541	0.541	0.523	0.670	1.494	0.375	0.347	0.347	0.305
25	1.977	0.108	0.108	0.108	0.333	0.245	1.021	0.333	0.333	0.333
26	1.984	0.179	0.179	0.179	0.367	0.356	0.705	0.333	0.333	0.333
27	0.794	0.328	0.352	0.352	0.454	0.673	0.359	0.289	0.356	0.356
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.634	0.491	0.400	0.371	0.734	1.279	0.808	0.414	0.308	0.278
30	1.226	0.717	0.213	0.215	0.902	1.584	1.303	0.589	0.205	0.206
31	0.699	0.420	0.409	0.433	0.478	0.836	0.201	0.331	0.280	0.389
32	0.920	0.308	0.348	0.370	0.557	0.858	0.723	0.287	0.342	0.371
33	0.610	0.380	0.191	0.563	0.409	0.943	0.483	0.291	0.054	0.655
34	1.077	0.239	0.294	0.255	0.406	0.483	0.438	0.272	0.416	0.312
35	1.095	0.660	0.554	0.657	0.660	1.930	0.037	0.548	0	0.452
36	0.800	0.231	0.186	0.186	0.434	0.419	0.736	0.390	0.305	0.305
37	0.954	0.286	0.092	0.209	0.286	0.325	0.083	0.926	0	0.074
38	1.290	0.222	0.139	0.162	0.260	0.260	0.288	0.580	0.158	0.262

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Table 3.B.8 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
39	0.464	0.469	0.374	0.374	0.650	1.054	0.619	0.430	0.285	0.285
40	1.005	0.359	0.243	0.337	0.485	0.692	0.592	0.413	0.215	0.372
41	0.828	0.964	0.069	0.069	0.964	.	.	.	.	.
42	0.666	0.529	0.523	0.523	0.529	.	.	.	.	.
43	0.790	0.076	0.076	0.076	0.076	.	.	.	.	.
44	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
45	0.946	0.184	0.184	0.184	0.306	0.315	0.487	0.333	0.333	0.333
46	1.340	0.742	0.742	0.944	0.742	.	.	.	.	.
47	0.494	0.876	0.442	0.400	0.876	.	.	.	.	.
48	1.500	0.186	0.186	0.202	0.321	0.346	0.547	0.320	0.320	0.360
49	0.796	0.224	0.187	0.177	0.472	0.438	0.846	0.380	0.319	0.301
50	0.648	0.417	0.294	0.294	0.454	0.588	0.176	0.754	0.123	0.123
51	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
52	0.955	0.432	0.293	0.293	0.494	0.636	0.272	0.659	0.171	0.171
53	1.148	0.258	0.258	0.258	0.463	0.547	0.654	0.333	0.333	0.333
54	0.802	0.074	0.074	0.074	0.965	1.492	4.225	0.333	0.333	0.333
55	0.995	0.349	0.349	0.349	0.680	1.069	0.994	0.333	0.333	0.333
56	44.23	0.194	0	0	0.194	.	.	.	.	.
57	0.009	0.506	0.354	0.354	0.506	.	.	.	.	.
58	1.163	0.542	0.241	0.267	0.599	0.738	0.359	0.789	0.088	0.123
59	1.027	0.438	0.320	0.280	0.511	0.637	0.209	0.723	0.190	0.087
60	1.042	0.348	0.348	0.348	0.669	1.038	0.963	0.333	0.333	0.333
61	1.174	0.127	0.254	0.457	0.254	0.534	0.077	0	0.003	0.997
62	0.636	0.335	0.174	0.477	0.419	0.811	0.691	0.334	0.124	0.542
63	0.991	0.292	0.140	0.253	0.292	0.374	0.063	0.829	0	0.171
64	1.462	0.709	0.112	0.060	0.738	.	.	.	.	.
65	1.163	0.463	0.231	0.231	0.463	.	.	.	.	.
66	0.878	0.339	0.377	0.254	0.480	0.560	0.128	0.333	0.648	0.020
67	2.192	0.341	0.341	0.338	0.341	.	.	.	.	.
68	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
69	0.851	0.214	0.065	0.299	0.305	0.433	0.941	0.378	0.125	0.496
70	1.094	0.247	0.208	0.265	0.398	0.489	0.627	0.347	0.272	0.382
71	1.391	0.212	0.212	0.212	0.409	0.431	0.680	0.333	0.333	0.333
72	0.517	0.421	0.421	0.421	0.588	1.018	0.487	0.333	0.333	0.333
73	1.302	0.381	0.148	0.148	0.381	.	.	.	.	.
74	0.531	0.316	0.317	0.300	0.336	0.465	0.028	0.456	0.498	0.046
75	0.828	0.964	0.069	0.069	0.964	.	.	.	.	.
76	1.747	0.256	0.181	0.089	0.256	.	.	.	.	.

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**Table 3.B.8 – continued from previous page**

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
77	1.378	0.179	0.159	0.179	0.383	0.368	0.824	0.346	0.308	0.346
78	0.652	0.541	0.478	0.478	0.625	1.236	0.301	0.461	0.269	0.269
79	1.020	0.314	0.296	0.229	0.440	0.483	0.296	0.455	0.383	0.162
80	1.186	0.223	0.148	0.185	0.544	0.520	1.203	0.378	0.287	0.334
81	1.034	0.331	0.265	0.283	0.396	0.509	0.286	0.477	0.230	0.293
82	1.986	0.264	0.072	0.116	0.876	0.962	2.606	0.406	0.276	0.318
83	0.245	0.450	0.091	0.091	0.450	.	.	.	.	.
84	0.837	0.348	0.370	0.370	0.389	0.611	0.098	0.203	0.399	0.399
85	1.013	0.232	0.205	0.258	0.303	0.389	0.366	0.332	0.245	0.424
86	0.463	0.581	0.449	0.449	0.805	1.837	0.899	0.423	0.289	0.289
87	1.068	0.341	0.341	0.387	0.341	.	.	.	.	.
88	0.767	0.787	0.198	0.244	0.833	1.267	0.547	0.876	0.048	0.076
89	0.852	0.065	0.145	0.065	0.169	0.119	0.230	0.088	0.824	0.088

Table 3.B.9: Individual estimate: betrayal aversion- tg

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
1	1.284	0.287	0.187	0.187	0.407	0.397	0.488	0.507	0.246	0.246
2	1.025	0.286	0.268	0.277	0.673	0.888	1.214	0.342	0.325	0.333
3	0.906	0.353	0.353	0.353	0.544	0.807	0.562	0.333	0.333	0.333
4	0.660	0.332	0.332	0.812	0.474	1.975	0.704	0.124	0.124	0.753
5	1.006	0.485	0.426	0.437	0.519	0.915	0.154	0.544	0.203	0.253
6	0.835	0.248	0.219	0.415	0.304	0.557	0.382	0.203	0.143	0.654
7	1.417	0.171	0.186	0.163	0.367	0.336	0.679	0.328	0.363	0.309
8	0.770	0.309	0.288	0.288	0.465	0.592	0.500	0.364	0.318	0.318
9	2.036	0.056	0.056	0.025	0.056	.	.	.	.	.
10	0.968	0.291	0.329	0.345	0.329	0.508	0.016	0	0.097	0.903
11	0.561	0.494	0.395	0.439	0.516	0.914	0.166	0.600	0.117	0.283
12	0.668	0.369	0.439	0.390	0.683	1.173	0.816	0.299	0.378	0.322
13	1.929	0.207	0.140	0.103	0.222	.	.	.	.	.
14	0.962	0.274	0.220	0.247	0.544	0.625	0.931	0.368	0.298	0.334
15	1.056	0.219	0.261	0.300	0.419	0.557	0.664	0.262	0.335	0.403
16	1.522	0.152	0.071	0.310	0.174	0.308	0.524	0.262	0.065	0.673
17	1.295	0.383	0.316	0.277	0.517	0.640	0.396	0.481	0.305	0.214
18	0.939	0.341	0.368	0.368	0.368	0.583	0.010	0	0.500	0.500
19	2.736	0.083	0.083	0.099	0.282	0.208	1.109	0.320	0.320	0.361
20	0.561	0.577	0.337	0.285	0.623	.	.	.	.	.
21	0.017	0	0	0.096	0.946	1.361	15.938	0.270	0.270	0.460
22	0.706	0.252	0.335	0.517	0.335	0.734	0.039	0	0	1
23	1.366	0.472	0.501	0.147	0.832	.	.	.	.	.
24	0.764	0.409	0.409	0.409	0.547	0.915	0.403	0.333	0.333	0.333
25	0.712	0.719	0.385	0.385	0.719	.	.	.	.	.
26	1.493	0.323	0.323	0.323	0.458	0.635	0.413	0.333	0.333	0.333
27	1.017	0.355	0.273	0.313	0.481	0.650	0.503	0.419	0.251	0.330
28	0.884	0.361	0.361	0.361	0.670	1.071	0.922	0.333	0.333	0.333
29	0.752	0.215	0.215	0.382	0.215	.	.	.	.	.
30	1.365	0.346	0.189	0.366	0.352	0.560	0.245	0.442	0.028	0.531
31	1.076	0.255	0.255	0.354	0.400	0.604	0.575	0.271	0.271	0.458
32	1.035	0.225	0.251	0.328	0.331	0.492	0.414	0.219	0.285	0.496
33	1.054	0.176	0.284	0.124	0.284	.	.	.	.	.
34	0.940	0.314	0.298	0.338	0.424	0.613	0.402	0.326	0.285	0.389
35	1.319	0.454	0.483	0.483	0.483	0.933	0.010	0	0.500	0.500
36	0.573	0.331	0.223	0.327	0.518	0.723	0.797	0.383	0.239	0.378
37	1.439	0.072	0.100	0.100	0.256	0.196	0.981	0.279	0.360	0.360
38	1.216	0.266	0.240	0.240	0.342	0.406	0.291	0.403	0.298	0.298

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Table 3.B.10 – continued from previous page

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
39	0.729	0.211	0.211	0.181	0.469	0.442	0.812	0.350	0.350	0.299
40	0.976	0.329	0.286	0.326	0.494	0.688	0.589	0.360	0.285	0.355
41	5.298	0.007	0.007	0.007	0.081	0.025	1.800	0.333	0.333	0.333
42	0.511	0.684	0.679	0.658	0.684	.	.	.	.	.
43	0.790	0.076	0.076	0.076	0.076	.	.	.	.	.
44	1.094	0.371	0.292	0.292	0.452	0.583	0.309	0.511	0.245	0.245
45	0.307	0.094	0.442	0.389	0.720	1.279	1.639	0.178	0.428	0.395
46	1.103	0.755	0.755	0.953	0.755	.	.	.	.	.
47	0.883	0.543	0.645	0.507	0.734	1.682	0.329	0.258	0.559	0.183
48	1.123	0.042	0.347	0.779	0.347	1.366	0.207	0	0.010	0.990
49	0.533	0.448	0.381	0.455	0.577	1.067	0.504	0.368	0.251	0.381
50	0.723	0.201	0.285	0.251	0.488	0.566	0.798	0.266	0.393	0.342
51	0.802	0.074	0.074	0.965	0.074	.	.	.	.	.
52	1.371	0.266	0.182	0.218	0.529	0.561	0.978	0.391	0.280	0.329
53	1.665	0.301	0.252	0.252	0.301	.	.	.	.	.
54	0.802	0.074	0.074	0.965	0.074	.	.	.	.	.
55	0.922	0.347	0.347	0.347	0.724	1.181	1.150	0.333	0.333	0.333
56	1.395	0.244	0.253	0.253	0.545	0.636	0.933	0.326	0.337	0.337
57	1.537	0.477	0.477	0.323	0.477	.	.	.	.	.
58	0.799	0.348	0.485	0.453	0.485	0.883	0.040	0	0.835	0.165
59	1.208	0.217	0.217	0.255	0.531	0.623	1.064	0.319	0.319	0.363
60	43.27	0	0	0	0	0	1.002	0.021	0.021	0.958
61	1.317	0.059	0.324	0.368	0.324	0.528	0.157	0	0.350	0.650
62	0.654	0.280	0.259	0.239	0.451	0.508	0.538	0.378	0.332	0.290
63	0.851	0.392	0.288	0.191	0.889	1.376	1.777	0.395	0.334	0.270
64	0.891	0.084	0.084	0.356	0.319	0.509	1.510	0.243	0.243	0.514
65	0.993	0.280	0.280	0.320	0.406	0.568	0.448	0.301	0.301	0.398
66	0.721	0.494	0.485	0.511	0.589	1.222	0.308	0.325	0.301	0.375
67	0.739	0.540	0.540	0.836	0.540	.	.	.	.	.
68	1.013	0.298	0.316	0.316	0.636	0.899	0.998	0.320	0.340	0.340
69	0.580	0.204	0.204	0.403	0.484	0.796	1.127	0.268	0.268	0.464
70	1.330	0.213	0.238	0.213	0.395	0.421	0.565	0.315	0.371	0.315
71	1.227	0.212	0.212	0.212	0.449	0.469	0.797	0.333	0.333	0.333
72	0.657	0.345	0.458	0.345	0.526	0.766	0.278	0.207	0.586	0.207
73	0.768	0.459	0.288	0.288	0.459	.	.	.	.	.
74	1.669	0.072	0.084	0.118	0.084	0.111	0.017	0	0	1
75	0.075	0.094	0.094	0.945	0.094	.	.	.	.	.
76	0.716	0.396	0.361	0.318	0.511	0.699	0.310	0.450	0.336	0.214

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**Table 3.B.10 – continued from previous page**

id	$\alpha$	$W(P(L))$	$W(P(R))$	$W(P(M))$	$W(P(L \cup R))$	$\eta$	$\gamma$	$P(L)$	$P(R)$	$P(M)$
77	1.039	0.388	0.242	0.166	0.488	.	.	.	.	.
78	1.045	0.288	0.275	0.365	0.346	0.552	0.287	0.252	0.212	0.536
79	0.750	0.296	0.346	0.281	0.434	0.547	0.291	0.288	0.472	0.240
80	2.908	0.195	0.174	0.174	0.375	0.356	0.686	0.364	0.318	0.318
81	0.968	0.286	0.372	0.205	0.430	.	.	.	.	.
82	1.297	0.198	0.198	0.235	0.683	0.814	1.613	0.323	0.323	0.354
83	0.790	0.076	0.076	0.076	0.076	.	.	.	.	.
84	0.753	0.467	0.497	0.471	0.497	.	.	.	.	.
85	1.168	0.227	0.253	0.350	0.271	0.447	0.178	0.087	0.173	0.740
86	0.359	0.507	0.484	0.484	0.507	.	.	.	.	.
87	1.037	0.413	0.413	0.462	0.413	.	.	.	.	.
88	0.861	0.563	0.282	0.323	0.563	.	.	.	.	.
89	0.643	0.328	0.262	0.262	0.382	0.468	0.224	0.549	0.225	0.225

### 3.C Experimental instructions

In this appendix we present the instructions we show to Players 2 in the experiment. The order of the presentation of the instructions of each experimental condition is randomized, accordingly to the randomization of the order of the conditions in the experiment. These instructions are translated from the original French instructions.

#### Beginning instructions

The experiment consists of five (5) parts and will last approximately 45 minutes. You will receive specific instructions for each part at the beginning of each of them. At the end of the experiment, only one part out of the five will be randomly selected to determine your final payment. Each of these five parts has the same chance of being randomly selected by the computer. In each part, you make several decisions. If a part is randomly selected for payment, one of the decisions in that part will be randomly selected by the computer. Each decision

has the same chance of being drawn at random. Therefore, only one of your decisions will affect your final payment, but it could be any of your decisions. Thus, it is in your best interest to make each decision as if it were the one that will be selected for payment.

Payments for your decisions will be expressed in experimental currency units (ECU). Please note that each ECU is equal to 1 euro. For example, 1 ECU = €1 and 15 ECU = €15.

## **Social ambiguity - coordination game**

You will now read the instructions for Part 1 of the experiment. Part 1 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.

### **First stage**

#### Instructions for the first sub-part of Part 1

In this part of the experiment, you are randomly paired with another participant, we call this person, Participant 2. You will never be informed of Participant 2's identity, nor will Participant 2 ever be informed of your identity. Your final payment will depend on your decision and the decision of Participant 2.

Your decision in this section will be to choose an action between Left, Right or Middle. Participant 2 will receive 5 euros. Then, Participant 2 will decide where he/she would prefer to spend these 5 euros between one of the following options: An Amazon voucher, a Google Play voucher or an Apple Store voucher. You will not be notified of Participant 2's decision until you receive payment for



this experiment. The values below are numerical examples of how Participant 2's decision affects your payment.

- If you choose **Left** and Participant 2 chooses an **Amazon voucher**, you will receive **30 ECU**.
- If you choose **Left** and Participant 2 chooses a **Google Play voucher**, you will receive **20 ECU**.
- If you choose **Left** and Participant 2 chooses an **Apple Store voucher**, you will receive **16 ECU**.
- If you choose **Right** and Participant 2 chooses an **Amazon voucher**, you will receive **16 ECU**.
- If you choose **Right** and Participant 2 chooses a **Google Play voucher**, you will receive **30 ECU**.
- If you choose **Right** and Participant 2 chooses an **Apple Store voucher**, you receive **20 ECU**.
- If you choose **Middle** and Participant 2 chooses an **Amazon voucher**, you will receive **20 ECU**.
- If you choose **Middle** and Participant 2 chooses a **Google Play voucher**, you will receive **16 ECU**.
- If you choose **Middle** and Participant 2 chooses an **Apple Store voucher**, you will receive **30 ECU**.

Your possible payments (in ECU), depending on your decision and the decision of Participant 2, are summarized in the table below.

Participant 2				
Your decision		Amazon voucher	Google Play voucher	Apple Store voucher
	Left	30	20	16
	Right	16	30	20
	Middle	20	16	30

Note that Participant 2 is informed that his or her choice will affect you, but he or she does not know in what direction. This means that Participant 2 does not know how your payment changes based on his or her decision.

### Example

Suppose you decide to choose the **Right** action and Participant 2 prefers to spend his or her 5 euros on a **Google Play voucher** (remember that you will not be informed of Participant 2's decision until you receive the payment for the experiment). The table below shows in **orange** the payment (in ECU) you will get in this scenario. If this decision is chosen at random for the payment, you earn 30 ECU.

Participant 2				
Your decision		Amazon voucher	Google Play voucher	Apple Store voucher
	Left	30	20	16
	Right	16	<b>30</b>	20
	Middle	20	16	30

### **Second stage**

#### Instructions for the second sub-part of Part 1

In the second and final subpart of this part of the experiment, you will choose between several options. The options will be presented in 12 tables (see an

example of the table below). Each row represents one option. For each option, you will be asked to indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between an **Amazon voucher**, a **Google Play voucher**, or an **Apple Store voucher**. This alternative changes from table to table, but it is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
30	A1	B1	You get <b>30 ECU</b> if Participant 2 chooses an <b>Amazon voucher</b> in the first sub-part of this part of the experiment or <b>16 ECU</b> if Participant 2 chooses a <b>Google Play voucher</b> or an <b>Apple Store voucher</b>
28	A2	B2	
26	A3	B3	
24	A4	B4	
22	A5	B5	
20	A6	B6	
18	A7	B7	
16	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
26	A1	B1	You get <b>30 ECU</b> if Participant 2 chooses an <b>Amazon voucher</b> in the first sub-part of this part of the experiment or <b>16 ECU</b> if Participant 2 chooses a <b>Google Play voucher or an Apple Store voucher</b>

- If you select **Alternative A** for this line, you earn **26 ECU**.
- If you select **Alternative B** for this line, you can earn **30 ECU or 16 ECU**. Your payment depends on the decision of Participant 2 that you were associated with in sub-part 1 of this part of the experiment (the most recent task you completed). Payment is determined as follows:
  - If Participant 2 chooses an **Amazon voucher**, you earn **30 ECU**.
  - If Participant 2 chooses either a **Google Play voucher or an Apple Store voucher**, you earn **16 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.

**Strategic uncertainty - coordination game**

You will now read the instructions for Part 2 of the experiment. Part 2 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.

## First stage

### Instructions for the first sub-part of Part 2

In this part of the experiment, you are again randomly paired with another participant. We call this new person Participant 2. However, this Participant 2 is a **different person** than the one you were paired with in the previous part of the experiment. You will never be informed of Participant 2's identity, nor will Participant 2 be informed of your identity. Your final payment will depend on your decision and the decision of Participant 2.

You and Participant 2 will each choose one of three actions: **Left, Right and Middle**. You will not be informed of Participant 2's decision until the end of the experiment and Participant 2 will not be informed of your decision until the end of the experiment. A numerical example of the payments (in ECU) for you and for Participant 2 are presented in the table below. In each cell, the first amount is your payment, and the second amount is Participant 2's payment. These payments can be summarized as follows:

- If you choose **Left** and Participant 2 chooses **Left**, you receive **7 ECU**.
- If you choose **Left** and Participant 2 chooses **Right**, you receive **5 ECU**.
- If you choose **Left** and Participant 2 chooses **Middle**, you receive **4 ECU**.
- If you choose **Right** and Participant 2 chooses **Left**, you receive **4 ECU**.
- If you choose **Right** and Participant 2 chooses **Right**, you receive **7 ECU**.
- If you choose **Right** and Participant 2 chooses **Middle**, you receive **5 ECU**.
- If you choose **Middle** and Participant 2 chooses **Left**, you receive **5 ECU**.

- If you choose **Middle** and Participant 2 chooses **Right**, you receive **4 ECU**.
- If you choose **Middle** and Participant 2 chooses **Middle**, you receive **7 ECU**.

		Participant 2		
		Left	Right	Middle
Your decision	Left	7,7	5,9	4,11
	Right	4,11	7,7	5,9
	Middle	5,9	4,11	7,7

### Example

Suppose you decide to choose the **Left** action and Participant 2 chooses the **Middle** action (remember that you will not be informed of Participant 2's decision until the end of the experiment). The table below shows in **orange** the payment (in ECU) that you and Participant 2 will have in this scenario. If this decision is chosen randomly for the payment, you will win 4 ECU and Participant 2 will win 11 ECU.

		Participant 2		
		Left	Right	Middle
Your decision	Left	7,7	5,9	<b>4,11</b>
	Right	4,11	7,7	5,9
	Middle	5,9	4,11	7,7

### **Second stage**

#### Instructions for the second sub-part of Part 2

In the second and final sub-part of this part of the experiment, you will choose between several options. The options will be presented in 12 tables (see

an example of the table below). Each row represents one option. For each option, you will be asked to indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between the **Left, Right or Middle** actions. This alternative changes from table to table, but it is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
7	A1	B1	You get <b>7 ECU</b> if Participant 2 chooses an <b>Left</b> in the first sub-part of this part of the experiment or <b>3.5 ECU</b> if Participant 2 chooses a <b>Right or Middle</b>
6.5	A2	B2	
6	A3	B3	
5.5	A4	B4	
5	A5	B5	
4.5	A6	B6	
4	A7	B7	
3.5	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
6	A1	B1	You get <b>7 ECU</b> if Participant 2 chooses an <b>Left</b> in the first sub-part of this part of the experiment or <b>3.5 ECU</b> if Participant 2 chooses a <b>Right or Middle</b>

- If you select **Alternative A** for this line, you earn **6 ECU**.
- If you select **Alternative B** for this line, you can win **7 ECU or 3.5 ECU**. Your payment depends on the decision done by the Participant 2 which you were associated with in sub-part 1 of this part of the experiment (the most recent task you completed). Payment would be determined as follows:
  - If Participant 2 chooses **Left**, you earn **7 ECU**.
  - If Participant 2 chooses **Right or Middle**, you earn **3.5 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.

**Social ambiguity - trust game**

You will now read the instructions for Part 3 of the experiment. Part 3 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.



## First stage

### Instructions for the first sub-part of Part 3

In this part of the experiment, you are again randomly paired with another participant. We call this new person Participant 2. However, this Participant 2 is **a different person** than the ones you were paired with in the previous parts of the experiment. You will never be informed of Participant 2's identity, nor will Participant 2 be informed of your identity. Depending on your decision, your payment may or may not depend on Participant 2's decision.

Your decision in this sub-section will be to choose an action between the **Left or Right** possibilities. Participant 2 receives 5 euros. Participant 2 decides where he or she would prefer to spend the 5 euros between one of the following options: **an Amazon voucher, a Google Play voucher or an Apple Store voucher**. You will not be informed of Participant 2's decision until the end of the experiment. If you chose **Left**, you will receive a sure payment, and Participant 2's decision does not affect your payment. If you choose **Right**, your payment is determined by Participant 2's decision. Participant 2 knows that your payment may or may not depend on their decision. However, Participant 2 does not know how his or her decision is associated with your payment.

A numerical example of possible payments for this part of the experiment can be summarized as follows:

- If you choose **Left**, you receive **30 ECU** for sure.
- If you choose **Right**, your payment depends on the decision of Participant 2, as follows:
  - If Participant 2 chooses an **Amazon voucher**, you receive **45 ECU**.

- If Participant 2 chooses a **Google Play voucher**, you receive **30 ECU**.
- If Participant 2 chooses an **Apple Store voucher**, you will receive **24 ECU**.

### Example

Suppose you decide to choose the **Right** action and Participant 2 prefers to spend his or her 5 euros on an **Amazon voucher** (remember that you will not be informed of Participant 2's decision until you receive the payment for the experiment).

Below you can see in **orange** the payment (in ECU) you will get in this scenario. If this decision is chosen randomly for the payment, you will earn 45 ECU.

- If you choose **Left**, you will receive **30 ECU** for sure.
- If you choose **Right**, your payment depends on Participant 2's decision, as follows:
  - If Participant 2 chooses an **Amazon voucher**, you receive **45 ECU**.
  - If Participant 2 chooses a **Google Play voucher**, you receive **30 ECU**.
  - If Participant 2 chooses an **Apple Store voucher**, you will receive **24 ECU**.

### **Second stage**

#### Instructions for the second sub-part of Part 3

In the second and final sub-part of this part of the experiment, you will choose between several options. The options will be presented in 12 tables (see an example of the table below). Each row represents one option. For each option, you will be asked to indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between an **Amazon voucher**, a **Google Play voucher**, or an **Apple Store voucher**. Alternative B changes from table to table, but it is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
45	A1	B1	You get <b>45 ECU</b> if Participant 2 chooses an <b>Amazon voucher</b> in the first sub-part of this part of the experiment or <b>24 ECU</b> if Participant 2 chooses a <b>Google Play</b> or an <b>Apple Store voucher</b>
42	A2	B2	
39	A3	B3	
36	A4	B4	
33	A5	B5	
30	A6	B6	
27	A7	B7	
24	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative

B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
39	A1	B1	You get <b>45 ECU</b> if Participant 2 chooses an <b>Amazon voucher</b> in the first sub-part of this part of the experiment or <b>24 ECU</b> if Participant 2 chooses a <b>Google Play</b> or an <b>Apple Store voucher</b>

- If you select **Alternative A** for this line, you earn **39 ECU**.
- If you select **Alternative B** for this line, you can earn **45 ECU** or **24 ECU**. Your payment depends on the decision of the Participant 2 you are associated with in the sub-part 1 of this part of the experiment (the most recent task you completed). The payment is determined as follows:
  - If Participant 2 chooses an **Amazon voucher**, you earn **45 ECU**.
  - If Participant 2 chooses either a **Google Play** or an **Apple Store voucher**, you earn **24 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.

## Betrayal aversion

You will now read the instructions for Part 4 of the experiment. Part 4 has two sub-parts. You will receive instructions for each sub-part before you make your decisions in each of them.

### First stage

#### Instructions for the first sub-part of Part 4

In this part of the experiment, you are again randomly paired with another participant. We call this new person Participant 2. However, this Participant 2 is a **different person** than the ones you were paired with in the previous parts of the experiment. You will never be informed of Participant 2's identity, nor will Participant 2 be informed of your identity. Your decision will affect Participant 2's payment. In addition, depending on your decision, your payment may or may not depend on Participant 2's decision.

Your decision in this section is to choose an action between the **Left or Right** options. Participant 2 decides between three options: **Left, Right or Middle**. You will not be informed of Participant 2's decision until you receive payment for the experiment. If you choose **Left**, you and Participant 2 receive a sure payment, and Participant 2's decision does not affect your payment. In contrast, if you choose **Right**, the payments for you and Participant 2 are determined by Participant 2's decision.

A numerical example of the possible payments for this part of the experiment can be summarized as follows:

- If you choose **Left**, you and Participant 2 receive **20 ECU** for sure.

- If you choose **Right**, your payment depends on Participant 2's decision, as follows:
  - If Participant 2 chooses **Left**, you receive **25 ECU** and Participant 2 receives **25 ECU**.
  - If Participant 2 chooses **Right**, you receive **20 ECU** and Participant 2 receives **28 ECU**.
  - If Participant 2 chooses **Middle**, you receive **18 ECU** and Participant 2 receives **32 ECU**.

### Example

Suppose you decide to choose the action **Right** and Participant 2 chooses the action **Right** (remember that you will not be informed of Participant 2's decision until you receive your payment).

Below you can see in **orange** the payment (in ECU) you will get in this scenario. If this decision is chosen at random for the payment, you win 20 ECU.

- If you choose **Left**, you and Participant 2 each get **20 ECU** for sure.
- If you choose **Right**, your payment depends on Participant 2's decision as follows:
  - If Participant 2 chooses **Left**, you receive **25 ECU** and Participant 2 receives **25 ECU**.
  - If Participant 2 chooses **Right**, you receive **20 ECU** and Participant 2 receives **28 ECU**.
  - If Participant 2 chooses **Middle**, you receive **18 ECU** and Participant 2 receives **32 ECU**.

## Second stage

### Instructions for the second sub-part of Part 4

In the second and final sub-part of this part of the experiment, you choose between several options. The options are presented in 12 tables (see an example of the table below). Each row represents an option. For each option, you must indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on the decision made by Participant 2 in the first sub-part of this part of the experiment. This means that the payment you can receive varies depending on what Participant 2 decided between **Left**, **Right** or **Middle** actions.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
25	A1	B1	You get <b>25 ECU</b> if Participant 2 chooses <b>Left</b> in the first sub-part of this part of the experiment or <b>18 ECU</b> if Participant 2 chooses <b>Right</b> or <b>Middle</b>
24	A2	B2	
23	A3	B3	
22	A4	B4	
21	A5	B5	
20	A6	B6	
19	A7	B7	
18	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

### Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
23	A1	B1	You get <b>25 ECU</b> if Participant 2 chooses <b>Left</b> in the first sub-part of this part of the experiment or <b>18 ECU</b> if Participant 2 chooses <b>Right or Middle</b>

- If you select **Alternative A** for this line, you earn **23 ECU**.
- If you select **Alternative B** for this line, you can earn **25 ECU or 18 ECU**. Your payment depends on the decision done by the Participant 2's that you were associated with in sub-part 1 of this part of the experiment (the most recent task you completed). Payment is determined as follows:
  - If Participant 2 chooses **Left**, you earn **25 ECU**.
  - If Participant 2 chooses **Right or Middle**, you earn **18 ECU**.

During this task, you will be able to use the back button to re-view the decisions that you and Participant 2 were asked to make in the first sub-part of this part of the experiment.



## Nature

In this part of the experiment, you must choose between several options. The options are presented in 12 tables (see an example of the table below). Each row represents an option. For each option, you must indicate whether you prefer Alternative A or Alternative B.

- **Alternative A** offers you a safe payment.
- **Alternative B** offers you a variable payment that depends on a random selection made by the computer. The computer chooses one of three options: **Left, Right or Middle**. Each option has an equal chance of being drawn. Alternative B changes from table to table, but is the same for all rows in a given table.

Example of a table with payments (in ECU):

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
20	A1	B1	You get <b>20 ECU</b> if the computer randomly chooses <b>Left</b> or <b>13 ECU</b> if the computer randomly chooses <b>Right or Middle</b>
19	A2	B2	
18	A3	B3	
17	A4	B4	
16	A5	B5	
15	A6	B6	
14	A7	B7	
13	A8	B8	

In each line you will be asked to indicate whether you prefer **Alternative A** or **Alternative B**.

Both alternatives are initially displayed in gray. You must click on one of the two alternatives to select it. Your selection will be highlighted in blue. You can change your selection at any time by clicking on the cell of the desired alternative, before moving on to the next screen. Once you confirm your decision, you cannot go back and change your previous decision.

If you select Alternative A for a given row, the computer will mark Alternative A for all previous rows (up to the first). Similarly, if you select Alternative

B for a line, the computer will mark Alternative B for all subsequent lines (up to the last one).

### Example

Suppose that the following option is randomly selected for payment:

Safe payment of alternative A	Alternative A	Alternative B	Variable payment of alternative B
20	A1	B1	You get <b>20 ECU</b> if the computer randomly chooses <b>Left</b> or <b>13 ECU</b> if the computer randomly chooses <b>Right or Middle</b>

- If you select **Alternative A** for this line, you win **20 ECU**.
- If you select **Alternative B** for this line, you can win **20 ECU or 13 ECU**. Your payment depends on which option the computer randomly selects. Remember that each option has the same chance of being drawn. The payment is determined as follows:

- If the computer selects **Left**, you win **20 ECU**.
- If the computer selects **Right or Middle**, you win **13 ECU**.

## 3.D Comparison of multi-stage and one stage approaches

We propose a multistage method in which the utility function and the probability weighting function are specified sequentially.<sup>13</sup> In this section, we compare our multi-stage approach with the one-stage approach in which the utility

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<sup>13</sup>In case of continuous valued source of uncertainty, we also allow to specify the distribution of beliefs only in the third stage (see Appendix 3.A).

and weighting functions are specified simultaneously. To that end we conduct parameter recovery and misspecification exercises (e.g. [Gao et al., 2020](#); [Kpegli et al., 2022](#); [Nilsson et al., 2011](#)).

### Simulated data

We consider six specifications resulting from the combination of two utility functions  $u(\cdot)$  and three weighting functions  $w(\cdot)$ .<sup>14</sup>

The two utility functions  $u(\cdot)$  are P(ower) (Eq. 3.16) and E(xponential) (Eq. 3.17):

$$U(z) = z^\alpha \tag{3.16}$$

$$u(z) = \frac{1 - \exp(-\alpha z)}{\alpha} \tag{3.17}$$

For the power utility,  $\alpha < 1$  (resp.  $\alpha > 1$ ) means concavity (resp. convexity) and  $\alpha = 1$  corresponds to the linear case. For the exponential utility,  $\alpha > 0$  (resp.  $\alpha < 0$ ) means concavity (resp. convexity) and  $\alpha \rightarrow 0$  corresponds to the linear case. To have a common measure of the utility curvature to facilitate comparisons, we adopt the following measure of the utility curvature over the range of outcomes  $[0, \bar{q}]$  ([Kpegli et al., 2022](#); [Abdellaoui et al., 2016](#))

$$\beta = \frac{1}{\bar{q}u(\bar{q})} \int_0^{\bar{q}} u(t)dt$$

with  $\beta > 0.5$  (resp.  $\beta < 0.5$ ) meaning concavity (resp. convexity) and  $\beta = 0.5$  corresponds to the linear case.

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<sup>14</sup>The vast majority of specifications in ambiguity studies rely on one of these six combination of utility and weighting functions (e.g. [Li et al., 2018](#); [Gutierrez and Kemel, 2021](#)).

The three weighting functions  $w(\cdot)$  are the specifications of GE87 (Eq. 3.18), P98 (Eq. 3.19) and CEG7 (Eq. 3.20)

$$W(P(E)) = \frac{\eta P(E)^\gamma}{\eta P(E)^\gamma + (1 - P(E))^\gamma} \quad (3.18)$$

$$W(P(E)) = \exp\left(-\eta\left(-\ln(P(E))\right)^\gamma\right) \quad (3.19)$$

$$W(P(E)) = \gamma P(E) + \eta \quad (3.20)$$

with  $\gamma > 0$ ,  $\eta > 0$ .

For the specification of CEG7, the pessimism and insensitivity indexes are given by  $1 - \eta - 2\gamma$  and  $1 - \eta$ , respectively (e.g. Abdellaoui et al., 2011a). For the specification of P98, the parameters  $\eta$  and  $\gamma$  are an index of pessimism and an anti-index of likelihood insensitivity, respectively (Abdellaoui et al., 2021a). For the specification of GE87, the parameters  $\eta$  and  $\gamma$  are an anti-index of pessimism and an anti-index of likelihood insensitivity, respectively (e.g. Gonzalez and Wu, 1999).<sup>15</sup> Insensitivity makes weighting the function flatter in the range of intermediate subjective probability and steeper near the ends. Hence, the weighting function follows an inverse S-shaped. Pessimism determines the elevation of the weighting function.

The calibration of lotteries follows the outcomes in Li et al. (2019, 2020) and the ones from our experiment. We consider 12 lotteries  $L = (x, y, E, E^c)$  that results from the combination of three pairs of outcomes  $(x, y) = (10, 0)$ ,  $(15, 0)$ , and  $(15, 8)$  and, four events  $E = E_1, E_2, E_3$  and  $E_{12}$ .

**Simulated data 1: P & GE87.** We simulate data for 250 ( $s = 1, 2, \dots, 250$ ) hypothetical subjects. For each subject  $s$ , we draw the parameters of weighting function  $\eta$  and  $\gamma$  of GE87 from  $\mathcal{U}(0.1, 1.5)$ . We draw the parameter of the power

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<sup>15</sup>For this specification, the crossing point is given by  $W(p^*) = p^* = \frac{1}{1+\eta^{\frac{1}{\gamma-1}}}$  and,  $W(\cdot)$  is well defined over all the probability range including the boundary  $W(0) = 0$  and  $W(1) = 1$ .

utility function  $\alpha$  from an uniform distribution  $\mathcal{U}(0.1, 2.1)$  (e.g. Abdellaoui et al., 2008; Spiliopoulos and Hertwig, 2019). For the beliefs, we draw  $P(E_1)$  and  $P(E_2)$  from  $U(0, 1)$  and keep only the cases where  $P(E_1) + P(E_2) < 1$ . We derive then  $P(E_3) = 1 - P(E_1) - P(E_2)$ . Then, the simulated  $\alpha$ ,  $\eta$ ,  $\gamma$ ,  $P(E_1)$ ,  $P(E_2)$ , and  $P(E_3)$  are plugged into the RDU formulas to generate *noiseless* certainty equivalents of the 12 lotteries. In the last step of the data generation process, we draw 12 random values from a normal distribution with expected value 0 and standard deviation  $\sigma = 0.25$ , which we add to the previously generated 12 *noiseless* certainty equivalents to obtain the *noisy* ones.

**Simulated data 2: P & P98.** similar as simulated data 1, but in this case the two-parameter weighting function of P98 is used. We draw  $\eta$  and  $\gamma$  of P98 from  $\mathcal{U}(0.1, 1.5)$ .

**Simulated data 3: P & CEG7.** Similar as simulated data 2, but in this case the two-parameter weighting function of CEG7 is used. We draw  $\eta$  and  $\gamma$  of CEG7 from  $\mathcal{U}(0, 1)$ .

**Simulated data 4: E & GE87.** Similar as simulated data 1, but in this case the CARA utility function is used. We draw  $\alpha$  from  $\mathcal{U}(-0.15, 0.15)$ .

**Simulated data 5: E & P98.** Similar as simulated data 2, but in this case the CARA utility function is used. We draw  $\alpha$  from  $\mathcal{U}(-0.15, 0.15)$ .

**Simulated data 6: E & CEG7.** Similar as simulated data 3, but in this case the CARA utility function is used. We draw  $\alpha$  from  $\mathcal{U}(-0.15, 0.15)$ .

### Simulation results

We conduct two types of estimations for each approach by using the six simulated data. In the first type of estimation, we estimate by using the correct specification of the utility and weighting functions that are behind the simulated data. This first type of estimation corresponds to the parameter recovery exercise in which

the purpose is to assess the ability of the two approaches to identify the targeted parameters (Murphy and ten Brincke, 2018; Gao et al., 2020; Kpegli et al., 2022).

In the second type of estimation, we make the estimation on each of the simulated data by assuming the 5 other specifications of utility and weighting functions that are not behind the simulated data. This second type of estimation corresponds to the misspecification exercise in which the purpose is to assess the extend to which a wrong specification of utility and weighting functions will affect the estimation results (Gao et al., 2020; Kpegli et al., 2022).

Table 3.D.1 provides the average of the squared difference between the true values of the parameters and their estimated values over the 250 hypothetical subjects. Table 3.D.1 shows evidence of the fact that the two-stage approach leads to smaller error than the one-stage approach. These results can be explained by the use of a semi-parametric method in the first stage of our method. The first stage provides a semi-parametric estimates in which the utility function is specified and no parametric assumption is made on event weights. Previous simulation results (e.g. Kim et al., 2007; Mahmoud et al., 2016; Kpegli et al., 2022) have shown that semi-parametric methods are preferable to parametric methods due to misspecification issues. Furthermore, the two-stage approach based on the power utility function in combination with the two-parameter weighting function of GE87 leads to smaller errors.

Table 3.D.1: Result of parameter recovery and misspecification exercises

	Specification		one-stage				two-stage			
	$u()$	$w()$	$u()$	$w()$	$P()$	pool	$u()$	$w()$	$P()$	pool
Parameter recovery										
1	E	CEG87	0.0010	0.0012	0.0096	<b>0.0039</b>	0.0010	0.0012	0.0096	<b>0.0039</b>
2	E	GE87	0.0011	0.0012	0.0022	<b>0.0015</b>	0.0011	0.0012	0.0020	<b>0.0014</b>
3	E	PR98	0.0011	0.0012	0.0031	<b>0.0018</b>	0.0011	0.0013	0.0028	<b>0.0017</b>
4	P	CEG87	0.0005	0.0007	0.0189	<b>0.0067</b>	0.0005	0.0007	0.0189	<b>0.0067</b>
5	P	GE87	0.0004	0.0006	0.0034	<b>0.0015</b>	0.0004	0.0006	0.0026	<b>0.0012</b>
6	P	PR98	0.0005	0.0007	0.0037	<b>0.0016</b>	0.0005	0.0007	0.0033	<b>0.0015</b>
<b>7</b>	<b>pool</b>	<b>pool</b>	<b>0.0008</b>	<b>0.0009</b>	<b>0.0068</b>	<b>0.0028</b>	<b>0.0008</b>	<b>0.0009</b>	<b>0.0065</b>	<b>0.0027</b>
Misspecification										
1	E	CEG7	0.0028	0.0069	0.0070	<b>0.0056</b>	0.0029	0.0070	0.0070	<b>0.0056</b>
2	E	GE87	0.0023	0.0064	0.0100	<b>0.0062</b>	0.0026	0.0059	0.0083	<b>0.0056</b>
3	E	P98	0.0026	0.0070	0.0076	<b>0.0057</b>	0.0028	0.0067	0.0070	<b>0.0055</b>
4	P	CEG7	0.0017	0.0018	0.0061	<b>0.0032</b>	0.0017	0.0018	0.0061	<b>0.0032</b>
5	P	GE87	0.0018	0.0021	0.0090	<b>0.0043</b>	0.0018	0.0019	0.0076	<b>0.0038</b>
6	P	P98	0.0019	0.0020	0.0074	<b>0.0038</b>	0.0019	0.0018	0.0068	<b>0.0035</b>
<b>7</b>	<b>pool</b>	<b>pool</b>	<b>0.0022</b>	<b>0.0044</b>	<b>0.0078</b>	<b>0.0048</b>	<b>0.0023</b>	<b>0.0042</b>	<b>0.0071</b>	<b>0.0045</b>
Parameter recovery and Misspecification										
1	E	CEG7	0.0019	0.0040	0.0083	0.0048	0.0020	0.0041	0.0083	<b>0.0048</b>
2	E	GE87	0.0017	0.0038	0.0061	0.0038	0.0018	0.0035	0.0052	<b>0.0035</b>
3	E	P98	0.0018	0.0041	0.0053	0.0038	0.0019	0.0040	0.0049	<b>0.0036</b>
4	P	CEG7	0.0011	0.0012	0.0125	0.0049	0.0011	0.0012	0.0125	<b>0.0049</b>
5	P	GE87	0.0011	0.0014	0.0062	0.0029	0.0011	0.0012	0.0051	<b>0.0025</b>
6	P	P98	0.0012	0.0013	0.0056	0.0027	0.0012	0.0012	0.0051	<b>0.0025</b>
<b>7</b>	<b>pool</b>	<b>pool</b>	<b>0.0015</b>	<b>0.0026</b>	<b>0.0073</b>	<b>0.0038</b>	<b>0.0015</b>	<b>0.0026</b>	<b>0.0068</b>	<b>0.0036</b>





## Chapter 4

# Against the Odds! The Tradeoff Between Risk and Incentives is Alive and Well

This chapter is based on a paper co-authored with Brice Corgnet, Roberto Hernan-Gonzalez and Adam Zylbersztein

## **Abstract**

The risk-incentives tradeoff (RIT) is a fundamental result of principal-agent theory. Yet, empirical evidence has been elusive. This could be due to a lack of robustness of the theory outside of the standard expected utility framework (EUT) or to confounding factors in the empirical tests. First, we theoretically study the existence of RIT under alternative theories: Rank-Dependent Utility (RDU) and Mean-Variance-Skewness (MVS). We show that RIT is remarkably robust under RDU, but not under MVS. Second, we use a novel experimental design that eliminates confounding factors and find evidence for RIT even in the case of risk-seeking agents, which is a distinct prediction of RDU. Our results provide support for the risk-incentives tradeoff and suggest that it applies to a broad range of situations including cases in which agents are risk-seeking (e.g., executive compensation).

**Keywords:** Risk-Incentives Tradeoff, Rank-Dependent Utility, Mean-Variance-Skewness, Experiments.

**JEL codes :** C92, D23, D86, M54

## 4.1 Introduction

Principal-agent theory has played a key role in understanding human behavior across disciplines ranging from finance, accounting, strategy and political science to neuroeconomics (Jensen and Meckling, 1976; Lambert, 2001; Miller, 2005; Brocas and Carrillo, 2008; Dranove et al., 2017). In economics, the principal-agent framework is a cornerstone of numerous fields including the theory of incentives. A central result in this literature is the existence of a tradeoff between providing incentives to foster the effort of risk-averse agents and protecting them against risk (Borch, 1962; Mirrlees, 1974; Holmström, 1979; Shavell, 1979; Milgrom and Roberts, 1992; Laffont and Martimort, 2002; Bolton and Dewatripont, 2005; Gibbons and Roberts, 2013). The risk-incentives tradeoff (RIT, henceforth) emerges because providing steeper incentives implies strengthening the link between output and rewards which, in turn, exposes agents to a greater risk whenever output is a noisy measure of effort. As a result, the optimal contract typically incorporates a variable pay that incentivizes the agent to exert effort and a fixed pay that partially hedges the agent against output shocks. These types of contracts are widespread, and unsurprisingly RIT has been applied to a wide variety of economic settings ranging from sharecropping to medical insurance (e.g., Zeckhauser, 1970; Stiglitz, 1974) and compensation setting in firms (Gibbons and Roberts, 2013).

Although the rationale for RIT is appealing, empirical evidence remains scarce (Garen, 1994; Prendergast, 2002; Lazear and Oyer, 2013). A glimpse of hope has recently come from laboratory studies reporting some evidence for RIT (Corgnet and Hernan-Gonzalez, 2019; Chowdhury and Karakostas, 2020). These lab studies control for possible confounding factors such as organizational hierarchies, implicit incentives or tacit knowledge that are notoriously difficult to control for in the field. Yet, the size of the effect reported in Corgnet and

Hernan-Gonzalez (2019) and Chowdhury and Karakostas (2020) remains small.<sup>1</sup> Furthermore, recent evidence from laboratory experiments by Dohmen et al. (2021) is not consistent with RIT since the presence of output risk does not lead agents to demand weaker incentive schemes, that is lower piece rates.

In this paper, we use theory and experiments to investigate whether the limited evidence for RIT is due to a lack of robustness of the underlying theory or to the confounding factors in empirical tests. Principal-agent models are notorious for their lack of tractability (Grossman and Hart, 1983; Rogerson, 1985) which has led researchers to focus on particular specifications such as the LEN (Linear Exponential Normal) model (see Milgrom and Roberts, 1992; Varian, 1992; Laffont and Martimort, 2002; Bolton and Dewatripont, 2005; Gibbons and Roberts, 2013; Besanko et al., 2017). In this model, the risk-neutral principal proposes the agent a linear contract composed of a fixed pay and a share of output. The risk-averse agent who maximizes expected utility (assumed to be exponential) then decides whether to accept the contract or not. In case of acceptance, the agent chooses a level of effort under the agreed-upon contract. Even though the principal cannot observe the level of effort, she can observe the final output, which is impacted by an additive (normally distributed) shock.

The classical version of RIT is derived assuming Expected Utility Theory (EUT, henceforth) and the LEN specification. Although the LEN model has often been discussed and defended by contract theorists on the basis of tractability and realism (Holmstrom and Milgrom, 1987; Diamond, 1998; Laffont and Martimort, 2002; Bolton and Dewatripont, 2005; Carroll, 2015; Holmström, 2017), little is known about the robustness of RIT in non-EUT settings. This led us to study the robustness of RIT to alternative theories that allow for distortions of probabilities

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<sup>1</sup>Corgnet and Hernan-Gonzalez (2019) report a 8.1% (Cohen's  $d = 0.34$ ) decrease in the piece rate value in their noise treatment as compared to a noise-free baseline. A similar decrease (12.7%) is also found by Chowdhury and Karakostas (2020), notwithstanding their EUT-based prediction of a one-third decrease.

(Rank-Dependent Utility theory, RDU, henceforth, [Quiggin, 1982](#)) and an explicit preference for skewness (Mean-Variance-Skewness, MVS, henceforth, [Spiliopoulos and Hertwig, 2019](#)). Risk attitudes have been traditionally characterized by the curvature of the utility function. However, non-EUT models characterize risk attitudes along different dimensions. For example, overall risk attitudes under RDU stem both from utility risk attitudes (i.e., the curvature of the utility function) and probability risk attitudes (i.e., probability weighting). Under MVS, overall risk attitudes depend on agents' preferences for variance and skewness.

We theoretically show that RIT is pervasive under RDU because it occurs not only when agents are overall risk-averse, but also when they are risk-neutral or risk-seeking. For example, RIT happens when overall risk-neutral or risk-seeking agents are moderately risk-seeking in the probability domain (i.e., they moderately overweight probabilities) and risk-averse in the utility domain (i.e., their utility function is concave). This result suggests that RIT might be more widespread than predicted by EUT. Yet, this observation contrasts with the limited empirical evidence for RIT.

In line with existing empirical evidence, MVS provides a setup in which RIT is less pervasive than under EUT. This happens because RIT does not occur for all risk-averse agents (as in EUT) and disappears for those that exhibit a preference for positive skewness. Furthermore, the optimal variable pay (fixed pay) can increase (decrease) with risk, which is what we refer to as reversed RIT. This occurs when the distribution of the shock is positively skewed and the aversion to variance is less pronounced than the value of skewness for a risk-averse agent exhibiting MVS preferences.

These theoretical results show that non-EUT models provide reasons for both hope and despair regarding the robustness of RIT. To test the predictions of the alternative theories, we develop a novel experimental testbed for RIT that

eliminates confounding factors. We focus on agents' decisions by eliciting the minimum fixed pay they are willing to accept for different values of the variable pay. As principals do not make contractual decisions (see, e.g., [Dohmen et al., 2021](#)) we can discard confounding factors related to their risk attitudes. This design also eliminates any asymmetry of information between the principal and the agent whose preferences are unknown. We also use monetary effort instead of a real-effort task (see e.g., [Anderhub et al., 2002](#); [Keser and Willinger, 2007](#); [Gächter and Königstein, 2009](#)) to discard other confounding factors often present in experimental data such as social motives and reference points (see [Corgnet and Hernan-Gonzalez, 2019](#)), as well as more general ones such as organizational hierarchies, delegation, implicit incentives, tacit knowledge, uncertainty and market dynamics ([Jensen and Meckling, 1995](#); [Raith, 2008](#); [Adams, 2005](#); [DeVaro and Kurtulus, 2010](#); [Edmans et al., 2012](#); [He et al., 2014](#)). We do not mean to underplay the importance of these factors but rather aim at implementing a testbed for the basic mechanism underlying RIT. It follows that a lack of evidence supporting RIT in our setup would be a definitive blow for the theory. To ensure that our design can be effectively used to study RIT, we analyze a BareBone (BB, henceforth) principal-agent model.

Our experiment shows that RIT is remarkably robust and more pervasive than predicted by EUT. In line with RDU but in contrast with EUT and MVS, RIT arises even when agents are risk-seeking. This finding has direct implications for various applications of the theory in which agents are risk-seeking, as is the case of executive compensation ([Garen, 1994](#); [Edmans and Gabaix, 2011](#); [Edmans et al., 2012, 2017](#)) and high-pay workers ([Ma et al., 2019](#)). Risk-seeking is likely to be pervasive in these cases because of selection effects ([MacCrimmon and Wehrung, 1990](#); [Brenner, 2015](#)). Furthermore, executive packages are often positively skewed due to, for example, the use of stock options ([Edmans et al.,](#)

2017). As a result, an agent who appears to be risk-averse when rewarded according to a linear contract might be risk-seeking when facing a skewed compensation package.

The remainder of the paper is organized as follows. Section 4.2 presents the theoretical models for RIT under EUT, RDU and MVS. In Section 4.3, we describe the experimental design. Section 4.4 presents the results of the experiment and Section 4.5 concludes.

## 4.2 Model

### 4.2.1 Standard setup and predictions

#### 4.2.1.1 Assumptions

A risk-neutral principal offers a contract to an agent to perform a task. If the agent does not accept the contract, he receives an outside option  $y_0$ . If he accepts the contract, then he has to exert effort  $e$  to produce output  $z = z(e)$ , where  $z = e + \tilde{\epsilon}$  and  $\tilde{\epsilon}$  is a random variable. Thus, there is a noisy relationship between effort and output. The cost of effort function  $C(e)$  is increasing and convex. The principal observes the level of output, but not the underlying level of effort. The principal maximizes her revenue  $\theta z$ , where  $\theta > 0$  denotes the marginal product of effort. To ease exposition, we consider a binary shock model (see e.g., [Milgrom and Roberts, 1992](#)), which is often used in empirical tests of the theory (see [Corgnet and Hernan-Gonzalez, 2019](#); [Dohmen et al., 2021](#)).<sup>2</sup> In Appendix 4.C we further show that our predictions qualitatively hold if we consider a continuous shock. In particular, this includes the special case of the normally distributed shock used in the LEN model (see e.g., [Milgrom and Roberts, 1992](#);

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<sup>2</sup>[Milgrom and Roberts \(1992\)](#) and [Laffont and Martimort \(2002\)](#) derive fundamental results in the theory of incentives using a model with binary shocks.

Bolton and Dewatripont, 2005). Below, we outline our assumptions.

**Assumption 0 (A0: Binary shock).** The shock  $\tilde{\epsilon}$  is a binary random variable defined as  $\tilde{\epsilon} = (-\epsilon, \frac{1-p}{p}\epsilon; 1-p, p)$ ,  $\epsilon \geq 0$  and  $p \in (0, 1]$  so that  $E(\tilde{\epsilon}) = 0$  and  $V(\tilde{\epsilon}) = \frac{1-p}{p}\epsilon^2$ .<sup>3</sup>

**Assumption 1 (A1: Risk-neutral principal).** The principal is risk-neutral and maximizes the expected payoff.

**Assumption 2 (A2: Linear contracts).** The principal proposes to the agent a contract  $(\alpha, \beta)$  that is linear in output and pays  $y = \alpha + \beta\theta z$ , where  $\alpha \in \mathbb{R}$  is the fixed pay and  $\beta > 0$  the variable pay.<sup>4</sup>

**Assumption 3 (A3: CARA utility).** The agent's utility function is  $u(x) = \frac{1-\exp(-rx)}{r}$  for  $r \neq 0$  and  $u(x) = x$  for  $r = 0$ .

With Assumption 3, we define utility risk attitudes in terms of the shape of the utility function. By contrast, the overall risk attitudes of the agent depend on his overall valuation of the contract which is only partly captured by the utility function. We define utility risk attitudes and overall risk attitudes as follows.

**Definition 1 (Utility risk attitudes).** Utility risk-aversion [risk-neutrality] (risk-seeking) corresponds to a concave,  $r > 0$  [linear,  $r = 0$ ] (convex,  $r < 0$ ) utility function.

**Definition 2 (Overall risk attitudes).** An agent exhibits overall risk-aversion [risk-neutrality] (risk-seeking) whenever his risk premium for accepting the contract is positive [null] (negative).

Definition 2 is a general (model-free) definition of risk attitudes due to Pratt (1971) and Arrow (1964). Under EUT, overall risk attitudes and utility risk attitudes always coincide. However, this is not the case under RDU or MVS

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<sup>3</sup>We consider continuous random shocks in Appendix 4.C.

<sup>4</sup>We assume linear contracts because they are theoretical tractable and empirically relevant (e.g., Holmström, 2017). Also, we do not require  $\beta \in [0, 1]$  (e.g., Milgrom and Roberts, 1992; Laffont and Martimort, 2002). Principal could then set  $\beta > 1$  and  $\alpha < 0$ , especially for risk-seeking agent.



where utility risk-aversion (utility risk-seeking) does not necessarily imply overall risk-aversion (risk-seeking).

In this paper, we consider the standard assumption of a concave utility function (i.e., Assumption 3' which is equivalent to Assumption 3 with  $r > 0$ ), unless stated otherwise.

**Assumption 3' (A3': Utility risk-averse agent).** The agent is utility risk-averse in the sense of  $r > 0$ .

For the sake of concision, hereafter we use the term risk attitudes (risk-aversion, risk-seeking or risk-neutrality) to refer to overall risk attitudes.

**Assumption 3'' (A3'': Relative risk-aversion).** The relative risk-aversion index evaluated at  $x$  is less than 1, that is  $-\frac{u''(x)}{u'(x)}x = rx < 1$ .

**Assumption 4 (A4: Public knowledge of the agent's risk-attitudes).** The principal knows the agent's risk attitudes.

**Assumption 5 (A5: Quadratic cost).** The cost of effort function is:  $C(e) = \psi e^2$  with  $\psi > 0$ .

Given these assumptions, the compensation associated with the contract, which is the random wage net of the cost of effort, can be described as a lottery  $L$ :

$$L := \left( \alpha + \beta\theta \left( e + \frac{1-p}{p}\epsilon \right) - \psi e^2, \alpha + \beta\theta(e - \epsilon) - \psi e^2; p, 1-p \right) \quad (4.1)$$

where the first three moments (i.e., mean  $E$ , variance  $V$  and skewness  $S$ ) are:

$$E(L) = \alpha + \beta\theta e - \psi e^2, \quad V(L) = \frac{1-p}{p} \beta^2 \theta^2 \epsilon^2 \quad \text{and} \quad S(L) = \frac{1-p}{p} \frac{1-2p}{p} \beta^3 \theta^3 \epsilon^3$$

Note that varying  $\epsilon$  does not affect the expected value of the lottery ( $E(L)$ ) but impacts variance ( $V(L)$ ) and skewness ( $S(L)$ ). By contrast, varying the fixed

pay ( $\alpha$ ) impacts the expected value of the lottery without affecting the other two moments. Finally, the variable pay ( $\beta$ ) impacts all three moments.

#### 4.2.1.2 Model specification under EUT, RDU and MVS

We first determine how the agent evaluates lottery  $L$  based on three different specifications: EUT, RDU and MVS.

##### EUT

Under EUT, the agent values the contract by its expected utility:

$$EU(L) = pu\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1-p)u\left(\alpha + \beta\theta(e - \epsilon) - \psi e^2\right) \quad (4.2)$$

In this model,  $\frac{\partial EU(L)}{\partial \epsilon} < 0$  as long as the utility function  $u(\cdot)$  is concave.<sup>5</sup>

##### RDU

Under RDU, the agent distorts probabilities using a probability weighting function  $w(p)$ , which is a strictly increasing function from  $[0, 1]$  to  $[0, 1]$  with  $w(0) = 0$  and  $w(1) = 1$ . Hence, risk attitudes not only stem from utility curvature (as in EUT), but also from probability weighting. Below, we define probability risk-aversion, risk-neutrality and risk-seeking.

**Definition 3 (Probability risk attitudes).** Under RDU, an agent exhibits probability risk-aversion [risk-neutrality] (risk-seeking) for a specific probability  $p$  if  $w(p) < p$  [ $w(p) = p$ ] ( $w(p) > p$ ).

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<sup>5</sup>By contrast, (2) increases with (is unaffected by) the shock magnitude if  $r < 0$  ( $r = 0$ ).

The agent's valuation of the contract then becomes:

$$\begin{aligned}
 RDU(L) = & w(p)u\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + \\
 & (1-w(p))u\left(\alpha + \beta\theta(e - \epsilon) - \psi e^2\right)
 \end{aligned} \tag{4.3}$$

For a probability risk-seeking agent, the valuation of the contract in (4.3) has an inverted J-shape with respect to  $\epsilon$  (see Figure 4.2.1). To grasp the intuition, consider an arbitrarily small shock ( $\epsilon_0$ ) making the agent approximately utility risk-neutral, thus exhibiting a linear utility function. In that case  $\frac{\partial RDU(L)}{\partial \epsilon} = w(p)\beta\theta\frac{1-p}{p} - (1-w(p))\beta\theta > 0 \iff w(p) > p$ . Hence, for that level of shock the agent is necessarily risk-seeking because he is both utility risk-neutral and probability risk-seeking. That is, for small shocks, risk attitudes are driven by probability weighting rather than by the curvature of the utility function. As shown in Figure 4.2.1, the valuation of the lottery ( $RDU(L)$ ) at  $\epsilon_0$  is above the utility of the expected value of the lottery ( $u(E[L])$ ), implying a negative risk premium and hence a risk-seeking agent.

However, as the shock increases in magnitude, utility risk-aversion increases up to a point in which utility risk-aversion exactly offsets probability risk-seeking, making the agent risk-neutral. This level of shock (denoted  $\epsilon_1$  in Figure 4.2.1) corresponds to a null risk premium associated with the contract lottery (i.e.,  $RDU(L) = u(E[L])$ ). Between  $\epsilon_0$  and  $\epsilon_1$ , there is also a level of shock (denoted  $\epsilon^*$  in Figure 4.2.1) for which the negative effect of increasing the shock magnitude due to utility risk-aversion is exactly equal to the positive effect due to probability risk-seeking. For shocks greater than  $\epsilon_1$ , a probability risk-seeking agent is risk-averse (i.e.,  $RDU(L) < u(E[L])$ ).

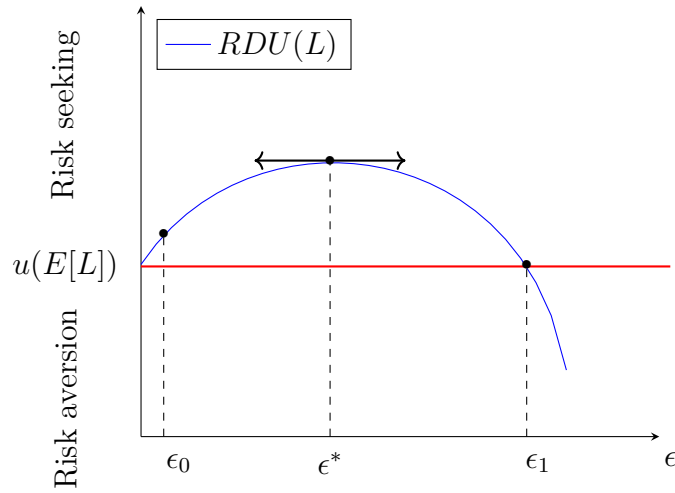


Figure 4.2.1: Valuation of the contract by a probability risk-seeking RDU agent (equation (4.3)) as a function of the shock magnitude.

**MVS** Under MVS, the agent evaluates a lottery according to its mean, variance and skewness (Kraus and Litzenberger, 1976; Spiliopoulos and Hertwig, 2019) as follows:

$$MVS(L) = E(L) + a_v V(L) + a_s S(L) \quad (4.4)$$

where  $a_v$  is a parameter that captures attitudes towards variance and  $a_s$  captures attitudes towards skewness. In line with the LEN framework and with empirical evidence (Kraus and Litzenberger, 1976; Spiliopoulos and Hertwig, 2019), we assume that the agent is averse to variance (i.e.,  $a_v < 0$ ) and seeks positive skewness (i.e.,  $a_s > 0$ ). Furthermore, in contrast to EUT, we explicitly consider following the literature (e.g., Spiliopoulos and Hertwig, 2019; Mitton and Vorkink, 2007) that  $a_v$  and  $a_s$  are unrelated.<sup>6</sup>

<sup>6</sup>Under EUT,  $a_v$  and  $a_s$  are linked via utility function. The third order Taylor approximation of the certainty equivalent incorporates attitudes towards variance and skewness due to the second and third derivatives of the utility function.

An MVS agent exhibits risk-aversion for any negatively-skewed lottery. For positively-skewed lotteries, he is risk-seeking (risk-averse) [risk-neutral] if  $-\frac{a_v}{a_s} < \tau_N(\beta, \epsilon)$  ( $-\frac{a_v}{a_s} > \tau_N(\beta, \epsilon)$ ) [ $-\frac{a_v}{a_s} = \tau_N(\beta, \epsilon)$ ], where  $\tau_N(\beta, \epsilon) := \frac{S(L)}{V(L)} = \frac{1-2p}{p}\beta\theta\epsilon$ . For any  $p \geq 1/2$ , we have  $\tau_N(\beta, \epsilon) \leq 0$  so that the agent is systematically risk-averse since  $-\frac{a_v}{a_s} > 0$ .

In the presence of aversion to variance ( $a_v < 0$ ) and preference for positive skewness ( $a_s > 0$ ), the valuation function (4.4) is J-shaped with respect to  $\epsilon$  when  $p < 1/2$  (see Figure 4.2.2). The intuition behind Figure 4.2.2 follows from the fact that for small (large) levels of the shock, the variance of  $L$  is larger (smaller) than its skewness. Hence, for a small level of shock (say  $\epsilon_0$ ), the agent is necessarily risk-averse since the aversion to variance outbalances the preference for positive skewness. This gives rise to a positive risk premium: the valuation of the lottery ( $MVS(L)$ ) lies below its expected value. For a sufficiently high level of shock magnitude ( $\forall \epsilon > \epsilon_1$  in Figure 4.2.2), the agent necessarily exhibits risk-seeking since the preference for positive skewness outbalances the aversion to variance. At some level of the shock (denoted  $\epsilon_1$  in Figure 4.2.2), the two effects cancel out so that the agent is risk-neutral with a null risk premium ( $MVS(L)=E[L]$ ). Finally, Figure 4.2.2 also features a level of shock  $\epsilon^*$  for which the negative effect of increasing the shock magnitude due to aversion to variance is exactly equal to the positive effect of increasing the shock magnitude due to the preference for positive skewness.

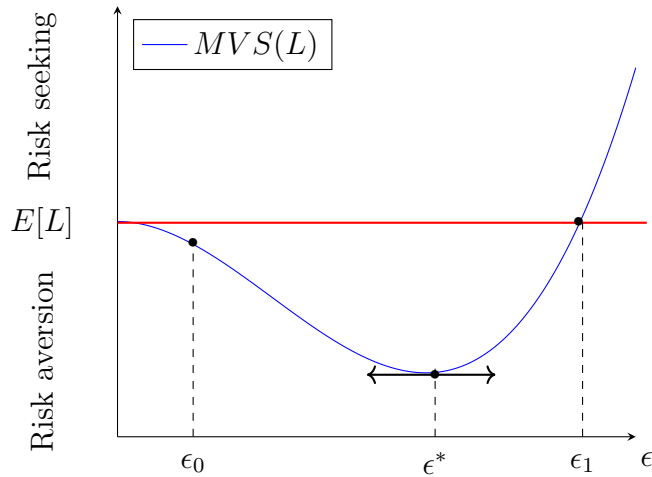


Figure 4.2.2: Valuation of the contract by an averse-to-variance ( $a_v < 0$ ) and preference-for-positive-skewness ( $a_s > 0$ ) MVS agent (equation (4.4)) as a function of the shock magnitude when  $p < 1/2$ .

#### 4.2.1.3 RIT predictions

For each theory, we can characterize the optimal contract: the fixed pay ( $\alpha^*$ ) and the variable pay ( $\beta^*$ ) proposed by the principal, as well as the optimal level of effort  $e^*$  provided by the agent. We provide the corresponding proofs in Appendix 4.A. Here, we focus on characterizing the conditions of existence of RIT for the optimal contract. Definition 4 below characterizes RIT and reversed RIT. RIT occurs when increasing the variable pay generates a trade-off between desirable and undesirable consequences, thus forcing the principal to set a compensation contract with an intermediate intensity of incentives (i.e.,  $0 < \beta^* < 1$ ). On the positive side, increasing the variable pay incentivizes the agent to exert more effort. On the negative side, it increases the level of risk faced by the agent because it makes his pay more sensitive to output shocks. It follows that under RIT an increase in the magnitude of the output shock requires the principal to set a contract that limits the agent's exposure to the shock. This is achieved by decreasing the variable pay while increasing the fixed

pay to ensure the agent is willing to accept the contract (see Definition 4i).

**Definition 4 (RIT and Reversed RIT)**

- i) RIT corresponds to the case in which the optimal variable pay (fixed pay) decreases (increases) in the output shock  $\epsilon$  for a given  $p$ .
- ii) Reversed RIT corresponds to the case in which the optimal variable pay (fixed pay) increases (decreases) in the output shock  $\epsilon$  for a given  $p$ .
- iii) No RIT corresponds to the case in which there is no relationship between the optimal pay and the output shock  $\epsilon$  for a given  $p$ .

Under EUT, RIT always occurs for risk-averse agents (Assumption 3'). For risk-neutral agents, there is no RIT because fixed pay and variable pay do not vary with the shock (see Definition 4iii). For risk-seeking agents, RIT is reversed because the optimal variable (fixed) pay increases (decreases) with the shock size. These results are standard in the LEN model (see e.g., [Milgrom and Roberts, 1992](#)). We nonetheless provide the details of the proofs in Appendix 4.A (Proposition A1) for the case of a binary shock and for the case of a general utility function and a continuous shock (see Propositions B1 to B3 and Proposition C1 in Appendices 4.B and 4.C).

Under RDU, RIT is even more pervasive than under EUT. As in EUT, it occurs whenever agents are risk-averse (see Proposition A2 in Appendix 4.A) given that the valuation function (4.3) is decreasing in the shock magnitude. In contrast to EUT, it can also occur when agents are risk-neutral or risk-seeking (see Proposition A3 in Appendix 4.A). In the case of a risk-seeking agent who overweighs probabilities, the value of the contract in (4.3) increases with fixed pay  $\alpha$  (irrespective of risk attitudes) and is inverse J-shaped with respect to the shock size (see Figure 4.2.1). For a small shock ( $\epsilon_0$  in Figure 4.2.1), (4.3) is increasing in the shock magnitude. In that case, the principal can offer the

agent a lower fixed pay while keeping his utility equal to the outside option ( $y_0$ ). As in EUT, this situation corresponds to reversed RIT. However, for an intermediate shock ( $\epsilon^* < \epsilon < \epsilon_1$  in Figure 4.2.1), the risk-seeking RDU agent's contract valuation is decreasing in the shock. This implies that the principal needs to offer the agent a higher fixed pay to keep his level of utility constant in response to a larger shock. Hence, for a risk-seeking RDU agent RIT emerges at an intermediate shock level. Example 1 provides a numerical illustration of RIT for a (moderately) risk-seeking RDU agent.

**Example 1 (RIT for a risk-seeking agent under RDU).** We consider  $r = 0.1$ ,  $(\psi, \theta, y_0) = (0.5, 1, 4)$ . In the absence of shock (i.e.,  $\epsilon = 0$ ), the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . In the presence of a shock ( $\epsilon = 1$ ) and given a RDU agent who overweights probability 0.1 such that  $w(p) = 0.15$ , we obtain  $\beta^* = 0.76$  and  $\alpha^* = 3.64$ . Thus, the optimal variable (fixed) pay in the presence of a shock is smaller (larger) than in its absence, which means RIT holds. Because the expected value of the contract ( $E(L^*) = 3.93$ ) is lower than its certainty equivalent (which is equal to the outside option  $y_0 = 4$  due to the participation constraint), the agent is risk-seeking for the optimal contract  $(\alpha^*, \beta^*) = (3.64, 0.76)$ . As a result, RIT is observed for a risk-seeking agent.

Under MVS, we show that RIT may not hold when agents are risk-averse which stands in stark contrast with EUT predictions. In particular, when the shock is positively skewed ( $p < 1/2$ ), RIT may not hold (and may even reverse) for risk-averse agents who value positive skewness (see Appendix 4.A, Propositions A4 and A5). This happens because the MVS-based valuation of the contract in (4.4) increases with fixed pay  $\alpha$  (irrespective of risk attitudes) and is J-shaped in the shock magnitude (see Figure 4.2.2). For a small shock ( $\epsilon_0$  in



Figure 4.2.2) and a risk-averse agent, the valuation (4.4) is decreasing in the shock size. In that case, the principal must offer the agent a higher fixed pay to maintain utility equal to the outside option ( $y_0$ ). As in EUT, this situation corresponds to RIT.

However, for an intermediate shock (see  $\epsilon^* < \epsilon < \epsilon_1$  in Figure 4.2.2) the value function of the risk-averse MVS agent is increasing in the shock size. This implies that the principal can offer the agent a lower fixed pay while maintaining his level of utility equal to the outside option. Unlike EUT, this situation corresponds to reversed RIT for a risk-averse agent. Finally, in line with EUT, a risk-seeking MVS agent systematically exhibits reversed RIT given that his valuation in (4.4) is increasing in the shock magnitude. Example 2 provides a numerical illustration of a situation in which reversed RIT occurs for a risk-averse agent under MVS.

**Example 2 (Reversed RIT for a risk-averse agent under MVS).** We consider  $(\psi, \theta, y_0) = (0.5, 1, 20)$  and  $a_v = -0.0229$  and  $a_s = 0.0037$  following the estimates provided in Spiliopoulos and Hertwig (2019). In the absence of shock (i.e.,  $\epsilon = 0$ ), the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 19.5$ . In the presence of a shock  $(\epsilon, p) = (1, 0.32)$ , we obtain  $\beta^* = 1.02$  and  $\alpha^* = 9.70$ . Thus, the optimal variable (fixed) pay in the presence of a shock is larger (smaller) than in the absence of shock implying reversed RIT. Because the expected value of contract ( $E[L^*]=20.09$ ) is higher than its certainty equivalent (20), the agent is risk-averse for the optimal contract  $(\alpha^*, \beta^*) = (9.70, 1.02)$ . As a result, we observe reversed RIT for a risk-averse agent.

We summarize our theoretical RIT predictions for EUT, RDU and MVS in Table 4.2.1. For each type of agent risk attitudes, we report the three theories

(EUT, MVS and RDU) for which RIT is present (left column), absent (middle column), or reversed (right column).

Table 4.2.1: RIT and risk-attitudes

Agent's risk attitudes	RIT	No RIT	Reversed RIT
Risk-averse	RDU-EUT-MVS	MVS	MVS
Risk-neutral	RDU	RDU-EUT-MVS	MVS
Risk-seeking	RDU	RDU	RDU-EUT <sup>†</sup> -MVS

<sup>†</sup> With Assumption 3', an agent cannot be risk-seeking under EUT. To consider risk-seeking agents, we need to consider convex utility giving rise to reversed RIT.

### 4.2.2 The BareBone model

Our aim is to test RIT in a BareBone (BB) experimental design that is robust to commonly observed deviations from standard Assumptions 1-5. In practice, the risk-neutrality of the principal cannot be ensured so that Assumption 1 does not necessarily hold in the lab. In addition, principals do not know the risk preferences of agents notwithstanding Assumption 4. To alleviate these issues, we adopt an empirical approach that directly elicits the minimum fixed pay ( $\alpha_m$ ) agents are ready to accept given a preset value of the variable pay ( $\beta$ ). This approach allows us to focus on agents' decisions abstracting away from principals' contractual decisions. In our BB approach, RIT can be defined as follows.

**Definition 5 (RIT and Reversed RIT in the BB model).** RIT (Reversed RIT) [No RIT] corresponds to the case in which the minimum fixed pay accepted by an agent ( $\alpha_m$ ) increases (decreases) [does not change] in the output shock  $\epsilon$  for given values of  $\beta$  and  $p$ .

Under EUT, we can derive Proposition 1 stating that a risk-averse agent demands a higher fixed pay when the shock magnitude increases, giving rise to RIT. This behavior boils down to an enhanced demand for insurance when facing greater risk. Proposition 1ii states that RIT holds under EUT for risk-averse agents in line with Table 4.2.1. In Appendix 4.C.1, we provide the proof of Proposition 1 and show its connection with Propositions A1 (Appendix 4.A), B1 (Appendix 4.B) and C1 (Appendix 4.C). In line with the diagonal entries in Table 4.2.1, we can also show that RIT is absent (reversed) under EUT when the agent is risk-neutral (risk-seeking) (see Appendix 4.C.1).

**Proposition 2.** (RIT with EUT).

- i) The minimum fixed pay increases in utility risk-aversion.
- ii) For risk-averse agents, the minimum fixed pay increases in  $\epsilon$  and  $\beta$ .

Under RDU, we show that RIT holds whenever the agent is probability risk-averse (see Proposition 2ii). By Assumption 3', this implies that the agent is also overall risk-averse. Furthermore, Proposition 2iii states that RIT also holds for a probability risk-seeking agent as long as the index of absolute risk aversion ( $r$ ) is above a certain threshold ( $r_{to}(\beta, \epsilon)$ ) such that his level of utility risk-aversion is sufficiently high. Interestingly, this threshold is lower than the value of the index of absolute risk aversion ( $r_N(\beta, \epsilon)$ ) for which a probability risk-seeking agent exhibits risk-neutrality given the contract  $(\alpha_m, \beta)$  (see Proposition 2iv). As a result, for any value of the index of absolute risk aversion  $r \in (r_{to}(\beta, \epsilon), r_N(\beta, \epsilon))$ , the agent is risk-seeking and exhibits RIT. Finally, Proposition 2v implies that the agent is more likely to exhibit RIT when the shock magnitude and the variable pay are large. It also implies that the agent is more likely to exhibit risk-seeking attitudes for a small shock and a low variable pay. In Appendix 4.C.1, we provide the proof of Proposition 2 and show its connection with

Propositions A2-A3 (Appendix 4.A), B2-B3 (Appendix 4.B) and C1 (Appendix 4.C).

**Proposition 3.** (RIT with RDU).

- i) The minimum fixed pay increases in utility risk-aversion and probability risk-aversion.
- ii) Under probability risk-aversion ( $w(p) < p$ ), the minimum fixed pay increases in  $\epsilon$ .
- iii) Under probability risk-seeking ( $w(p) > p$ ), there exists a threshold  $r_{to}(\beta, \epsilon) > 0$  such that the minimum fixed pay increases (decreases) in  $\epsilon$  if and only if  $r > r_{to}(\beta, \epsilon)$ .
- iv) We have  $r_{to}(\beta, \epsilon) < r_N(\beta, \epsilon)$ , where  $r_N(\beta, \epsilon)$  is the level of absolute risk aversion such that a probability risk-seeking agent exhibits risk-neutrality for the contract  $(\alpha_m, \beta)$ .
- v) The two thresholds  $r_{to}(\beta, \epsilon)$  and  $r_N(\beta, \epsilon)$  decrease in  $\epsilon$  and  $\beta$ .

Under MVS, we show that RIT holds whenever the shock is negatively skewed ( $p \geq 1/2$ ) in which case the agent is risk-averse (see Proposition 3ii). Furthermore, Proposition 3iii shows that for a positively skewed shock ( $p < 1/2$ ), RIT [reversed RIT] holds as long as the value of the ratio,  $\tau := -\frac{a_v}{a_s}$ , between aversion to variance and preference for positive skewness is above [below] a certain threshold ( $\tau_{to}(\beta, \epsilon)$ ), that is as long as the agent has a sufficiently high [low] aversion to variance relative to his preference for positive skewness. Given that  $\tau_{to}(\beta, \epsilon)$  is higher than the ratio ( $\tau_N(\beta, \epsilon)$ ) for which an MVS agent exhibits risk-neutrality given the contract  $(\alpha_m, \beta)$  (see Proposition 3iv), a risk-averse MVS agent exhibits reversed RIT for any  $-\frac{a_v}{a_s} \in (\tau_N(\beta, \epsilon), \tau_{to}(\beta, \epsilon))$ .<sup>7</sup> Finally,

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<sup>7</sup>From Definition 2 (overall risk attitudes) and equation (4.4) of MVS, the risk premium in MVS is equal to  $a_v V(L) + a_s S(L)$ . Risk neutrality corresponds to  $a_v V(L) + a_s S(L) = 0$  or equivalently to  $-\frac{a_v}{a_s} = \frac{S(L)}{V(L)} := \tau_N(\beta, \epsilon)$  and risk-aversion (risk-seeking) corresponds to  $a_v V(L) + a_s S(L) > 0$  ( $< 0$ ) or equivalently to  $-\frac{a_v}{a_s} < (>) \tau_N$ .

Proposition 3v implies that a MVS agent is more likely to exhibit reversed RIT when the shock magnitude and the variable pay are large. It also implies that the agent is more likely to exhibit risk-seeking attitudes for a high shock magnitude and a high level of variable pay. In Appendix 4.C.1, we provide the proof for Proposition 3 and show its connection with Propositions A4-A5 (Appendix 4.A).

**Proposition 4.** (RIT under MVS).

- i) The minimum fixed pay increases in the aversion to variance  $a_v$ . In addition, if  $p < 1/2$  ( $p > 1/2$ ), the minimum fixed pay decreases (increases) in the preference for positive skewness  $a_s$ .
- ii) If the shock is negatively skewed ( $p \geq \frac{1}{2}$ ) then the minimum fixed pay increases in  $\epsilon$ .
- iii) If the shock is positively skewed ( $p < \frac{1}{2}$ ), there exists a threshold  $\tau_{to}(\beta, \epsilon) := \frac{3}{2} \frac{1-2p}{p} \beta \theta \epsilon$  such that the minimum fixed pay increases (decreases) in  $\epsilon$  if and only if  $-\frac{a_v}{a_s} > \tau_{to}(\beta, \epsilon)$ .
- iv) We have  $\tau_{to}(\beta, \epsilon) > \tau_N(\beta, \epsilon) := \frac{1-2p}{p} \beta \theta \epsilon$ , where  $\tau_N(\beta, \epsilon)$  is the level of  $-\frac{a_v}{a_s}$  such that the agent exhibits risk-neutrality for the contract  $(\alpha_m, \beta)$ .
- v) The two thresholds  $\tau_{to}(\beta, \epsilon)$  and  $\tau_N(\beta, \epsilon)$  increase in  $\epsilon$  and  $\beta$ .

Propositions 2, 3 and 4 show that our BB model can be used to study RIT. Predictions in Table 4.2.1 thus carry on to the BB model. The next section provides details of the experimental test of the BB model predictions.

### 4.3 Experimental design

In line with the BB model, we study RIT using the minimum fixed pay  $(\alpha_m)$  accepted by the agent.

### 4.3.1 Elicitation of minimum fixed pay

We elicit the minimum fixed pay ( $\alpha_m$ ) an agent is willing to accept given the incentive contract ( $\beta$ ), as well as the magnitude and the probability of occurrence of the shock ( $\epsilon, p$ ). We thus elicit  $\alpha_m$  for various combinations of  $(\beta, \epsilon, p)$  based on the following indifference condition:

$$L(\alpha_m|\beta, \epsilon, p) \sim y_0$$

where  $y_0$  is the riskless outside option and  $L(\cdot)$  is the lottery associated with a given incentive contract ( $\beta$ ) and a given shock ( $\epsilon, p$ ) as defined in (4.1). We vary the triplet  $(\beta, \epsilon, p)$  while fixing the parameters of the cost of effort function ( $\psi = 2.5$ ), the marginal product of effort ( $\theta = 100$ ), and the outside option ( $y_0 = 1,000$ ). We consider 30 combinations of  $(\beta, \epsilon, p) \in \{0.3, 0.5, 0.7\} \times \{3, 4\} \times \{0.1, 0.25, 0.33, 0.5, 0.75\}$ .<sup>8</sup> For each combination, we also assume that the agent implements the optimal level of effort  $e^*$  that maximizes the value of the lottery so that we elicit  $\alpha_m$  as follows:

$$L(\alpha_m|\beta, \epsilon, p; e^*) \sim y_0$$

Where  $e^* = \frac{\beta\theta}{2\psi}$ . In the experiment, we automatically implement the optimal level of effort because it is a trivial decision for the agent. This allows us to focus on the choice of  $\alpha_m$ . For each combination  $(\beta, \epsilon, p)$ , we elicit  $\alpha_m$  using a multiple price list à la Holt and Laury (2002) in which we vary the fixed pay of a contract in increments of 50 between 0 and 1,000 for a total of 21 possible values. We set an upper bound equal to the value of the outside option (1,000).<sup>9</sup> Figure 4.3.1

<sup>8</sup>We do not consider the trivial case of  $\epsilon = 0$  for which the task boils down to picking the highest value in a table of numbers.

<sup>9</sup>The lower bound of 0 does not appear to be restrictive in our experiment as only 1.1% of the decisions revealed a minimum fixed pay that is less or equal to 0.

provides an example of a decision screen for the combination  $(\beta, \epsilon, p) = (0.7, 3, 0.5)$ , where Option A corresponds to the sure payoff associated with the outside option and Option B represents all the possible payments associated with lottery  $L(\alpha_i | 0.7, 3, 0.5; e^*)$ . The value of fixed pay is such that  $\alpha_i = (i - 1) \times 50$ , where  $i$  is the row number between 1 and 21. For  $(\beta, \epsilon, p) = (0.7, 3, 0.5)$ , we have that  $e^* = \frac{\beta\theta}{2\psi} = 14$ . Thus, for row  $i = 1$ , Option B displays the two possible payments associated with  $L(0 | 0.7, 3, 0.5; 14)$ : 280 if the shock is negative and 700 otherwise. The likelihood of a given payment is visually represented by the frequency of cells in which it appears. Different amounts appear in different colors to facilitate the reading of the table. In total, participants face 30 tables, each corresponding to a different combination of  $(\beta, \epsilon, p)$ . All amounts in tables are in euro cents. To avoid hedging issues (Charness et al., 2016), one of the 30 tables is selected at random for payment upon a successful completion of the experiment.

For each table, participants pick a single row corresponding to their switching point, i.e., the point beyond which they prefer Option B over Option A. Participants cannot select multiple switching points. In the example presented in Figure 4.3.1, the participant picked Option A for the first 10 rows and switched to Option B afterwards (see orange cells on the left of the table). This implies that the minimum fixed pay ( $\alpha_m$ ) the participant is willing to accept for this contract is in the interval (450, 500). In that example, we estimate  $\alpha_m$  to be the midpoint of the interval, that is 475 (e.g., Abdellaoui et al., 2008a; Gonzalez and Wu, 1999a).

TABLE #6

Option A		Option B										
1000	A1	B1	280	280	280	280	280	700	700	700	700	700
1000	A2	B2	330	330	330	330	330	750	750	750	750	750
1000	A3	B3	380	380	380	380	380	800	800	800	800	800
1000	A4	B4	430	430	430	430	430	850	850	850	850	850
1000	A5	B5	480	480	480	480	480	900	900	900	900	900
1000	A6	B6	530	530	530	530	530	950	950	950	950	950
1000	A7	B7	580	580	580	580	580	1000	1000	1000	1000	1000
1000	A8	B8	630	630	630	630	630	1050	1050	1050	1050	1050
1000	A9	B9	680	680	680	680	680	1100	1100	1100	1100	1100
1000	A10	B10	730	730	730	730	730	1150	1150	1150	1150	1150
1000	A11	B11	780	780	780	780	780	1200	1200	1200	1200	1200
1000	A12	B12	830	830	830	830	830	1250	1250	1250	1250	1250
1000	A13	B13	880	880	880	880	880	1300	1300	1300	1300	1300
1000	A14	B14	930	930	930	930	930	1350	1350	1350	1350	1350
1000	A15	B15	980	980	980	980	980	1400	1400	1400	1400	1400
1000	A16	B16	1030	1030	1030	1030	1030	1450	1450	1450	1450	1450
1000	A17	B17	1080	1080	1080	1080	1080	1500	1500	1500	1500	1500
1000	A18	B18	1130	1130	1130	1130	1130	1550	1550	1550	1550	1550
1000	A19	B19	1180	1180	1180	1180	1180	1600	1600	1600	1600	1600
1000	A20	B20	1230	1230	1230	1230	1230	1650	1650	1650	1650	1650
1000	A21	B21	1280	1280	1280	1280	1280	1700	1700	1700	1700	1700

Figure 4.3.1: Example of the decision screen for  $(\beta, \epsilon, p) = (0.7, 3, 0.5)$ . In this example, the participant selected Option A for the first 10 rows (cells A1 to A10 in orange) and selected Option B from the last 11 rows (cells B11 to B21 in orange). Therefore, this participant switched from Option A in row 10 to Option B in row 11. This switching point corresponds to a fixed pay between  $450 = (10 - 1) \times 50$  and  $500 = (11 - 1) \times 50$ .

Prior to the 30 decisions, participants completed an incentivized training phase to get accustomed to the graphical representation of lottery payments. The probability training phase starts with a graphical simulation of the outcomes of a lottery in which the value 100 appears twice in the table while the value 400 appears 7 times. Participants learn that after a sufficient number of draws the frequency of occurrence of 100 (400) equals the underlying probability of 0.22 (0.78). A sequence of random draws is visually presented to the participants for at least 5 seconds. In the next 7 tables, participants estimate the frequency of occurrence of a given value after 100,000 random draws. These frequencies are calibrated to cover all the relevant frequencies used in the main experimental



task: 0.1, 0.25, 0.33, 0.50, and 0.75. An answer within a 5% range of the actual frequency is worth 10 cents. Our design simplifies previous RIT experiments in two ways. First, we focus on the agent's decision to accept or reject a contract that is exogenously set by the experimenter (see e.g., [Dohmen et al., 2021](#)). As previously mentioned, this allows us to leave aside issues related to unknown risk preferences and asymmetric information between the agent and the principal. Furthermore, it allows us to discard fairness motives that can affect the principal's offer and the agent's acceptance decision. As observed in other principal-agent experiments, an equal split of revenues is often a modal response (see e.g., [Anderhub et al., 2002](#); [Keser and Willinger, 2007](#); [Gächter and Königstein, 2009](#); [Corgnet and Hernan-Gonzalez, 2019](#)).

In contrast to [Corgnet and Hernan-Gonzalez \(2019\)](#) and [Dohmen et al. \(2021\)](#) who implement a real-effort task, our design relies on a monetary measure of effort (as in [Chowdhury and Karakostas, 2020](#)). Not using a real-effort task to elicit effort allows us to specify the cost of effort function and focus on the agent's acceptance decision. In our design, providing effort consists in making a money transfer at a monetary cost to the agent. The optimal effort decision turns out to be trivial to calculate and is automatically computed by our experimental software. The use of monetary effort allows us to present agent's choices in a payoff table (see Figure 4.3.1). We expect this layout contributes to downplaying the role of reference points so that we can center our analysis of RIT under non-EUT models on probability distortions (RDU) and attitudes towards variance and skewness (MVS).<sup>10</sup> In RIT setups using a real-effort task, reference dependence appears to play a role in explaining the impact of output shocks

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<sup>10</sup>Despite experiencing a potential negative shock, agents were typically not shown any losses. In very few instances, a small loss of 30 appeared in the first row when the shock was 4, the fixed pay was 0, and the variable pay was 0.3. This occurred in less than 0.5% of the cells presented to participants. Furthermore, these rows involved trivial decisions and were not critical switching points between Options A and B.

on effort (Corgnet and Hernan-Gonzalez, 2019; Dohmen et al., 2021).<sup>11</sup> The rationale is that people may exert higher effort in the presence of a shock than in its absence in order to offset any potential monetary loss. In our monetary effort design, this simple mechanism does not apply because the agent cannot hedge against monetary losses by increasing monetary effort. Indeed, monetary effort implies a monetary cost and thus perceived as a loss by the agent. This argument also reflects the fact that the increase in effort due to output shock observed in real-effort tasks (Sloof and Van Praag, 2010; Corgnet and Hernan-Gonzalez, 2019; Dohmen et al., 2021) is not observed when monetary effort is used (Chowdhury and Karakostas, 2020).<sup>12</sup>

### 4.3.2 Preliminary survey session

Two days before completing the main experimental task (as discussed in Section 4.3.1), participants completed a series of individual tests and questionnaires. This preliminary set of tasks includes a numeracy test (Schwartz et al., 1997; Cokely et al., 2012), a probability weighting elicitation task (Kpegli et al., 2023) for the relevant set of probabilities (i.e., 0.1, 0.25, 0.33, 0.5 and 0.75), probability training mimicking the setup used in the main experimental session, loss aversion measurement (Brink and Rankin, 2013), risk attitude measurement (Holt and Laury, 2002) and a 7-item modified version of the cognitive reflection test (Frederick, 2005; Toplak et al., 2014).

### 4.3.3 Procedure

The design has been approved by the local ethical committee at the GATE research institute and pre-registered on the AsPredicted website (#82616). We

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<sup>11</sup>See Appendix 4.D for an analysis of RIT under reference-dependence.

<sup>12</sup>Extensive data confirming this claim is also available from the authors upon request.

recruited a total of 237 participants from a pool of more than 2,000 students at a major experimental economic laboratory in France.<sup>13</sup> All sessions were conducted online using Qualtrics. The average duration was 23 (29) minutes for the main (survey) sessions. The average earnings for the two sessions were 18.54 euros including a 4 euro flat fee paid for completing both sessions. The complete set of instructions is available in Appendix 4.E.

## 4.4 Results

### 4.4.1 Risk attitude parameters and classification of agents

The aim of this section is twofold. First, we test the assumptions about risk attitude components (utility function, probability weighting function, attitudes towards variance and skewness) underlying our theoretical predictions. That is, we aim to empirically check if agents exhibit a concave utility function ( $r > 0$ ) under EUT, and overweight small probabilities ( $w(p) > p$ ) and underweight intermediate and high probabilities ( $w(p) < p$ ) under RDU. For MVS, we also check whether people exhibit an aversion to variance ( $a_v < 0$ ) and a preference for skewness ( $a_S > 0$ ) (MVS). Second, using these three models we classify participants into types by identifying the specification that best fits their decisions.

#### 4.4.1.1 Risk attitude parameters

We use agents' switching points in the minimum fixed pay elicitation task to determine their certainty equivalents for binary lotteries with various probabilities.

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<sup>13</sup>This is 20% less than the pre-registered target number (300) due to lower response rate than expected. This can be explained by the sudden increase in COVID cases at that specific time and location. Only 4 participants dropped out between the main experimental task and the survey sessions.

In addition to the 30 certainty equivalents from agents' switching points elicited in the main sessions, we also use 15 additional certainty equivalents obtained in the probability weighting elicitation task in the preliminary survey session. With 45 certainty equivalents per subject, we can estimate the probability weighting function and utility curvature at the individual level under RDU following [Kpegli et al. \(2023\)](#), as well as utility curvature for EUT and attitudes towards variance and skewness under MVS. Appendix 4.C.2 provides details of the estimation procedure.

Tables 4.4.1 to 4.4.3 summarize the results obtained at the individual level. Under EUT, Table 4.4.1 indicates that 192 participants (81.01%) have concave utility under EUT ( $r > 0$ ). Under RDU, Table 4.4.2 indicates that 209 participants (88.19%) exhibit a concave utility function. In addition, the number of participants who overweight probabilities 0.1, 0.25, 0.33, 0.5 and 0.75 are 215 (90.72%), 178 (75.11%), 142 (59.92%), 92 (38.82%) and 46 (19.41%), respectively. In total, the number of participants who exhibit both concave utility and overweighting of small probabilities 0.1, 0.25 and 0.33 are 201 (84.81%), 163 (68.78%) and 133 (56.12%). Finally, the number of participants who exhibit both concave utility and underweighting of probabilities 0.5 and 0.75 equal 126 (53.16%) and 164 (69.20%). These average results are in line with the typical concave utility function and inverse S-shaped probability weighting found in the literature. Under MVS, Table 4.4.3 indicates that 193 (80.59%) and 191 participants (81.43%) exhibit an aversion to variance and a preference for skewness, respectively. In total, 187 participants (78.90%) exhibit both characteristics.

Table 4.C.2 in Appendix 4.C.2 summarizes aggregate estimates for the whole sample. Under EUT, the estimate of the CARA coefficient of absolute risk aversion  $r$  is 0.0038 (p-value  $< 0.001$ ,  $t$ -test). This value indicates concavity of the utility function, which implies risk aversion under EUT. Under RDU, the

Table 4.4.1: Utility curvature under EUT

	Number	Percentage
Concave	192	81.01 %
Convex	45	18.99 %
Total	237	100 %

estimate of  $r$  is 0.0023 (p-value  $< 0.001$ ). This value indicates concave utility pointing to utility risk-aversion. The estimated probability weighting function (see Figure 4.4.1) is inverse S-shaped with overweighting for  $p \leq 0.33$  (probability risk-seeking) and underweighting for  $p \geq 0.5$  (probability risk-aversion). Our estimation results are consistent with the empirical literature on RDU (e.g., [Tversky and Kahneman, 1992a](#); [Gonzalez and Wu, 1999a](#); [Bleichrodt and Pinto, 2000](#); [Bruhin et al., 2010](#)). Under MVS, the coefficients of attitudes towards variance and skewness are  $a_v = -0.00097$  (p-value  $< 0.001$ ) and  $a_s = 4.8 \times 10^{-7}$  (p-value  $< 0.001$ ). These estimates indicate an aversion to variance and a preference for positive skewness and once again stand in line with previous studies (e.g., [Spiliopoulos and Hertwig, 2019](#)).

Overall, the basic assumptions underlying our three models are validated by our experimental data on certainty equivalents. On average, participants exhibit a positive CARA coefficient that is below 1 (for both EUT and RDU), an inverse S-shaped probability weighting function (for RDU), and an aversion to variance and a preference for skewness (for MVS).

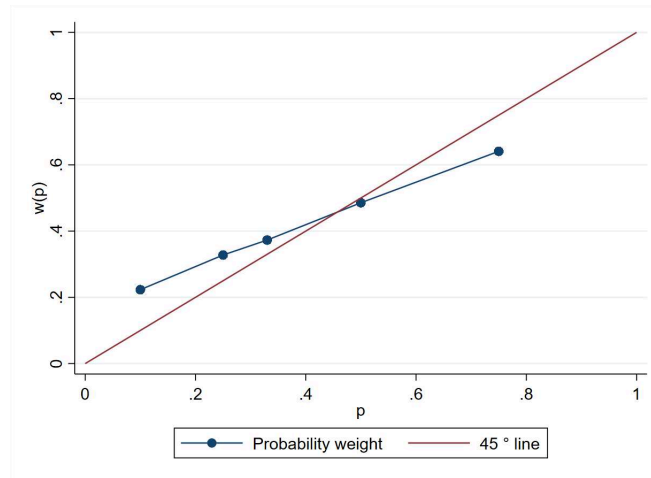
Table 4.4.2: Utility curvature and probability weighting under RDU

Number (%)	Underweighting	Overweighting	Total
Probability	$p = 0.1$		
Concave	8 (3.38%)	201 (84.81%)	209 (88.19%)
Convex	14 (5.91%)	14 (5.91%)	28 (11.81%)
Total	22 (9.28%)	215 (90.72%)	237 (100%)
Probability	$p = 0.25$		
Concave	46 (19.41%)	163 (68.78%)	209 (88.19%)
Convex	13 (5.49%)	15 (6.33%)	28 (11.81%)
Total	59 (24.89%)	178 (75.11%)	237 (100%)
Probability	$p = 0.33$		
Concave	76 (32.07%)	133 (56.12%)	209 (88.19%)
Convex	19 (8.02%)	9 (3.80%)	28 (11.81%)
Total	95 (40.08%)	142 (59.92%)	237 (100%)
Probability	$p = 0.50$		
Concave	126 (53.16%)	83 (35.02%)	209 (88.19%)
Convex	19 (8.02%)	9 (3.80%)	28 (11.81%)
Total	145 (61.18%)	92 (38.82%)	237 (100%)
Probability	$p = 0.75$		
Concave	164 (69.20%)	45 (18.99%)	209 (88.19%)
Convex	27 (11.39%)	1 (0.42%)	28 (11.81%)
Total	191 (80.59%)	46 (19.41%)	237 (100%)

Table 4.4.3: Attitudes towards variance and skewness under MVS

Number (%)	Aversion to skewness	Preference for skewness	Total
Preference for variance	40 (16.88%)	4 (1.69%)	44 (18.57%)
Aversion to variance	6 (2.53%)	187 (78.90%)	193 (81.43%)
Total	46 (19.41 %)	191 (80.59 %)	237 (100%)

Figure 4.4.1: Estimated probability weights under RDU



#### 4.4.1.2 Classification of agent types

Based on the previous estimates of risk attitude parameters, we use Akaike Information Criterion (AIC) to classify participants as either EUT, RDU or MVS (see Appendix 4.C.2 for details of the classification procedure). Doing so, we find that the decisions of 66 (27.85 %), 160 (67.51%) and 11 (4.64%) participants are best explained by EUT, RDU and MVS, respectively. In sum, the choices of a vast majority of our participants are in line with RDU. Next, we test the RIT predictions of the various theories, which are formally stated in Propositions 1 to 3 and summarized in Table 4.2.1.

#### 4.4.2 RIT and risk attitudes

We start by estimating model-free risk attitudes for all participants. To do that, we compare the fixed pay in the absence of shock  $\alpha_m^0 = 1000 - \frac{\beta^2 \theta^2}{4\psi}$  with the fixed pay  $\alpha_m^3$  ( $\alpha_m^4$ ) elicited for shock  $\epsilon = 3$  ( $\epsilon = 4$ ). This procedure is used because the minimum value of the fixed pay an agent is ready to accept in the absence of shock is equal to the minimum fixed pay a risk-neutral agent

would require when  $\epsilon \neq 0$ . The difference in the elicited minimum fixed pay in the presence of a small shock ( $\alpha_m^3$ ) and  $\alpha_m^0$  enables us to measure the risk premium of the agent associated with the contract  $(\alpha_m^3, \beta)$ . This risk premium equals the difference between the expected value of the accepted contract (which is calculated as the average of the expected values of the last accepted and the first rejected contracts), and the outside option ( $y_0 = 1,000$ ) which equals the certainty equivalent of the contract. Thus, an agent is considered to be risk-averse (risk-seeking) [risk-neutral] if  $\alpha_m^0 < \alpha_m^3$  ( $\alpha_m^0 > \alpha_m^3$ ) [ $\alpha_m^0 = \alpha_m^3$ ] given the contract  $(\alpha_m^3, \beta)$ . Similarly, the difference in the elicited minimum fixed pay in the presence of a large shock ( $\alpha_m^4$ ) and  $\alpha_m^0$  measures the risk premium of the agent associated with the contract  $(\alpha_m^4, \beta)$ . Thus, an agent is considered to be risk-averse (risk-seeking) [risk-neutral] if  $\alpha_m^0 < \alpha_m^4$  ( $\alpha_m^0 > \alpha_m^4$ ) [ $\alpha_m^0 = \alpha_m^4$ ] given the contract  $(\alpha_m^4, \beta)$ .

Table 4.4.4 provides aggregate estimates of the underlying risk attitudes associated with individual choices for the two values of the shock considered in our experiment. Given  $(\alpha_m^3, \beta)$ , the percentage of choices in which people are risk-averse, risk-neutral and risk-seeking are 49.96%, 20.34% and 29.70%, respectively. Increasing the shock size when considering the contract  $(\alpha_m^4, \beta)$  shifts these preferences towards more risk-aversion.



Table 4.4.4: Risk attitudes and contracts<sup>†</sup>

Number (%)	$\epsilon = 3$		$\epsilon = 4$	
Risk-averse ( $\alpha_m^0 < \alpha_m^\epsilon$ )	1,776	(49.96 %)	2,052	(57.72 %)
Risk-neutral ( $\alpha_m^0 = \alpha_m^\epsilon$ )	723	(20.34 %)	598	(16.82 %)
Risk-seeking ( $\alpha_m^0 > \alpha_m^\epsilon$ )	1,056	(29.70 %)	905	(25.46 %)
Total	3,555	(100 %)	3,555	(100 %)

<sup>†</sup> Note that  $\alpha_m^\epsilon$  is measured as a midpoint of a range of values that is equal to 50, which is 5% of the outside option value. To account for this imprecision in our measure, we classify a participant as risk-neutral if  $|\alpha_m^\epsilon - \alpha_m^0| < 25$ , risk-averse if  $\alpha_m^\epsilon - \alpha_m^0 \geq 25$  and risk-seeking if  $\alpha_m^\epsilon - \alpha_m^0 \leq -25$ .

We now consider individual-level analyses. An agent exhibits RIT (reversed RIT) [no RIT] if  $\alpha_m^3 < \alpha_m^4$  ( $\alpha_m^3 > \alpha_m^4$ ) [ $\alpha_m^3 = \alpha_m^4$ ], that is the agent asks for a higher (lower) [identical] minimum fixed pay for a larger shock.<sup>14</sup> Table 4.4.5 provides an overview of our empirical findings on the occurrence of RIT depending on individual risk attitudes.

**Result 1 (RIT and risk attitudes at the individual level):** Most risk-averse (50.96%) and risk-seeking (60.04%) agents make choices that are consistent with RIT. Most risk-neutral agents (52.42%) make choices that are consistent with the absence of RIT.

According to the theoretical predictions in Table 4.2.1, the data should be concentrated on the diagonal of Table 4.4.5 under EUT. However, we observe that only 41.29% of the choices are on the diagonal, thus rejecting EUT predictions. The main deviation from EUT resides in the fact that risk-seeking agents also

<sup>14</sup>RIT could also be defined using the differences  $\alpha_m^3 - \alpha_m^0$  and  $\alpha_m^4 - \alpha_m^0$ . Instead, we use the term “risk attitudes” to refer to these differences as they coincide with the existence of a risk premium for contracts  $(\alpha_m^3, \beta)$  and  $(\alpha_m^4, \beta)$ .

make choices that are consistent with RIT ('Risk-seeking and RIT' cell) – a pattern predicted by RDU, but not by MVS.

We then split the cells in Table 4.4.5 according to the estimated risk preferences under EUT, MVS and RDU (see Tables 4.C.4- 4.C.8 in Appendix 4.C.3). In particular, we focus on the decomposition of the most populated cell in Table 6 ('Risk-seeking and RIT'). Not surprisingly, most choices (63.88%) in this cell are characterized by a convex utility function under EUT (see Table 4.C.4). Since agents characterized by a convex utility function should exhibit reversed RIT, our findings are incompatible with EUT (see Proposition 1).

Under MVS, most choices in the 'Risk-seeking and RIT' cell show an aversion to variance and a preference for positive skewness (61.67%, see Table 4.C.8). However, agents should not exhibit RIT in this case under MVS (see Proposition 3).

Under RDU, most choices in the 'Risk-seeking and RIT' cell are characterized by a concave utility coupled with overweighting of probabilities (61.20%, see Table 4.C.6). This pattern is consistent with RDU, which predicts that RIT is observed for risk-seeking agents when they exhibit utility risk-aversion and probability risk-seeking (see Propositions 2iii and 4iv, and Example 1). The alternative pattern of risk-seeking attitudes in which agents exhibit utility risk-seeking and probability risk-aversion (probability risk-seeking) characterizes only 11.36% (8.04%) of the choices in the 'Risk-seeking and RIT' cell.

A direct implication of Propositions 2v and 3v is that RDU and MVS have opposite predictions regarding the relationship between the shock magnitude, the variable pay, RIT and risk-attitudes. To test these predictions, we estimate an ordered logit model (see Table 4.4.6) to assess the effect of the shock magnitude ( $\epsilon$ ) and the variable pay ( $\beta$ ) on risk attitudes (first three columns) and the

occurrence of RIT (last three columns).

**Result 2 (Shock size, variable pay, individual risk attitudes and RIT)**

An increase in the variable pay ( $\beta$ ) or the shock size ( $\epsilon$ ) increases the likelihood of risk-aversion while decreasing the likelihood of risk-neutrality and risk-seeking attitudes. In addition, an increase in the variable pay increases the probability of RIT while decreasing the probabilities of No-RIT and Reversed-RIT.

Result 2 corroborates the RDU predictions (Proposition 2v) and contradicts MVS (Proposition 3v). This result also contradicts EUT which posits that both RIT and risk attitudes should not be impacted by changes in the variable pay or the shock.

We now turn to the aggregate analysis of risk attitudes and RIT. Figure 4.4.2 plots the average risk premium associated with a given combination of parameters  $(p, \beta, \epsilon)$ . Across the 30 combinations, participants are risk-averse (i.e., exhibit positive risk premium) in 80% of the cases (24 out of 30 combinations). Yet, participants are risk-seeking (i.e., exhibit a negative risk premium) for  $(p, \beta, \epsilon) = (0.1, 0.3, 3)$ ,  $(0.25, 0.3, 3)$  and  $(0.33, 0.3, 3)$ , and risk-neutral for  $(p, \beta, \epsilon) = (0.1, 0.5, 3)$ ,  $(0.1, 0.3, 4)$  and  $(0.25, 0.3, 4)$ . In Figure 4.4.3 we show that the difference in minimum fixed pay across shocks ( $\alpha_m^4 - \alpha_m^3$ ) is systematically positive pointing to RIT at the aggregate level for all 30 combinations of parameters regardless of risk attitudes. These aggregate results once again provide support for RDU while contradicting MVS and EUT. We summarize these aggregate findings below.

**Result 3 (RIT at the aggregate level):** RIT holds at the aggregate level for all combinations of parameters.

Figure 4.4.2: Risk premium:  $\alpha_m^3 - \alpha_m^0$  and  $\alpha_m^4 - \alpha_m^0$

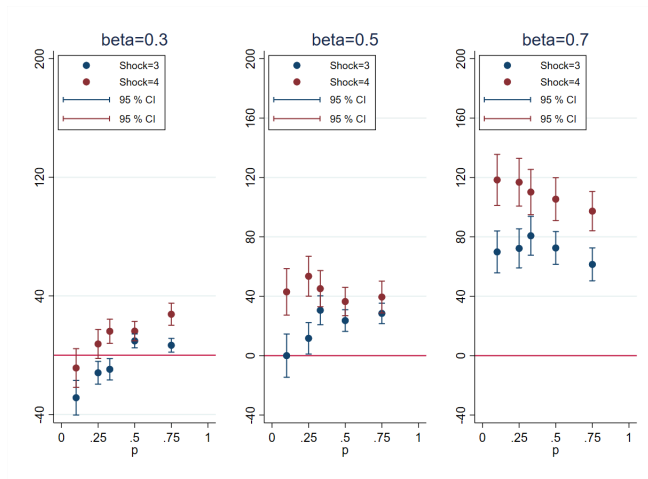


Figure 4.4.3: RIT and the variation in fixed pay  $\alpha_m^4 - \alpha_m^3$

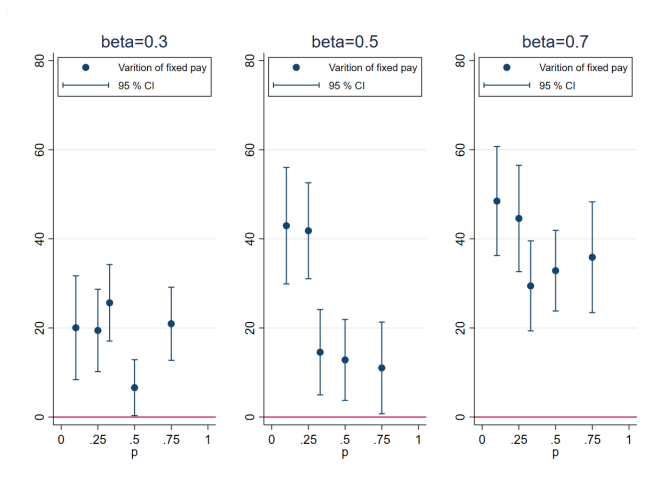


Table 4.4.5: RIT and risk attitudes

Risk attitudes \ RIT	RIT			Total
	RIT : $\alpha_m^3 < \alpha_m^4$	No RIT : $\alpha_m^3 = \alpha_m^4$	Reversed RIT : $\alpha_m^3 > \alpha_m^4$	
Risk-averse <sup>†</sup> : $\alpha_m^0 < \alpha_m^3$	905 50.96 %	474 26.69 %	397 22.35 %	1776 100 %
Risk-neutral <sup>†</sup> : $\alpha_m^0 = \alpha_m^3$	231 31.95 %	379 52.42 %	113 15.63 %	723 100 %
Risk-seeking <sup>†</sup> : $\alpha_m^0 > \alpha_m^3$	634 60.04 %	238 22.54 %	184 17.42 %	1056 100 %
Total	1770 49.79 %	1091 30.69 %	694 19.52 %	3555 100 %

<sup>†</sup> To account for the estimation inaccuracy due to the use of midpoint of the range of possible values of  $\alpha_m^3$  (see Figure 4.3.1), we classify subject as risk-neutral if  $|\alpha_m^3 - \alpha_m^0| < 25$ , risk-averse if  $\alpha_m^3 - \alpha_m^0 \geq 25$  and risk-seeking if  $\alpha_m^3 - \alpha_m^0 \leq -25$ .

Table 4.4.6: Ordered logit (average marginal effects)<sup>(a)</sup>

	Risk attitudes			RIT		
	Aversion	Neutral	Seeking	RIT	No-RIT	Reversed RIT
$\beta$	0.882***	-0.163***	-0.719***	0.376***	-0.137***	-0.239***
$\epsilon$	0.0675***	-0.0126***	-0.0549***	(b)	(b)	(b)
$p$	-0.020	0.004	0.016	-0.185***	0.068***	0.118***

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  for the significance of coefficient tests.

<sup>(a)</sup> Control variables include: numeracy test score, cognitive reflection test score, gender, and age.

<sup>(b)</sup> We cannot estimate the marginal effect  $\epsilon$  on RIT because we already exploit the data on both small and large shocks to estimate RIT.

## 4.5 Conclusion

This paper studies the tradeoff between risk and incentives (RIT) under alternatives to the standard EUT model: the mean-variance-skewness (MVS) model and the the rank-dependent utility (RDU) model. At a theoretical level, we show that RIT is a robust phenomenon under RDU (and notwithstanding EUT and MVS) because it can be observed even when agents are risk-seeking. By contrast, we show that RIT is less robust under MVS than under EUT since it may not hold even for risk-averse agents, thus offering a possible explanation for the limited empirical support for the tradeoff.

To test the predictions of the three theories, we develop a novel experimental design that eliminates the potential confounds appearing in the existing literature. To our surprise, we found extensive evidence for RIT. Most strikingly, RIT emerges even in situations in which agents are risk-seeking, which is a distinct prediction of RDU.

Our findings are not only reassuring for the principal-agent theory, but also suggest RIT predictions can be applied to a broader range of situations than originally anticipated. These situations include contractual settings in which agents are likely to exhibit risk-seeking attitudes such as executive compensation (Garen, 1994; Edmans and Gabaix, 2011; Edmans et al., 2012, 2017; Ma et al., 2019). It follows that risk-seeking agents might demand a fixed monetary compensation for any additional risk. This novel finding can also have interesting implications in fields like finance and entrepreneurship. For example, financial advisors might need to craft portfolios with a substantial share of safe assets for clients that are otherwise categorized as risk-tolerant. Furthermore, our findings suggest that, unlike “Knightian” theory of entrepreneurship (Knight, 1921; Kihlstrom and Laffont, 1979; Newman, 2007), risk-seeking entrepreneurs might want to share part of the risk associated with new ventures.

## 4.A Proofs for Section 4.2.1.3

### EUT

The main implications of Assumptions A0, A1, A2, A3', A3'', A4, A5 are captured in Proposition A1.

**Proposition A1 (Risk-incentives tradeoff with EUT):** Under A0, A1, A2, A3', A4 and A5 EUT, optimal variable pay  $\beta^*(\epsilon, r, \psi, \theta)$  decreases with  $\epsilon$  whereas optimal fixed pay  $\alpha^*(\epsilon, r, \psi, \theta)$  increases with  $\epsilon$ .

### Proof of Proposition A1

Given the linear contract  $(\alpha, \beta)$ , the objective function of an expected utility agent with a cost function  $C(e) = \psi e^2$  is given by

$$EU(L) = pu(y_+) + (1 - p)u(y_-)$$

with  $u(y) = \frac{1 - \exp(-ry)}{r}$ ,  $y_+ = \alpha + \beta\theta(e + \frac{1-p}{p}\epsilon) - \psi e^2$  and  $y_- = \alpha + \beta\theta(e - \epsilon) - \psi e^2$ .

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[pu'(y_+) + (1 - p)u'(y_-)] = 0$$

Since  $pu'(y_+) + (1 - p)u'(y_-) \neq 0$ , it turns out that the best response effort function of the agent is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the best response effort function is an increasing function of the variable pay and does not vary with respect to the shock  $\epsilon$ , the relative risk-aversion coefficient  $r$  and the fixed pay  $\alpha$ . The proof with  $p = 1/2$  is provided in Appendix A2 of [Corgnet and Hernan-Gonzalez \(2019\)](#). The optimization problem of the principal is to maximize the expected value of  $\theta z - y$  by accounting for agent's incentive compatibility constraint (IC) and participation constraint (PC)

$$\left\{ \begin{array}{l} \max_{\alpha, \beta} \theta e - (\alpha + \beta \theta e) \\ s.t. : \\ e = \frac{\beta \theta}{2\psi} \\ \alpha + \beta \theta e - \psi e^2 - \frac{1-p}{2p} r \beta^2 \theta^2 \epsilon^2 \simeq y_0 \end{array} \right.$$

The participation constraint is an application of the [Pratt \(1964\)](#) approximation of the risk premium to the agent's maximization problem as in [Milgrom and Roberts \(1992\)](#). The optimal linear contact  $(\alpha^*, \beta^*)$  of the principal is given by

$$\beta^*(\epsilon, r, \psi, \theta) \simeq \frac{1}{1 + 2\psi r \epsilon^2 \frac{1-p}{p}} \quad (4.5)$$

$$\alpha^*(\epsilon, r, \psi, \theta) \simeq y_0 + \frac{1}{2} \left( \frac{1-p}{p} r \epsilon^2 - \frac{1}{2\psi} \right) \left( \theta \beta^*(\epsilon, r, \psi, \theta) \right)^2 \quad (4.6)$$

Furthermore, the expression of  $\beta^*(\epsilon, r, \psi, \theta)$ , yields

$$\frac{\partial \beta^*(\epsilon, r, \psi, \theta)}{\partial \epsilon} < 0$$

$$\frac{\partial \beta^*(\epsilon, r, \psi, \theta)}{\partial r} < 0$$



For  $k = \frac{1-p}{p}\epsilon$ , Assumption 3'' yields  $r[\alpha + \beta\theta k] < 1$ . Using  $e > \epsilon$  and  $e = \frac{\beta\theta}{2\psi}$ , we have

$$\frac{1-p}{p}r\epsilon^2 - \frac{1}{2\psi} < 0 \quad (4.7)$$

Inequalities (4.7) and (4.6) jointly imply

$$\text{sign}\left(\frac{\partial\alpha^*(\epsilon, r, \psi, \theta)}{\partial t}\right) = -\text{sign}\left(\frac{\partial\beta^*(\epsilon, r, \psi, \theta)}{\partial t}\right) \quad \text{for } t = \epsilon, r, \psi, \theta$$

In particular

$$\frac{\partial\alpha^*(\epsilon, r, \psi, \theta)}{\partial\epsilon} > 0$$

$$\frac{\partial\alpha^*(\epsilon, r, \psi, \theta)}{\partial r} > 0$$

**Remark:** expressions (4.5) and (4.6) also hold for risk-neutral agent ( $r = 0$ ) and risk-seeking agent ( $r < 0$ ) as long as the second-order condition obtained from the derivative of the first-order condition A1.2 is negative. Hence, for a risk-neutral agent the fixed pay and performance do not vary with  $\epsilon$ . For a risk-seeking agent, we have reversed RIT. Also, note that the agent's optimal level of effort  $e^*$  is given by

$$e = \frac{\theta}{2\psi}\beta^*(\epsilon, r, \psi, \theta)$$

It turns out that the partial derivatives  $\frac{\partial e^*(\epsilon, r, \psi, \theta)}{\partial\epsilon}$  and  $\frac{\partial e^*(\epsilon, r, \psi, \theta)}{\partial r}$  are negatives as  $\frac{\partial\alpha^*(\epsilon, r, \psi, \theta)}{\partial\epsilon}$  and  $\frac{\partial\alpha^*(\epsilon, r, \psi, \theta)}{\partial r}$  are negative. QED.

## RDU

Before showing the proofs, let us first state and provide some explanations of Lemma 1 and Propositions A2 and A3. Under RDU, we derive our first lemma

below:

**Lemma 1** Under RDU, maximizing the objective function of the agent amounts to maximizing his certainty equivalent CE:

$$CE = \alpha + \beta\theta e - \psi e^2 + \left(\frac{w(p)}{p} - 1\right) - \frac{\beta^2\theta^2\epsilon^2}{2} \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right) \times A_a(\alpha + \beta\theta e - \psi e^2) + o(\epsilon^2) \quad (4.8)$$

with  $A_a(z) = -\frac{u''(z)}{u'(z)}$  being the absolute risk-aversion index evaluated at the outcome  $z$  and  $o(\epsilon^2)$  denoting the approximation error.

Lemma 1 provides an approximation of the certainty equivalent. This approximation allows us to generate a closed-form solution for the optimal contract  $(\alpha^*, \beta^*)$  by assuming CARA utility function (Milgrom and Roberts, 1992), that is  $A_a(z) = r$  for all  $z$ . Similar to EUT, we capture RIT in RDU in Proposition A2ii below.

**Proposition A2 (RIT with RDU).**<sup>15</sup> Under A0, A1, A2, A3', A3'', A4, A5 and assuming RDU agent, for any probability  $p \in (0, 1)$ :

- i) Optimal variable pay  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  decreases with  $r$  and probability risk-aversion whereas the fixed pay  $\alpha^*(\epsilon, r, w(p), \psi, \theta)$  increases with  $r$  and probability risk-aversion.
- ii) If the agent exhibits probability risk-aversion, the optimal variable pay  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  decreases with  $\epsilon$  whereas the optimal fixed pay  $\alpha^*(\epsilon, r, w(p), \psi, \theta)$  increases with  $\epsilon$ .
- iii) If the agent exhibits probability risk-seeking, there is  $r_{to}(\beta^*, \epsilon)$  such that for  $r < r_{to}(\beta^*, \epsilon)$  the optimal variable pay  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  increases with  $\epsilon$  and the

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<sup>15</sup>In Appendix 4.D, we extend proposition A2 to the case of the prospect theory agent exhibiting loss aversion and reference-dependence.

optimal fixed pay  $\alpha^*(\epsilon, r, w(p), \psi, \theta)$  decreases with  $\epsilon$ .

Proposition A2iii points to the absence of RIT under probability risk-seeking. Furthermore, Proposition A3 provides results on RIT under general risk attitudes which are a combination of utility curvature and probability risk attitudes.

**Proposition A3 (Risk attitudes and absence of tradeoff with RDU):**

Assume that the agent exhibits probability risk-seeking for a given probability  $p$ . Let  $r_N(\beta^*, \epsilon)$  be the absolute risk-aversion index that allows probability risk-seeking agent to exhibit risk-neutrality for the lottery

$$L = \left( \alpha^* + \beta^* \theta \left( e^* + \frac{1-p}{p} \epsilon \right) - \psi e^{*2}, \alpha^* + \beta^* \theta \left( e^* - \epsilon \right) - \psi e^{*2}; p, 1-p \right)$$

associated with the optimal linear contract  $(\alpha^*, \beta^*)$ . Then,  $r_N(\beta^*, \epsilon) > r_{to}(\beta^*, \epsilon)$ .

Figure 4.A.1 illustrates Proposition A3. It shows that, in line with RIT a principal facing a risk-averse agent who exhibits probability risk-seeking proposes an optimal variable pay  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  that decreases in  $\epsilon$ . In addition, a principal facing an agent who exhibits probability risk-seeking with absolute risk-aversion index  $r \in (r_{to}(\beta^*, \epsilon), r_N(\beta^*, \epsilon))$  also proposes an optimal variable pay  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  that decreases in  $\epsilon$ . Note that such agent exhibits risk-seeking behavior since  $r < r_N(\beta^*, \epsilon)$ . Finally, the principal only proposes an optimal variable pay  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  that increases in  $\epsilon$  when facing an agent that exhibits probability risk-seeking with absolute risk-aversion index  $r \in (0, r_{to}(\beta^*, \epsilon))$ . Unlike EUT, RIT under RDU depends on the probability of the binary shock and becomes more pervasive because it now applies to risk-seeking agent (on top of risk-averse agent, as in EUT).

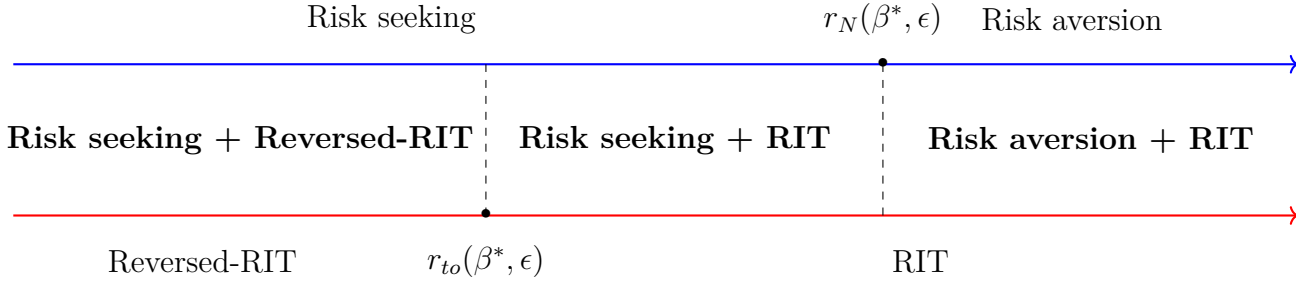


Figure 4.A.1: Risk attitudes and RIT with RDU (agent exhibits  $w(p) > p$ )

### Proof of Lemma 1

In the Lemma, we derive an equivalent of the Pratt (1964) approximation of risk premium for RDU and use it to provide incentive compatibility and participation constraints as in Milgrom and Roberts (1992). To do so, let us first consider a binary random variable  $\tilde{x} = (x + \frac{1-p}{p}\sigma, x - \sigma; p, 1 - p)$  with  $\sigma > 0$ ,  $p \in (0, 1)$  so that  $E(\tilde{x}) = x$  and  $V(\tilde{x}) = \frac{1-p}{p}\sigma^2$ . Under RDU theory, the certainty equivalent ( $ce$ ) of  $\tilde{x}$  satisfies

$$u(ce) = w(p) \left[ u\left(x + \frac{1-p}{p}\sigma\right) - u(x - \sigma) \right] + u(x - \sigma) \quad (4.9)$$

Applying second-order Taylor approximation to the right-hand side (RHS) of expression (4.9) around the expected value  $x$  leads to

$$RHS = u(x) + \sigma \left( \frac{w(p)}{p} - 1 \right) u'(x) + \frac{\sigma^2}{2} \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right) u''(x) + o(\sigma^2) \quad (4.10)$$

with  $o(\sigma^2)$  denoting the approximation error such that  $\lim_{\sigma \rightarrow 0} \frac{o(\sigma^2)}{\sigma^2} = 0$ . We furthermore impose the following linear form for the certainty equivalent with an unknown slope  $a$

$$ce = x + a\sigma^2 + o(\sigma^2) \quad (4.11)$$

Plugging (4.11) into (4.9) and applying first-order Taylor approximation on the left-hand side (LHS) of the expression (4.9) around the expected value  $x$  yields

$$LHS = u(x) + a\sigma^2 u'(x) + o(\sigma^2) \quad (4.12)$$

Since LHS=RHS, according to (4.9), we can identify the unknown slope  $a$

$$a = \frac{1}{\sigma} \left( \frac{w(p)}{p} - 1 \right) + \frac{1}{2} \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right) \frac{u''(x)}{u'(x)} \quad (4.13)$$

Let  $A_a(z) = -\frac{u''(z)}{u'(z)}$  be the absolute risk-aversion index evaluated at  $x$ . Plugging (4.13) in (4.11) gives the Pratt (1964) risk premium  $\pi$  under RDU for the binary random variable  $\tilde{x} = (x + \frac{1-p}{p}\sigma, x - \sigma; p, 1-p)$ .

$$\pi := x - ce = -\left(\frac{w(p)}{p} - 1\right)\sigma + \frac{\sigma^2}{2} \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right) A_a(x) + o(\sigma^2) \quad (4.14)$$

So that the certainty equivalent is

$$ce = x + \left(\frac{w(p)}{p} - 1\right)\sigma - \frac{\sigma^2}{2} \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right) A_a(x) + o(\sigma^2) \quad (4.15)$$

Note that RDU becomes EUT if  $w(p) = p$ . Since  $V(\tilde{x}) = \frac{1-p}{p}\sigma^2$ , (4.14) collapses to the usual Pratt (1964) formula  $\pi = -\frac{1}{2} \frac{u''(x)}{u'(x)} V(\tilde{x}) + o(\sigma^2)$  whenever  $w(p) = p$ . Relation (4.15) allows us to define the incentive compatibility and participation constraints. In the context of RDU (see Section 4.2), we set  $x = \alpha + \beta\theta e - \psi e^2$  and  $\sigma = \beta\theta\epsilon$  so that the certainty equivalent equation (4.15) becomes:

$$ce = \alpha + \beta\theta e - \psi e^2 + \left(\frac{w(p)}{p} - 1\right)\beta\theta\epsilon - \frac{\beta^2\theta^2\epsilon^2}{2} \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right) \times \quad (4.16)$$

$$A_a(\alpha + \beta\theta e - \psi e^2) + o(\epsilon^2)$$

QED.

### Proof of Proposition A2

Given the linear contract  $(\alpha, \beta)$ , the objective function of a RDU agent with cost function  $C(e) = \psi e^2$  is given by

$$RDU(L) = w(p)u(y_+) + (1 - w(p))u(y_-)$$

with  $u(x) = \frac{1 - \exp(-rx)}{r}$ ,  $y_+ = \alpha + \beta\theta(e + \frac{1-p}{p}\epsilon) - \psi e^2$  and  $y_- = \alpha + \beta\theta(e - \epsilon) - \psi e^2$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[w(p)u'(y_+) + (1 - w(p))u'(y_-)] = 0$$

Since  $w(p)u'(y_+) + (1 - w(p))u'(y_-) \neq 0$ , it turns out that the optimal effort function of the agent is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the optimal effort function is increasing in the variable pay and does not vary with respect to chock  $\epsilon$ , the relative risk-aversion coefficient  $r$ , the fixed pay  $\alpha$  and probability risk attitude  $w(p)$ .

#### Point i)

The optimization problem of the principal is to maximize the expected value of  $\theta z - y$  by accounting for the agent's incentive compatibility constraint (IC)

and participation constraint (PC):

$$\left\{ \begin{array}{l} \max_{\alpha, \beta} \quad \pi = \theta e - (\alpha + \beta \theta e) \\ s.t. : \\ e = \frac{\beta \theta}{2\psi} \\ \alpha + \beta \theta e - \psi e^2 + \left( \frac{w(p)}{p} - 1 \right) \beta \theta \epsilon - \frac{\beta^2 \theta^2 \epsilon^2}{2} \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right) r \simeq y_0 \end{array} \right.$$

Like in Proposition A1 above, the participation constraint is an application of the [Pratt \(1964\)](#) approximation of the risk premium. The optimal linear contract  $(\alpha^*, \beta^*)$  of the principal is given by

$$\beta^*(\epsilon, r, w(p), \psi, \theta) \simeq \frac{1 + \frac{2\psi\epsilon}{\theta} \left( \frac{w(p)}{p} - 1 \right)}{1 + 2\psi r \epsilon^2 \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right)} \quad (4.17)$$

$$\alpha^*(\epsilon, r, w(p), \psi, \theta) \simeq y_0 + \frac{1}{2} \left[ r \epsilon^2 \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right) - \frac{1}{2\psi} \right] (\theta \beta^*)^2 - \epsilon \theta \beta^* \quad (4.18)$$

Expression (4.17) implies that

$$Sign\left(\frac{\partial \beta^*}{\partial r}\right) = -Sign\left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right) \times Sign\left(1 + \frac{2\psi\epsilon}{\theta} \left(\frac{w(p)}{p} - 1\right)\right) \quad (4.19)$$

Note that  $1 + \frac{w(p)}{p} \frac{1-2p}{p} = w(p) \left(\frac{1-p}{p}\right)^2 + 1 - w(p)$ . Since  $w(p) < 1$ , it turns out that

$$1 + \frac{w(p)}{p} \frac{1-2p}{p} > 0 \quad (4.20)$$

This means that the certainty equivalent  $ce$  (4.16) decreases in  $r$  (or equivalently, the risk premium increases in  $r$ ).<sup>16</sup>

<sup>16</sup>See also Theorem 6.1 in [Eckhoudt and Laeven \(2015\)](#).

Since  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  is positive, the relation 4.20 and the expression of  $\beta^*(\epsilon, r, w(p), \psi, \theta)$  jointly imply that

$$1 + \frac{2\psi\epsilon}{\theta} \left( \frac{w(p)}{p} - 1 \right) > 0 \quad (4.21)$$

Plugging (4.20) and (4.21) into the relation (4.19) yields

$$\frac{\partial \beta^*(\epsilon, r, w(p), \psi, \theta)}{\partial r} < 0$$

For  $k = \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right)\epsilon > 0$ , we have under Assumption 3" that  $r[\alpha + \beta\theta k] < 1$ . Then, for  $e > \epsilon$  and  $e = \frac{\beta\theta}{2\psi}$ , we have that

$$r\epsilon^2 \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right) - \frac{1}{2\psi} < 0 \quad (4.22)$$

Relations (4.22) and (4.18) imply for  $t = \epsilon, r, w(p), \psi, \theta$  that

$$\text{sign}\left(\frac{\partial \alpha^*(\epsilon, r, w(p), \psi, \theta)}{\partial t}\right) = -\text{sign}\left(\frac{\partial \beta^*(\epsilon, r, w(p), \psi, \theta)}{\partial t}\right) \quad (4.23)$$

In particular, we have that

$$\frac{\partial \alpha^*(\epsilon, r, \psi, \theta)}{\partial r} > 0$$

From (4.17), we have that

$$\text{Sign}\left(\frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta}\right) = \text{Sign}\left(1 - r\theta\epsilon \frac{1-2p}{p} + 2\psi r\epsilon^2 \frac{1-p}{p}\right) \quad (4.24)$$

with  $\delta = w(p)$ . Let us now consider (4.24) under two cases:  $p \geq \frac{1}{2}$  and  $p < \frac{1}{2}$ .

For  $p \geq \frac{1}{2}$ , we have  $\frac{1-2p}{p} \leq 0$  so that  $\frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta}$  is positive.



For  $p < \frac{1}{2}$ , we have  $\frac{1-2p}{p} > 0$ . Take  $k = \frac{\epsilon}{\beta^*(\epsilon, r, \delta, \psi, \theta)} \frac{1-2p}{p} > 0$ . It follows from Assumption 3" that  $1 - r\theta\beta^*(\epsilon, r, w(p), \psi, \theta)k = 1 - r\theta\epsilon \frac{1-2p}{p} > 0$ . Thus, for  $p < \frac{1}{2}$  we have  $\frac{\partial\beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial\delta}$  also positive. This means that for all  $p$

$$\frac{\partial\beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial\delta} > 0 \quad (4.25)$$

From (4.23) and (4.25), it also follows that

$$\frac{\partial\alpha^*(\epsilon, r, \delta, \psi, \theta)}{\partial\delta} < 0 \quad (4.26)$$

Note that probability risk-aversion corresponds to a lower level of  $\delta$ . Hence, equations (4.25) and (4.26) mean that the optimal variable pay  $\beta^*(\epsilon, r, \delta, \psi, \theta)$  decreases as the probability risk-aversion increases while the fixed pay  $\alpha^*(\epsilon, r, \delta, \psi, \theta)$  increases as the probability risk-aversion increases.

**Point ii)**

It follows from the expression (4.17) that

$$\text{Sign}\left(\frac{\partial\beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial\epsilon}\right) = \text{Sign}\left(A(\epsilon, r, \delta, \psi, \theta)\right) \quad (4.27)$$

with

$$\begin{aligned} A(\epsilon, r, \delta, \psi, \theta) = & \theta^{-1} \left( \frac{w(p)}{p} - 1 \right) \left[ 1 - 2\psi r \epsilon^2 \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right) \right] \\ & - 2r\epsilon \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right) \end{aligned} \quad (4.28)$$

From 4.20 and 4.22 we have respectively that  $1 + \frac{w(p)}{p} \frac{1-2p}{p} > 0$  and  $1 - 2\psi r \epsilon^2 \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right) > 0$ . If the agent exhibits probability risk-aversion or probability

risk-neutral for probability  $p$  (i.e.,  $w(p) \leq p$ ), (4.27) and (4.28) jointly imply

$$\frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \epsilon} < 0$$

while (4.23) implies

$$\frac{\partial \alpha^*(\epsilon, r, \delta, \psi, \theta)}{\partial \epsilon} > 0$$

Recall that  $e^*(\epsilon, r, \delta, \psi, \theta) = \frac{\theta}{2\psi} \beta^*(\epsilon, r, \delta, \psi, \theta)$ . Hence,

$$\frac{\partial e^*(\epsilon, r, \delta, \psi, \theta)}{\partial \epsilon} < 0 \quad \text{as} \quad \frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \epsilon} < 0$$

**Point iii)** Assume that the agent exhibits probability risk-seeking for probability  $p$  (i.e.,  $w(p) > p$ ). Hence, (4.27) and (4.28) jointly imply the following equivalence

$$r < r_{to}(\beta^*, \epsilon) \quad \Longleftrightarrow \quad \frac{\partial \beta^*(\epsilon, r, \psi, \theta)}{\partial \epsilon} > 0$$

with

$$r_{to}(\beta^*, \epsilon) \cong \frac{1}{2\epsilon} \frac{\frac{w(p)}{p} - 1}{\left(\theta + \epsilon\psi\left(\frac{w(p)}{p} - 1\right)\right) \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right)} \quad (4.29)$$

From (4.23), it also follows that

$$r < r_{to}(\beta^*, \epsilon) \quad \Longleftrightarrow \quad \frac{\partial \alpha^*(\epsilon, r, \delta, \psi, \theta)}{\partial \epsilon} < 0$$

Since  $e^*(\epsilon, r, \delta, \psi, \theta) = \frac{\theta}{2\psi} \beta^*(\epsilon, r, \delta, \psi, \theta)$ , we have

$$r < r_{to}(\beta^*, \epsilon) \quad \Longleftrightarrow \quad \frac{\partial e^*(\epsilon, r, \psi, \theta)}{\partial \epsilon} > 0$$

Also, we have

$$\begin{aligned} \frac{\partial e^*(\epsilon, r, \delta, \psi, \theta)}{\partial r} < 0 & \quad \text{as} & \quad \frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial r} < 0 \\ \frac{\partial e^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta} > 0 & \quad \text{as} & \quad \frac{\partial \beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial \delta} > 0 \end{aligned}$$

QED.

### Proof of Proposition A3

From Lemma 1, the absolute risk-aversion index  $r_N(\beta^*, \epsilon)$  that makes an agent with probability risk-seeking behavior to exhibit risk-neutrality (i.e., null risk premium) for the lottery

$$L^* = \left( \alpha^* + \theta\beta^* \left( e^* + \frac{1-p}{p}\epsilon \right) - \psi e^{*2}, \alpha^* + \theta\beta^* \left( e^* - \epsilon \right) - \psi e^{*2}; p, 1-p \right)$$

associated with the optimal linear contract  $(\alpha^*, \beta^*)$  and optimal effort  $e^*$  is given by

$$r_N(\beta^*, \epsilon) \cong \frac{2}{\epsilon\theta\beta^*} \frac{\frac{\delta}{p} - 1}{1 + \frac{\delta}{p} \frac{1-2p}{p}}$$

with  $\delta = w(p)$ .

From Proposition A2, the threshold  $r_{to}(\beta^*, \epsilon)$  of the absolute risk-aversion index of an agent with probability risk-seeking behavior that leads the principal to propose an optimal variable pay  $\beta^*(\epsilon, r, \delta, \psi, \theta)$  that decreases in  $\epsilon$  is

$$r_{to}(\beta^*, \epsilon) \cong \frac{1}{2\epsilon} \frac{\frac{w(p)}{p} - 1}{\left( \theta + \epsilon\psi \left( \frac{w(p)}{p} - 1 \right) \right) \left( 1 + \frac{w(p)}{p} \frac{1-2p}{p} \right)}$$

Computing the difference between the two thresholds leads to

$$\text{Sign}(r_N(\beta^*, \epsilon) - r_{to}(\beta^*, \epsilon)) = \text{Sign}\left[N(\beta^*(\epsilon, r, \delta, \psi, \theta))\right]$$

with

$$N(\beta^*(\epsilon, r, \delta, \psi, \theta)) = 4 - \beta^*(\epsilon, r, \delta, \psi, \theta) + \frac{4\epsilon\psi}{\theta} \left(\frac{w(p)}{p} - 1\right)$$

Recall that  $\frac{\partial\beta^*(\epsilon, r, \delta, \psi, \theta)}{\partial r} < 0$  so that we have  $\frac{\partial N(\beta^*(\epsilon, r, \delta, \psi, \theta))}{\partial r} < 0$ .

Furthermore, we have  $\lim_{r \rightarrow 0} N(\beta^*(\epsilon, r, \delta, \psi, \theta)) = 3 + \frac{2\epsilon\psi}{\theta} \left(\frac{w(p)}{p} - 1\right)$ . Hence, for all  $r > 0$  we have  $N(\beta^*(\epsilon, r, \delta, \psi, \theta)) > 0$  so that  $r_N(\beta^*, \epsilon) > r_{to}(\beta^*, \epsilon)$ .

QED.

## MVS

Before providing the proofs, we first state and provide some explanations for Propositions A4 and A5.

**Proposition A4 (Risk-incentives tradeoff with MVS).** Under A0, A1, A2 and A4 and assuming the agent is MVS as specified in (4.4):

- i) Optimal variable pay  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$  decreases with  $a_v$
- ii) Optimal variable pay  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$  increases (resp. decreases) with  $a_s$  for  $p < \frac{1}{2}$  (resp.  $p > \frac{1}{2}$ ).
- iii) If  $p \geq \frac{1}{2}$ , the optimal variable pay  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$  decreases with  $\epsilon$ .
- iv) If  $p < \frac{1}{2}$ , there is  $g(\epsilon, p, a_v, a_s, \psi, \theta)$  such that if  $g(\epsilon, p, a_v, a_s, \psi, \theta) < \frac{9}{4}$ , then  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$  increases with  $\epsilon$ .

Proposition A4iv shows that the absence of the tradeoff can be expected for  $p < 1/2$ , i.e., when the lottery

$$L^* = \left( \alpha^* + \theta\beta^* \left( e^* + \frac{1-p}{p}\epsilon \right) - \psi e^{*2}, \alpha^* + \theta\beta^* \left( e^* - \epsilon \right) - \psi e^{*2}; p, 1-p \right)$$

associated with the optimal contract  $(\alpha^*, \beta^*)$  is positively skewed. Since risk attitudes are driven by both aversions to variance and preference for positive skewness, it remains unclear if the absence of the tradeoff arises for a risk-seeking or a risk-averse agent. Proposition B5 provides such information.

**Proposition A5 (Risk attitudes and absence of tradeoff with MVS):**

Consider  $p < 1/2$ . Hence, we have the following results:

- i) At the optimal contract, agent's risk-aversion (risk-seeking) corresponds to  $g(\epsilon, p, a_v, a_s, \psi, \theta) > 1$  ( $g(\epsilon, p, a_v, a_s, \psi, \theta) < 1$ )
- ii) If the agent is a risk-seeker, then the optimal variable pay  $\beta^*(\epsilon, p, a_v, a_s, \psi, \theta)$  increases with  $\epsilon$
- iii) For  $g(\epsilon, p, a_v, a_s, \psi, \theta) \in \left(1, \frac{9}{4}\right)$ , the agent exhibits risk-aversion and the optimal variable pay  $\beta^*$  increases with  $\epsilon$ .

According to Proposition A5, if the agent exhibits risk-seeking behavior at the optimal contract proposed by the principal, then the optimal variable pay  $\beta^*(\epsilon, p, a_v, a_s, \psi, \theta)$  increases with  $\epsilon$ . However, if the agent is risk-averse at the optimal contract proposed by the principal [i.e.,  $g(\epsilon, p, a_v, a_s, \psi, \theta) > 1$ ], the optimal variable pay  $\beta^*(\epsilon, p, a_v, a_s, \psi, \theta)$  can either increase or decrease with  $\epsilon$  depending on whether  $g(\epsilon, p, a_v, a_s, \psi, \theta)$  is greater or smaller than  $\frac{9}{4}$ .

**Remark [RDU vs. MVS]:** Proposition A5 echoes Proposition A3 for RDU once we consider, in line with literature (e.g., [Gonzalez and Wu, 1999a](#); [Tversky and Wakker, 1995](#); [Gonzalez-Jimenez, 2019](#); [Kpegli et al., 2023](#)), that overweight-

ing occurs for  $p < \frac{1}{2}$ . Then, both MVS and RDU predict the possibility of the absence of tradeoff only for  $p < \frac{1}{2}$ . However, the MVS and RDU provide different rationale for the absence of tradeoff. The RDU rules out the possibility of the absence of the tradeoff for a risk-averse agent. In contrast, MVS points to the absence of tradeoff for certain risk-averse agent and all risk-seeking agents.

**Proof of Proposition A4:** Given the linear contract  $(\alpha, \beta)$ , the objective function of an MVS agent with a cost function  $C(e) = \psi e^2$  is given by

$$MVS(L) = \alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p} \beta^2 \theta^2 \epsilon^2 + a_s \frac{1-p}{p} \frac{1-2p}{p} \beta^3 \theta^3 \epsilon^3$$

The first-order condition of the agent's maximization problem leads to the optimal effort function  $e(\beta)$  that increases in the variable pay:

$$e = \frac{\beta\theta}{2\psi}$$

The principal's optimization problem is to maximize the expected value of  $\theta z - y$  by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC).

$$\begin{cases} \max_{\alpha, \beta} & \theta e - (\alpha + \beta\theta e) \\ s.t. : & \\ & e = \frac{\beta\theta}{2\psi} \\ & \alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p} \beta^2 \theta^2 \epsilon^2 + a_s \frac{1-p}{p} \frac{1-2p}{p} \beta^3 \theta^3 \epsilon^3 = y_0 \end{cases}$$

which is equivalent to

$$\max_{\beta} \theta^2 \left[ \frac{\beta}{2\psi} + a_v \frac{1-p}{p} \beta^2 \epsilon^2 + a_s \frac{1-2p}{p} \frac{1-p}{p} \beta^3 \theta \epsilon^3 - \frac{\beta^2}{4\psi} \right] - y_0$$

The first-order condition is given by

$$\frac{1}{2\psi} + 2a_v\beta\frac{1-p}{p}\epsilon^2 + 3a_s\frac{1-2p}{p}\frac{1-p}{p}\beta^2\theta\epsilon^3 - \frac{\beta}{2\psi} = 0 \quad (4.30)$$

The second-order condition is given by

$$2a_v\frac{1-p}{p}\epsilon^2 + 6a_s\frac{1-2p}{p}\frac{1-p}{p}\beta\theta\epsilon^3 - \frac{1}{2\psi} < 0 \quad (4.31)$$

Equation (4.30) implicitly defines the optimal variable pay  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ . In particular, it follows that the optimal variable pay in the absence of shock ( $\epsilon = 0$ ) is given by  $\beta^*(0, a_v, a_s, \psi, \theta) = 1$ . Moreover, for  $a_s \rightarrow 0$  we have

$$\lim_{a_s \rightarrow 0} \beta^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{1}{1 - 4a_v\frac{1-p}{p}\psi\epsilon^2} < 1 = \beta^*(0, a_v, a_s, \psi, \theta)$$

Also, for  $p = \frac{1}{2}$ , we have  $\beta^*(\epsilon, a_v, 0, \psi, \theta) = \frac{1}{1 - 4a_v\frac{1-p}{p}}$ . For  $\epsilon > 0$  and  $p \neq \frac{1}{2}$ , the two possible solutions of (4.30) are given by

$$\beta_1^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\frac{1}{2\psi} - 2a_v\frac{1-p}{p}\epsilon^2 - \sqrt{\left(2a_v\frac{1-p}{p}\epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s\frac{1-2p}{p}\frac{1-p}{p}\frac{\theta\epsilon^3}{\psi}}}{6a_s\frac{1-2p}{p}\frac{1-p}{p}\theta\epsilon^3}$$

$$\beta_2^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\frac{1}{2\psi} - 2a_v\frac{1-p}{p}\epsilon^2 + \sqrt{\left(2a_v\frac{1-p}{p}\epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s\frac{1-2p}{p}\frac{1-p}{p}\frac{\theta\epsilon^3}{\psi}}}{6a_s\frac{1-2p}{p}\frac{1-p}{p}\theta\epsilon^3}$$

When  $\epsilon > 0$ , the right solution needs to satisfy the continuity condition

$\lim_{\epsilon \rightarrow 0} \beta_i^*(\epsilon, a_v, a_s, \psi, \theta) = 1$ ,  $i = 1, 2$ . Using this continuity condition, and applying

l'Hôpital's rule, it follows that the solution is given by  $\beta_1^*(\epsilon, a_v, a_s, \psi, \theta)$ :<sup>17</sup>

$$\beta^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\frac{1}{2\psi} - 2a_v \frac{1-p}{p} \epsilon^2 - \sqrt{\left(2a_v \frac{1-p}{p} \epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s \frac{1-2p}{p} \frac{1-p}{p} \frac{\theta \epsilon^3}{\psi}}{6a_s \frac{1-2p}{p} \frac{1-p}{p} \theta \epsilon^3} \quad (4.32)$$

**Point i and ii)**

Implicit function theorem on (4.30) leads to

$$\frac{\partial \beta^*(\epsilon, a_v, a_s, \psi, \theta)}{\partial a_v} > 0$$

Since  $e^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\theta}{2\psi} \beta^*(\epsilon, a_v, a_s, \psi, \theta)$ , it also follows  $\frac{\partial e^*}{\partial a_v} > 0$ . Note that the aversion to variance corresponds to  $a_v < 0$ . Hence,  $\frac{\partial \beta^*}{\partial a_v} > 0$  and  $\frac{\partial e^*}{\partial a_v} > 0$  mean that the optimal variable pay and optimal effort both decrease as the aversion to variance increases.

Also, from (4.30) we have that

$$\begin{aligned} \frac{\partial \beta^*}{\partial a_s} > 0 & \quad \text{if} \quad p < \frac{1}{2} \quad (\text{positive skewness}) \\ \frac{\partial \beta^*}{\partial a_s} < 0 & \quad \text{if} \quad p > \frac{1}{2} \quad (\text{negative skewness}) \end{aligned}$$

The optimal variable pay increases as the preference for positive skewness increases if  $p < \frac{1}{2}$  (i.e., positive skewness) and decreases as the preference for positive skewness increases if  $p > \frac{1}{2}$  (i.e., negative skewness). Also, because  $e^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\theta}{2\psi} \beta^*(\epsilon, a_v, a_s, \psi, \theta)$ , it also follows

$$\begin{aligned} \frac{\partial e^*}{\partial a_s} > 0 & \quad \text{if} \quad p < \frac{1}{2} \quad (\text{positive skewness}) \\ \frac{\partial e^*}{\partial a_s} < 0 & \quad \text{if} \quad p > \frac{1}{2} \quad (\text{negative skewness}) \end{aligned}$$

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<sup>17</sup>Another way to find the right solution is to plug the two possible solutions into the second-order condition (4.31) to see that it is solely satisfied by (4.32).



**Point iii)**

From (4.30), the implicit function theorem implies that

$$\text{Sign}\left[\frac{\partial\beta^*}{\partial\epsilon}\right] = \text{Sign}\left[4a_v + 9a_s\frac{1-2p}{p}\theta\epsilon\beta^*(\epsilon, a_v, a_s, \psi, \theta)\right] \quad (4.33)$$

with  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$  given in (4.32). Since  $a_v < 0$ ,  $a_s > 0$  and  $\beta^*(\epsilon, a_v, a_s, \psi, \theta) > 0$  it turns out that for  $p \geq \frac{1}{2}$  we have  $\frac{\partial\beta^*}{\partial\epsilon} < 0$ .

Since  $e^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\theta}{2\psi}\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ , it also follows that  $\frac{\partial e^*}{\partial\epsilon} < 0$  for  $p \geq \frac{1}{2}$ .

**Point iv)**

For  $p < \frac{1}{2}$ , either  $\frac{\partial\beta^*}{\partial\epsilon} < 0$  and  $\frac{\partial\beta^*}{\partial\epsilon} > 0$  are possible according to (4.33) and (4.32). Replacing (4.32) in (4.33), it turns out that

$$\frac{\partial\beta^*}{\partial\epsilon} > 0 \iff g(\epsilon, a_v, a_s, \psi, \theta) < \frac{9}{4} \quad (4.34)$$

with

$$g(\epsilon, a_v, a_s, \psi, \theta) := -\frac{6a_v\frac{1-p}{p}\epsilon^2}{\frac{1}{2\psi} - 2a_v\frac{1-p}{p}\epsilon^2 - \sqrt{\left(2a_v\frac{1-p}{p}\epsilon^2 - \frac{1}{2\psi}\right)^2 - 6a_s\frac{1-2p}{p}\frac{1-p}{p}\frac{\theta\epsilon^3}{\psi}}} \quad (4.35)$$

Since  $e^*(\epsilon, a_v, a_s, \psi, \theta) = \frac{\theta}{2\psi}\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ , it also follows that when  $p < \frac{1}{2}$  we have  $\frac{\partial e^*}{\partial\epsilon} > 0$  if and only if  $g(\epsilon, a_v, a_s, \psi, \theta) < \frac{9}{4}$ .

For example, [Spiliopoulos and Hertwig \(2019\)](#) estimate  $a_v = -0.0229$  and  $a_s = 0.0037$ . Using these estimated values and setting  $(\epsilon, p, \psi, \theta) = (0.7, 0.1, 0.5, 1)$ , the condition (4.34) holds. This yields  $\beta^*(\epsilon, a_v, a_s, \psi, \theta) = 1.12$

which is greater than the variable pay of 1 corresponding to the absence of noise.  
QED.

**Proof of Proposition A5:**

**Point i)**

At the optimal contract, the agent is risk-averse if  $a_v + a_s \frac{1-2p}{p} \theta \epsilon \beta^*(\epsilon, a_v, a_s, \psi, \phi) < 0$  and risk-seeking if  $a_v + a_s \frac{1-2p}{p} \theta \epsilon \beta^*(\epsilon, a_v, a_s, \psi, \theta) > 0$ . Using the expression (4.32) of  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$  it follows that the agent is risk-averse at the optimal contract if  $g(\epsilon, a_v, a_s, \psi, \theta) > 1$  and risk-seeking if  $g(\epsilon, a_v, a_s, \psi, \theta) < 1$ .

**Point ii)**

First, note that for any  $p < \frac{1}{2}$  and variable pay  $\beta > 0$  we have

$$a_v + \frac{9}{4} a_s \frac{1-2p}{p} \beta \theta \epsilon > a_v + a_s \frac{1-2p}{p} \beta \theta \epsilon \quad (4.36)$$

Second, for any  $p < \frac{1}{2}$  and a given triplet  $(\alpha, \beta, e)$ , the MVS decision maker exhibits risk-seeking for the positively skewed lottery  $L = \left( \alpha + \theta \beta \left( e + \frac{1-p}{p} \epsilon \right) - \psi e^2, \alpha + \theta \beta (e - \epsilon) - \psi e^2; p, 1-p \right)$  if

$$a_v + a_s \frac{1-2p}{p} \beta \theta \epsilon > 0 \quad (4.37)$$

Hence, if the agent exhibits risk-seeking for the optimal triplet  $(\alpha^*, \beta^*, e^*)$ , then we should have

$$a_v + a_s \frac{1-2p}{p} \beta^* \theta \epsilon > 0 \quad (4.38)$$

Given the expression (4.32) of the optimal variable pay  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ , the condition (4.38) holds iff

$$g(\epsilon, a_v, a_s, \psi, \theta) < 1 \quad (4.39)$$

with  $g(\epsilon, a_v, a_s, \psi, \theta)$  given in (4.35).

It follows that when the condition (4.38) holds, the agent exhibits risk-seeking for the positively skewed lottery  $L^* = \left( \alpha^* + \theta\beta^* \left( e^* + \frac{1-p}{p}\epsilon \right) - \psi e^{*2}, \alpha^* + \theta\beta^* \left( e^* - \epsilon \right) - \psi e^{*2}; p, 1-p \right)$ . Being risk-seeking means that (4.39) holds, and hence from (4.36) we have that the optimal variable pay satisfies  $a_v + a_s \frac{1-2p}{p} \beta^* \theta \epsilon > 0$ . Hence, we have  $\frac{\partial \beta^*}{\partial \epsilon} > 0$  and in particular  $\beta^*(\epsilon, a_v, a_s, \psi, \theta) > 1$  for  $\epsilon > 0$ .

**Point iii)**

For any  $p < \frac{1}{2}$  and an agent who exhibits risk-aversion at the optimal triplet  $(\alpha^*, \beta^*, e^*)$  with an optimal variable pay  $\beta^*$  that increases with  $\epsilon$ , we have

$$a_v + a_s \frac{1-2p}{p} \beta^* \theta \epsilon < 0 < a_v + \frac{9}{4} a_s \frac{1-2p}{p} \beta^* \theta \epsilon \quad (4.40)$$

Given the expression (4.32) for the optimal variable pay  $\beta^*(\epsilon, a_v, a_s, \psi, \theta)$ , the condition that ensures (4.40) is given by

$$g(\epsilon, a_v, a_s, \psi, \theta) \in \left( 1, \frac{9}{4} \right) \quad (4.41)$$

with  $g(\epsilon, a_v, a_s, \psi, \theta)$  given in (4.35).

It follows that when the condition (4.41) holds, the agent exhibits risk-aversion at the optimal triplet  $(\alpha^*, \beta^*, e^*)$  such that variable pay  $\beta^*$  increases with  $\epsilon$ .

QED.

## 4.B Extension to general utility function

In section 4.2, we employ the LEN model with CARA utility function. This approach provides a closed-form solution to the principal-agent problem through the Arrow-Pratt approximation of the risk premium. We investigate the robustness of the results under general utility specification for EUT and RDU. Denote by  $A_a(z) = -\frac{u''(x)}{u'(x)}$  the absolute risk-aversion index evaluated at  $x$ .

We provide the followings results and their proofs.

**Proposition B1 (Consistency of results under EUT):** the optimal variable pay is a decreasing function of  $\epsilon$ .

Proposition B1 shows that the tradeoff between risk and incentives in EUT framework does not depend on the utility function specifications and is not driven by approximation errors in the Arrow-Pratt risk premium.

**Example 3 (An illustration of Proposition B1 using expo-power utility function):**

To illustrate this point, we consider the expo-power utility function (Saha, 1993)  $u(z) = \frac{1 - \exp(-rz^\gamma)}{r}$  of which CARA (CRRA) is a special case when  $r = 1$  ( $r \rightarrow 0$ ). The alternative level of utility is given by  $y_0 = \frac{1 - \exp(-ry_0^\gamma)}{r}$  with  $y_0$  being the alternative (outside) outcome. We set  $(r, \gamma) = (0.029, 0.731)$  as found by Holt and Laury (2002) and  $(\psi, \theta, y_0) = (0.5, 1, 4)$ . In the absence of shock ( $\epsilon = 0$ ), the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . In the presence of shock  $(\epsilon, p) = (1, 0.5)$ , the optimal variable pay is  $\beta^* = 0.89$  and the optimal fixed pay is  $\alpha^* = 3.65$ . Hence, the optimal variable pay in absence of shock is indeed greater than the variable pay in the presence of the

shock.<sup>18</sup>

**Proposition B2 (Consistency of results under RDU):**

- i) If the agent's absolute risk-aversion index does not sufficiently decrease with the outcome, then the optimal variable pay decreases with the probability risk-aversion.
- ii) If the agent exhibits probability risk-aversion or probability risk-neutrality, then the optimal variable pay decreases with  $\epsilon$ .
- iii) Assume the agent exhibits probability risk-seeking and that for any couple  $(\alpha, \beta)$  the ratio between the average slope of the probability weighting function on the interval  $(0, p)$  and the average slope of the probability weighting on the interval  $(p, 1)$  are greater than the ratio between the slope of the utility function at the lowest possible value of the reward (net of cost) and the slope of the utility function at the highest possible value (net of cost). Then, the optimal variable pay is greater in the presence of shock than in its absence.
- iv) There exist  $A_a^{to}(\beta)$  such that if the agent exhibits probability risk-seeking and  $A_a\left(\alpha + \frac{\beta^2\theta^2}{4\psi}\right) < A_a^{to}(\beta, \epsilon)$  for any couple  $(\alpha, \beta)$ , then the optimal variable pay is greater in the presence of the shock than in its absence.

**Proposition B3 (Risk attitudes and absence of tradeoff with RDU):**

Assume that the agent exhibits probability risk-seeking for a given probability  $p$ . Denote by  $A_a^N\left(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\right)$  the absolute risk-aversion index that allows a probability risk-seeking agent to exhibit risk-neutrality for the lottery  $L^* = \left(\alpha^* + \theta\beta^*\left(e^* + \frac{1-p}{p}\epsilon\right) - \psi e^{*2}, \alpha^* + \theta\beta^*\left(e^* - \epsilon\right) - \psi e^{*2}; p, 1-p\right)$  associated with the optimal linear contract  $(\alpha^*, \beta^*)$ . Then,  $A_a^N\left(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\right) > A_a^{to}(\beta^*, \epsilon)$ .

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<sup>18</sup>Note that the problem does not have an explicit analytic solution. Our solution is numerical.

Propositions B2 and B3 are generalizations of Propositions A2 and A3. They show that the results on the comparisons of the variable pay in the absence of shock and in its presence shown under CARA utility function specification also hold under a general setting where the utility function is just required to be increasing and concave.

**Example 4 (An illustration of Proposition B3: presence of tradeoff with risk-seeking agent using expo-power utility function):** Consider again the expo-power utility function  $u(z) = \frac{1 - \exp(-rz^\gamma)}{r}$  with  $(r, \gamma) = (0.029, 0.731)$  as found by [Holt and Laury \(2002\)](#). We set  $(\psi, \theta, y_0) = (0.5, 1, 4)$ , with  $y_0$  being the alternative (outside) outcome. In the absence of shock ( $\epsilon = 0$ ), the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . In the presence of shock, we set  $(\epsilon, p, w(p)) = (1, 0.1, 0.15)$ . The optimal variable pay is  $\beta^* = 0.95$  and the optimal fixed pay is  $\alpha^* = 3.37$ . The optimal variable pay in the absence of shock is greater than the variable pay in the presence of shock. We have the expected value  $E[L^*] = 3.83$  and the certainty equivalent of  $L^*$  is 4. Hence, the agent exhibits risk-seeking at the optimal contract  $(\alpha^*, \beta^*) = (3.37, 0.95)$  where the tradeoff between risk and incentives is observed.

**Example 5 (An illustration of Proposition 12: absence of tradeoff with risk-seeking agent using expo-power utility function):** Consider the parameter calibration from example 4 with the only change being  $w(0.1) = 0.2$ . In the absence of a shock ( $\epsilon = 0$ ), the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . In the presence of a shock, the optimal variable pay is  $\beta^* = 1.17$  and the optimal fixed pay is  $\alpha^* = 2.73$ . The optimal variable pay in the absence of a shock is less than the variable pay in presence of a shock. We have that the expected value is  $E[L^*] = 3.41$  and the certainty equivalent of

$L^*$  is 4. Hence, the agent exhibits risk-seeking behavior at the optimal contract  $(\alpha^*, \beta^*) = (2.73, 1.17)$  where the tradeoff between risk and incentives is not observed.

**Proof of Proposition B1:**

Given the linear contract  $(\alpha, \beta)$ , the objective function of a EUT agent with cost function  $C(e) = \psi e^2$  is given by

$$EU(L) = pu(y_+) + (1 - p)u(y_-)$$

with  $u(x) = \frac{1 - \exp(-rx)}{r}$ ,  $y_+ = \alpha + \beta\theta(e + \frac{1-p}{p}\epsilon) - \psi e^2$  and  $y_- = \alpha + \beta\theta(e - \epsilon) - \psi e^2$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[pu'(y_+) + (1 - p)u'(y_-)] = 0$$

Since  $pu'(y_+) + (1 - p)u'(y_-) \neq 0$ , it turns out that the agent's optimal effort function is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the optimal effort function is an increasing function of the variable pay and does not vary with respect to  $\epsilon$ , the utility function or the fixed pay  $\alpha$ .

The optimization problem of the principal is to maximize the expected value of  $\theta z - y$  by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\begin{cases} \max_{\alpha, \beta} & \theta e - (\alpha + \beta \theta e) \\ \text{s.t. :} & \\ & e = \frac{\beta \theta}{2\psi} \\ & pu\left(\alpha + \beta \theta \left(e + \frac{1-p}{p} \epsilon\right) - \psi e^2\right) + (1-p)u\left(\alpha + \beta \theta (e - \epsilon) - \psi e^2\right) = u(y_0) \end{cases}$$

which is equivalent to

$$\begin{cases} \max_{\alpha, \beta} & \frac{\theta^2}{2\psi} (\beta - \beta^2) - \alpha \\ \text{s.t. :} & \\ & pu\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} + \frac{1-p}{p} \beta \theta \epsilon\right) + (1-p)u\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} - \epsilon\right) = y_0 \end{cases}$$

The corresponding Lagrangian function is given by

$$\mathcal{L}(\alpha, \beta, \mu) = \frac{\theta^2}{2\psi} (\beta - \beta^2) - \alpha + \mu \left[ pu\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} + \frac{1-p}{p} \beta \theta \epsilon\right) + (1-p)u\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} - \epsilon\right) - y_0 \right]$$

Denote by

$$y'_+ = \theta \left( \frac{1-p}{p} \epsilon + \frac{\beta \theta}{2\psi} \right) > 0$$

$$y'_- = \theta \left( -\epsilon + \frac{\beta \theta}{2\psi} \right) > 0$$

Then, the first-order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial \beta} = \frac{\theta^2}{2\psi} (1 - 2\beta) + \mu \left[ pu'(y_+) y'_+ + (1-p)u'(y_-) y'_- - y_0 \right] = 0 \quad (4.42)$$

$$\frac{\partial \mathcal{L}}{\partial \alpha} = -1 + \mu \left[ pu'(y_+) + (1-p)u'(y_-) \right] = 0 \quad (4.43)$$



$$\frac{\partial \mathcal{L}}{\partial \mu} = pu(y_+) + (1-p)u(y_-) - y_0 = 0 \quad (4.44)$$

with  $y_- = \alpha + \frac{\beta^2 \theta^2}{4\psi} - \beta\theta\epsilon$  and  $y_+ = \alpha + \frac{\beta^2 \theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon$ .

Note that from (4.42) and (4.43), it turns out that the optimal variable pay  $\beta$  satisfies

$$\beta = 1 + (1-p) \frac{2\psi\epsilon}{\theta} \frac{u'(y_+) - u'(y_-)}{pu'(y_+) + (1-p)u'(y_-)} \leq 1 \quad (4.45)$$

This shows that the optimal variable pay in the absence of shock ( $\epsilon = 0$ ) is 1. Since  $u'(y_+) < u'(y_-)$ , it also follows that the optimal variable pay in the absence of shock is greater than the optimal variable pay in the presence of shock ( $\epsilon > 0$ ). Let us now derive an even stronger result according to which the optimal variable pay is a decreasing function of  $\epsilon$ .

Totally differentiating the first-order conditions (4.42)-(4.44) with respect to  $\beta, \alpha, \mu$  and  $\epsilon$  leads to

$$Hess(\alpha, \beta, \mu) \times \begin{pmatrix} \frac{d\beta}{d\epsilon} \\ \frac{d\alpha}{d\epsilon} \\ \frac{d\mu}{d\epsilon} \end{pmatrix} = - \begin{pmatrix} \frac{\partial^2 \beta}{\partial \beta \partial \epsilon} \\ \frac{\partial^2 \beta}{\partial \alpha \partial \epsilon} \\ \frac{\partial^2 \beta}{\partial \mu \partial \epsilon} \end{pmatrix} \quad (4.46)$$

with  $Hess(\alpha, \beta, \mu)$  being the Hessian matrix defined as follows

$$Hess(\alpha, \beta, \mu) = \begin{pmatrix} \frac{\partial^2 \mathcal{L}}{\partial \beta^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} \\ \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} \\ \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} & \frac{\partial^2 \mathcal{L}}{\partial \mu^2} \end{pmatrix}$$

Assuming that there exists at least a local maximum so that the determinant of the Hessian matrix is positive, it follows from (4.46) that

$$\text{Sign}\left(\frac{d\beta}{d\epsilon}\right) = \text{Sign}(E) \quad (4.47)$$

with

$$E = \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} \left( \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} \right) - \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \epsilon} \left( \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} \right)$$

$$\mu = \frac{1}{pu'(y_+) + (1-p)u'(y_-)} \quad (4.48)$$

$$\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} = \mu \theta (1-p) \left[ u'(y_+) - u'(y_-) + \beta \left( u''(y_+) y'_+ - u''(y_-) y'_- \right) \right]$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \alpha} = pu'(y_+) + (1-p)u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} = \mu \beta \theta (1-p) \left( u''(y_+) - u''(y_-) \right) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} = py'_+ u'(y_+) + (1-p)y'_- u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \epsilon} = \beta \theta (1-p) \left( u'(y_+) - u'(y_-) \right) < 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} = \mu \left[ py'_+ u''(y_+) + (1-p)y'_- u''(y_-) \right] \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha^2} = \mu \left[ pu''(y_+) + (1-p)u''(y_-) \right] \leq 0$$

Using all the previous derivatives, we have

$$\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} = \theta (1-p) \left( u'(y_+) - u'(y_-) \right) - \mu \frac{\theta^2 \beta \epsilon}{p} (1-p) \times$$

$$u'(y_+) u'(y_-) \left( (1-p)A_a(y_+) + pA_a(y_-) \right) \leq 0 \quad (4.49)$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} = \mu \theta \epsilon (1-p) u'(y_+) u'(y_-) (A_a(y_-) - A_a(y_+)) \geq 0$$

$$E = \theta(1-p) \left[ \left( u'(y_+) - u'(y_-) \right) \frac{1}{\mu} - \mu \beta \theta \epsilon u'(y_+) u'(y_-) \left( u'(y_+) A_a(y_-) + \frac{1-p}{p} u'(y_-) A_a(y_+) \right) \right]$$

Since the utility function is concave, we have  $u'(y_+) < u'(y_-)$ ,  $A_a(y_-) > 0$  and  $A_a(y_+) > 0$  so that  $E < 0$ . It turns out that

$$\frac{d\beta}{d\epsilon} < 0$$

To illustrate this, consider again the expo-power utility function (Saha, 1993). The alternative level of utility is given by  $y_0 = \frac{1 - \exp(-r y_0^\gamma)}{r}$  with  $y_0$  the alternative (outside) outcome. Hence, the first-order conditions are given by

$$\begin{aligned} \frac{\partial L}{\partial \beta} = \frac{\theta^2}{2\psi} (1-2\beta) + \mu \gamma \theta \left[ p \left( \frac{1-p}{p} \epsilon + \frac{\beta \theta}{2\psi} \right) \exp \left( -r \left( \alpha + \beta \theta \frac{1-p}{p} \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^\gamma \right) \left( \alpha + \beta \theta \frac{1-p}{p} \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^{\gamma-1} \right. \\ \left. + (1-p) \left( -\epsilon + \frac{\beta \theta}{2\psi} \right) \exp \left( -r \left( \alpha - \beta \theta \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^\gamma \right) \left( \alpha - \beta \theta \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^{\gamma-1} \right] = 0 \end{aligned}$$

$$\begin{aligned} \frac{\partial L}{\partial \alpha} = -1 + \mu \gamma \left[ p \exp \left( -r \left( \alpha + \beta \theta \frac{1-p}{p} \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^\gamma \right) \left( \alpha + \beta \theta \frac{1-p}{p} \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^{\gamma-1} + \right. \\ \left. (1-p) \exp \left( -r \left( \alpha - \beta \theta \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^\gamma \right) \left( \alpha - \beta \theta \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^{\gamma-1} \right] = 0 \end{aligned}$$

$$\frac{\partial L}{\partial \mu} = p \frac{1 - \exp \left( -r \left( \alpha + \beta \theta \frac{1-p}{p} \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^\gamma \right)}{r} + (1-p) \frac{1 - \exp \left( -r \left( \alpha - \beta \theta \epsilon + \frac{\beta^2 \theta^2}{4\psi} \right)^\gamma \right)}{r}$$

$$-\frac{1 - \exp(-ry_0^\gamma)}{r} = 0$$

We set  $(r, \gamma) = (0.029, 0.731)$  as in by [Holt and Laury \(2002\)](#) and  $(\psi, \theta, y_0) = (0.5, 1, 4)$ . In the absence of a shock ( $\epsilon = 0$ ), the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . In the presence of a shock, we set  $(\epsilon, p) = (1, 0.5)$ . The optimal variable pay is  $\beta^* = 0.92$  and the optimal fixed pay is  $\alpha^* = 3.61$ . The optimal variable pay in the absence of shock is thus greater than the variable pay in the presence of a shock.

QED.

### Proof of Proposition B2

Given the linear contract  $(\alpha, \beta)$ , the objective function of an expected utility agent with cost function  $C(e) = \psi e^2$  is given by

$$RDU(L) = w(p)u(y_+) + (1 - w(p))u(y_-)$$

with  $u(x) = \frac{1 - \exp(-rx)}{r}$ ,  $y_+ = \alpha + \beta\theta(e + \frac{1-p}{p}\epsilon) - \psi e^2$  and  $y_- = \alpha + \beta\theta(e - \epsilon) - \psi e^2$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[w(p)u'(y_+) + (1 - w(p))u'(y_-)] = 0$$

Since  $w(p)u'(y_+) + (1 - w(p))u'(y_-) \neq 0$ , it turns out that the optimal effort function is given by

$$e = \frac{\beta\theta}{2\psi}$$

Hence, the optimal effort function is an increasing function of the variable pay and does not vary with respect to  $\epsilon$ , the utility curvature, the fixed pay  $\alpha$  or the probability risk attitude captured by  $w(p)$ .

**Point i)**

The optimization problem of the principal is to maximize the expected value of  $\theta z - y$  by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\left\{ \begin{array}{l} \max_{\alpha, \beta} \theta e - (\alpha + \beta \theta e) \\ s.t. : \\ e = \frac{\beta \theta}{2\psi} \\ w(p)u\left(\alpha + \beta \theta \left(e + \frac{1-p}{p} \epsilon\right) - \psi e^2\right) + (1 - w(p))u\left(\alpha + \beta \theta (e - \epsilon) - \psi e^2\right) = y_0 \end{array} \right.$$

which is equivalent to

$$\left\{ \begin{array}{l} \max_{\alpha, \beta} \frac{\theta^2}{2\psi} (\beta - \beta^2) - \alpha \\ s.t. : \\ w(p)u\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} + \frac{1-p}{p} \beta \theta \epsilon\right) + (1 - w(p))u\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} - \epsilon\right) = y_0 \end{array} \right.$$

The corresponding Lagrangian function is given by

$$\mathcal{L}(\alpha, \beta, \mu) = \frac{\theta^2}{2\psi} (\beta - \beta^2) - \alpha + \mu \left[ w(p)u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right) + (1-w(p))u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \epsilon\right) - y_0 \right]$$

Denote by

$$y'_+ = \theta\left(\frac{1-p}{p}\epsilon + \frac{\beta\theta}{2\psi}\right) > 0$$

$$y'_- = \theta(-\epsilon + \frac{\beta\theta}{2\psi}) > 0$$

Then, the first-order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial \beta} = \frac{\theta^2}{2\psi} (1 - 2\beta) + \mu \left[ w(p)u'(y_+)y'_+ + (1 - w(p))u'(y_-)y'_- \right] = 0 \quad (4.50)$$

$$\frac{\partial \mathcal{L}}{\partial \alpha} = -1 + \mu \left[ w(p)u'(y_+) + (1 - w(p))u'(y_-) \right] = 0 \quad (4.51)$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = w(p)u(y_+) + (1 - w(p))u(y_-) - y_0 = 0 \quad (4.52)$$

with  $y_- = \alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon$  and  $y_+ = \alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon$ .

Denote by  $\delta := w(p)$ . Then, totally differentiating the first-order conditions (4.50)-(4.52) with respect to  $\beta, \alpha, \mu$  and  $\delta$  leads to

$$Hess(\alpha, \beta, \mu) \times \begin{pmatrix} \frac{d\beta}{d\delta} \\ \frac{d\alpha}{d\delta} \\ \frac{d\mu}{d\delta} \end{pmatrix} = - \begin{pmatrix} \frac{\partial^2 \beta}{\partial \beta \partial \delta} \\ \frac{\partial^2 \beta}{\partial \alpha \partial \delta} \\ \frac{\partial^2 \beta}{\partial \mu \partial \delta} \end{pmatrix} \quad (4.53)$$

with  $Hess(\alpha, \beta, \mu)$  being the Hessian matrix defined as follows

$$Hess(\alpha, \beta, \mu) = \begin{pmatrix} \frac{\partial^2 \mathcal{L}}{\partial \beta^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} \\ \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} \\ \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} & \frac{\partial^2 \mathcal{L}}{\partial \mu^2} \end{pmatrix}$$

Assuming that there exists at least a local maximum so that the determinant of the Hessian matrix is positive, it follows from (4.53) that

$$Sing\left(\frac{d\beta}{d\delta}\right) = Sign(\Delta) \quad (4.54)$$

with

$$\Delta = \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} \left( \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \delta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \delta} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} \right) - \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \delta} \left( \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} \right)$$

$$\mu = \frac{1}{pu'(y_+) + (1-p)u'(y_-)} \quad (4.55)$$

$$\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \delta} = \mu [u'(y_+)y'_+ - u'(y_-)y'_-]$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \alpha} = w(p)u'(y_+) + (1-w(p))u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \delta} = \mu(u'(y_+) - u'(y_-)) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} = w(p)y'_+u'(y_+) + (1-w(p))y'_-u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \delta} = u(y_+) - u(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} = \mu \left[ w(p)y'_+ u''(y_+) + (1 - w(p))y'_- u''(y_-) \right] \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha^2} = \mu \left[ w(p)u''(y_+) + (1 - w(p))u''(y_-) \right] \leq 0$$

Using all the previous derivatives, we have

$$\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \delta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \delta} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} = \mu \frac{\theta \epsilon}{p} u'(y_+) u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} = \mu \frac{\theta \epsilon}{p} u'(y_+) u'(y_-) w(p)(1 - w(p)) (A_a(y_-) - A_a(y_+)) \geq 0$$

Hence

$$\begin{aligned} \Delta = & \mu \frac{\theta \epsilon}{p} u'(y_+) u'(y_-) \left[ w(p)u'(y_+) + (1 - w(p))u'(y_-) \right. \\ & \left. - w(p)(1 - w(p))(u(y_+) - u(y_-))(A_a(y_-) - A_a(y_+)) \right] \end{aligned} \quad (4.56)$$

Clearly  $\Delta > 0$  (i.e.,  $\frac{d\beta}{d\delta} > 0$ ) under CARA utility assumption, indicating that the approximation errors in Arrow-Pratt risk premium does not alter the results established in previous propositions. For utility function such that  $A_a(y_-) - A_a(y_+) \rightarrow 0$ , we have  $\Delta > 0$  (i.e.,  $\frac{d\beta}{d\delta} > 0$ ).

**Point ii)**



From (4.50) and (4.51), it turns out that the optimal variable pay  $\beta^*$  satisfies the following equation

$$\beta = 1 + \frac{2\psi\epsilon}{\theta} \frac{w(p)\frac{1-p}{p}u'(y_+) - (1-w(p))u'(y_-)}{w(p)u'(y_+) + (1-w(p))u'(y_-)} \leq 1 \quad (4.57)$$

Thus, the optimal variable pay in the absence of shock ( $\epsilon = 0$ ) is 1. Since  $u'(y_+) < u'(y_-)$ , it also follows under the assumption of probability risk-aversion/neutrality (i.e.,  $w(p) \leq p$ ) that the optimal variable pay in the absence of shock is greater than the optimal variable pay in the presence of shock ( $\epsilon > 0$ ).

Now, we show a stronger result according to which the optimal variable pay is indeed a decreasing function of  $\epsilon$  under the assumption of probability risk-aversion/neutrality.

Totally differentiating the first-order conditions (4.50)-(4.52) with respect to  $\beta, \alpha, \mu$  and  $\epsilon$  leads to

$$Hess(\alpha, \beta, \mu) \times \begin{pmatrix} \frac{d\beta}{d\epsilon} \\ \frac{d\alpha}{d\epsilon} \\ \frac{d\mu}{d\epsilon} \end{pmatrix} = - \begin{pmatrix} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} \\ \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} \\ \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \epsilon} \end{pmatrix} \quad (4.58)$$

with  $Hess(\alpha, \beta, \mu)$  being the Hessian matrix defined as follows

$$Hess(\alpha, \beta, \mu) = \begin{pmatrix} \frac{\partial^2 \mathcal{L}}{\partial \beta^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} \\ \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} \\ \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} & \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} & \frac{\partial^2 \mathcal{L}}{\partial \mu^2} \end{pmatrix}$$

Assuming there exists at least a local maximum so that the determinant of the Hessian matrix is positive, it follows from (4.58) that

$$\text{Sing}\left(\frac{d\beta}{d\epsilon}\right) = \text{Sign}(R) \quad (4.59)$$

with

$$E = \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} \left( \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} \right) - \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \epsilon} \left( \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} \right)$$

$$\mu = \frac{1}{pw'(y_+) + (1-p)u'(y_-)} \quad (4.60)$$

$$\frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} = \mu \theta \left[ w(p) \frac{1-p}{p} u'(y_+) - (1-w(p))u'(y_-) + \beta \left( w(p) \frac{1-p}{p} u''(y_+)y'_+ - (1-w(p))u''(y_-)y'_- \right) \right]$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \alpha} = w(p)u'(y_+) + (1-w(p))u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} = \mu \beta \theta \left( w(p) \frac{1-p}{p} u''(y_+) - (1-w(p))u''(y_-) \right)$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \beta} = w(p)y'_+u'(y_+) + (1-w(p))y'_-u'(y_-) > 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \epsilon} = \beta \theta \left( w(p) \frac{1-p}{p} u'(y_+) - (1-w(p))u'(y_-) \right) < 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} = \mu \left[ w(p)y'_+u''(y_+) + (1-w(p))y'_-u''(y_-) \right] \leq 0$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha^2} = \mu \left[ w(p)u''(y_+) + (1 - w(p))u''(y_-) \right] \leq 0$$

Using all the previous derivatives, we have

$$\begin{aligned} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \epsilon} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} &= \theta \left( w(p) \frac{1-p}{p} u'(y_+) - (1-w(p))u'(y_-) \right) \\ &\quad - \mu \frac{\theta^2 \beta \epsilon}{p} w(p)(1-w(p))u'(y_+)u'(y_-) \times \quad (4.61) \\ &\quad \left( \frac{1-p}{p} A_a(y_+) + A_a(y_-) \right) \leq 0 \end{aligned}$$

$$\frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \beta} \frac{\partial^2 \mathcal{L}}{\partial \alpha \partial \mu} - \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \frac{\partial^2 \mathcal{L}}{\partial \beta \partial \mu} = \mu \frac{\theta \epsilon}{p} w(p)(1-w(p))u'(y_+)u'(y_-) \left( A_a(y_-) - A_a(y_+) \right) \geq 0$$

Hence

$$R = R_1 - R_2$$

with

$$\begin{aligned} R_1 &= \theta \left( w(p)u'(y_+) + (1-w(p))u'(y_-) \right) \left( w(p) \frac{1-p}{p} u'(y_+) - (1-w(p))u'(y_-) \right) \\ R_2 &= \frac{\beta \theta^2 \epsilon u'(y_+)u'(y_-) \frac{w(p)}{p} (1-w(p)) \left( \frac{w(p)}{p} u'(y_+)A_a(y_-) + \frac{1-w(p)}{p} u'(y_-)A_a(y_+) \right)}{w(p)u'(y_+) + (1-w(p))u'(y_-)} \end{aligned}$$

Since the utility function is increasing and concave, we have  $0 < u'(y_+) < u'(y_-)$ ,  $A_a(y_-) > 0$  and  $A_a(y_+) > 0$  so that  $R_2 > 0$ .

Also note that the agent's probability risk-aversion/risk-neutrality (i.e.,  $w(p) \leq p$ ) implies  $R_1 < 0$ . It follows that in the presence of probability risk-aversion/risk-neutrality we have  $R < 0$  and hence

$$\frac{d\beta}{d\epsilon} < 0$$

**Point iii)**

Recall that the equation (4.57) satisfies by the optimal variable pay

$$\beta = 1 + \frac{2\psi\epsilon}{\theta} \frac{w(p)\frac{1-p}{p}u'(y_+) - (1-w(p))u'(y_-)}{w(p)u'(y_+) + (1-w(p))u'(y_-)} \leq 1 \quad (4.62)$$

It follows directly that

$$\beta > 1 \quad \iff \quad \frac{\frac{w(p)}{p}}{\frac{1-w(p)}{1-p}} > \frac{u'(y_-)}{u'(y_+)} > 1$$

**Point iv)**

From (4.62), it follows directly

$$\beta > 1 \quad \iff \quad w(p)\frac{1-p}{p}u'\left(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\right) - (1-w(p))u'\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right)$$

Denote by

$$H(\epsilon) = w(p)\frac{1-p}{p}u'\left(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\right) - (1-w(p))u'\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right) + o(\epsilon)$$

Then, the first-order Taylor approximation of  $H(\epsilon)$  around  $\epsilon = 0$  gives

$$\frac{H(\epsilon)}{u'(\alpha + \frac{\beta^2\theta^2}{4\psi})} = \frac{w(p)}{p} - 1 - \left(1 + \frac{w(p)}{p} \frac{1-2p}{p}\right) \beta\theta\epsilon A_a\left(\alpha + \frac{\beta^2\theta^2}{4\psi}\right) \quad (4.63)$$

with  $o(\epsilon)$  the approximation error which is such that  $\lim_{\epsilon \rightarrow 0} \frac{o(\epsilon)}{\epsilon} = 0$ . It turns out that  $H(\epsilon) > 0$  if the following condition holds

$$A_a\left(\alpha + \frac{\beta^2\theta^2}{4\psi}\right) < \frac{1}{\beta\theta\epsilon} \frac{\frac{w(p)}{p} - 1}{1 + \frac{w(p)}{p} \frac{1-2p}{p}} := A_a^{to}(\beta, \epsilon) \quad (4.64)$$

QED.

**Proof of Proposition B3:**

From Lemma 1, the absolute risk-aversion index  $A_a^N\left(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\right)$  that makes an agent with probability risk-seeking behavior to exhibit risk-neutrality (i.e., risk premium equals 0) for the lottery  $L = \left(\alpha^* + \beta^*\theta\left(e^* + \frac{1-p}{p}\epsilon\right) - \psi e^{*2}, \alpha^* + \beta^*\theta\left(e^* - \epsilon\right) - \psi e^{*2}; p, 1-p\right)$  associated with the optimal linear contract  $(\alpha^*, \beta^*)$  and optimal effort  $e^*$  is given by

$$A_a^N\left(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\right) := \frac{2}{\theta\epsilon\beta^*} \frac{\frac{\delta}{p} - 1}{1 + \frac{\delta}{p} \frac{1-2p}{p}} \quad (4.65)$$

with  $\delta = w(p)$

From Proposition B2, the threshold  $A_a^{to}(\beta^*, \epsilon)$  of the absolute risk-aversion index of an agent with probability risk-seeking behavior that leads the principal to propose an optimal variable pay that is greater in presence of the shock than in its absence is given by

$$A_a^{to}(\beta^*, \epsilon) \cong \frac{1}{\beta\theta\epsilon} \frac{\frac{w(p)}{p} - 1}{1 + \frac{w(p)}{p} \frac{1-2p}{p}} \quad (4.66)$$

Since  $A_a^N\left(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\right) \simeq 2A_a^{to}(\beta^*, \epsilon)$ , then  $A_a^N\left(\alpha^* + \frac{\beta^{*2}\theta^2}{4\psi}\right) > 2A_a^{to}(\beta^*, \epsilon)$

As an example, consider the expo-power utility function (Saha, 1993). The alternative level of utility is given by  $y_0 = \frac{1 - \exp(-ry_0^\gamma)}{r}$  with  $y_0$  being the alternative (outside) outcome. Hence, the first-order conditions are given by

$$\begin{aligned} \frac{\partial L}{\partial \beta} = & \frac{\theta^2}{2\psi}(1-2\beta) + \mu\gamma\theta \left[ w(p) \left( \frac{1-p}{p}\epsilon + \frac{\beta\theta}{2\psi} \right) \exp\left(-r\left(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^\gamma\right) \left(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^{\gamma-1} \right. \\ & \left. + (1-w(p)) \left( -\epsilon + \frac{\beta\theta}{2\psi} \right) \exp\left(-r\left(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^\gamma\right) \left(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^{\gamma-1} \right] = 0 \end{aligned}$$

$$\begin{aligned} \frac{\partial L}{\partial \alpha} = & -1 + \mu\gamma \left[ w(p) \exp\left(-r\left(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^\gamma\right) \left(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^{\gamma-1} + \right. \\ & \left. (1-w(p)) \exp\left(-r\left(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^\gamma\right) \left(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^{\gamma-1} \right] = 0 \end{aligned}$$

$$\begin{aligned} \frac{\partial L}{\partial \mu} = & w(p) \frac{1 - \exp\left(-r\left(\alpha + \beta\theta\frac{1-p}{p}\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^\gamma\right)}{r} + (1-w(p)) \frac{1 - \exp\left(-r\left(\alpha - \beta\theta\epsilon + \frac{\beta^2\theta^2}{4\psi}\right)^\gamma\right)}{r} \\ & - \frac{1 - \exp(-ry_0^\gamma)}{r} = 0 \end{aligned}$$

- We set  $(r, \gamma) = (0.029, 0.731)$  as found by Holt and Laury (2002) and  $(\psi, \theta, y_0) = (0.5, 1, 4)$ . In the absence of shock ( $\epsilon = 0$ ), the optimal variable

pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . In the presence of a shock  $(\epsilon, p, w(p)) = (1, 0.1, 0.15)$ , the optimal variable pay is  $\beta^* = 0.95$  and the optimal fixed pay is  $\alpha^* = 3.37$ . The optimal variable pay in the absence of a shock is greater than the variable pay in presence of a shock. The expected value is  $E[L] = 3.83$  and the certainty equivalent of  $L$  is 4. Hence, the agent exhibits risk-seeking at the optimal contract  $(\alpha^*, \beta^*) = (3.37, 0.95)$  where the tradeoff between risk and incentive is observed.

- Consider the calibration from the previous example with one change:  $w(0.1) = 0.2$ . In the absence of a shock (i.e.,  $\epsilon = 0$ ), the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . In the presence of a shock  $(\epsilon, p) = (1, 0.1)$ , the optimal variable pay is  $\beta^* = 1.17$  and the optimal fixed pay is  $\alpha^* = 2.73$ . The optimal variable pay in the absence of shock is less than the variable pay in the presence of shock. The expected value is  $E[L] = 3.41$  and the certainty equivalent of  $L$  is 4. Hence, the agent exhibits risk-seeking at the optimal contract  $(\alpha^*, \beta^*) = (2.73, 1.17)$  where the tradeoff between risk and incentive is not observed.

QED.

## 4.C - Extension to continuous random shocks

In Section 2, we focus on binary shocks. Herein, we extend this framework to the case of continuous random shocks. We denote by  $f(\cdot)(F(\cdot))$  the probability density (cumulative distribution) function of a continuous random shock  $\tilde{\epsilon}$  such that  $E(\tilde{\epsilon}) = 0$  and  $V(\tilde{\epsilon})$ . We further assume that the distribution is symmetric around 0, that is  $f(\epsilon) = f(-\epsilon)$  for all  $\epsilon > 0$ .

**Proposition C1 (Consistency of results under RDU):**<sup>19</sup>

- i) Assume that the agent exhibits probability risk-aversion or probability risk-neutrality (i.e.,  $w'(\cdot) \geq 0$ ). Hence, the optimal variable pay is greater in the absence of shock than in its presence.
- ii) Assume that the agent exhibits probability risk-seeking (i.e.,  $w'(\cdot) < 0$ ) or inverse-s-shaped probability weighting (i.e.,  $\exists a \in (0, 1)$  such that  $w''(p) < 0$  for  $p \in (0, a)$  and  $w''(p) > 0$  for  $p \in (a, 1)$ ). Hence the optimal performance can be greater in the presence of shock than in its absence.

**Proof of Proposition C1:**

Given the linear contract  $(\alpha, \beta)$ , the objective function of an expected utility agent with cost function  $C(e) = \psi e^2$  is given by

$$RDU(L) = \int_{-\infty}^{+\infty} u(\alpha + \beta\theta(e + \epsilon) - \psi e^2) d[1 - w(1 - F(\epsilon))] \quad (4.67)$$

Noting that  $d[1 - w(1 - F(\epsilon))] = w'(1 - F(\epsilon))f(\epsilon)d\epsilon$ , the derivative of (4.67) with respect to  $e$  is given by

$$(\beta\theta - 2\psi e) \int_{-\infty}^{+\infty} u'(\alpha + \beta\theta(e + \epsilon) - \psi e^2) w'(1 - F(\epsilon)) f(\epsilon) d\epsilon = 0$$

Since both  $u(\cdot)$  and  $w(\cdot)$  are strictly increasing functions, it turns out that the optimal effort function of the agent is given by

$$e = \frac{\beta\theta}{2\psi}$$

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<sup>19</sup>We focus here on symmetric distributions for which MVS boils down to mean-variance preference. The mean-variance preference corresponds to the RDU with quadratic utility function and probabilistic risk-neutrality (i.e., linear weighting function). In this context, the tradeoff between risk and incentive holds.



Hence, the optimal effort function is an increasing function of the variable pay and does not vary with respect to  $\epsilon$ , the utility curvature  $r$ , the fixed pay  $\alpha$  or the probability risk attitude captured by  $w(p)$ .

**Point i)**

The principal's optimization problem is to maximize the expected value of  $\theta z - y$  by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\left\{ \begin{array}{l} \max_{\alpha, \beta} \theta e - (\alpha + \beta \theta e) \\ s.t. : \\ e = \frac{\beta \theta}{2\psi} \\ \int_{-\infty}^{+\infty} u(\alpha + \beta \theta (e + \epsilon) - \psi e^2) w'(1 - F(\epsilon)) f(\epsilon) d\epsilon = y_0 \end{array} \right.$$

which is equivalent to

$$\left\{ \begin{array}{l} \max_{\alpha, \beta} \frac{\theta^2}{2\psi} (\beta - \beta^2) - \alpha \\ s.t. : \\ \int_{-\infty}^{+\infty} u\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} + \beta \theta \epsilon\right) w'(1 - F(\epsilon)) f(\epsilon) d\epsilon = y_0 \end{array} \right.$$

The corresponding Lagrangian function is given by

$$\mathcal{L}(\alpha, \beta, \mu) = \frac{\theta^2}{2\psi} (\beta - \beta^2) - \alpha + \mu \left[ \int_{-\infty}^{+\infty} u\left(\alpha + \frac{\beta^2 \theta^2}{4\psi} + \beta \theta \epsilon\right) w'(1 - F(\epsilon)) f(\epsilon) d\epsilon - y_0 \right]$$

The first-order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial \beta} = \frac{\theta^2}{2\psi}(1-2\beta) + \mu\theta \int_{-\infty}^{+\infty} \left(\frac{\beta\theta}{2\psi} + \epsilon\right) u' \left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\right) w'(1-F(\epsilon)) f(\epsilon) d\epsilon = 0 \quad (4.68)$$

$$\frac{\partial \mathcal{L}}{\partial \alpha} = -1 + \mu \int_{-\infty}^{+\infty} u' \left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\right) w'(1-F(\epsilon)) f(\epsilon) d\epsilon = 0 \quad (4.69)$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = \int_{-\infty}^{+\infty} u \left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\right) w'(1-F(\epsilon)) f(\epsilon) d\epsilon - y_0 = 0 \quad (4.70)$$

From (4.68) and (4.69), it follows that the optimal variable pay  $\beta^*$  satisfies the following equation

$$\beta = 1 + \frac{2\psi \int_{-\infty}^{+\infty} \epsilon u \left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\right) w'(1-F(\epsilon)) f(\epsilon) d\epsilon}{\theta \int_{-\infty}^{+\infty} u \left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\right) w'(1-F(\epsilon)) f(\epsilon) d\epsilon} \quad (4.71)$$

It follows directly from (4.71) that if  $w'(\cdot) \geq 0$ , then  $\int_{-\infty}^{+\infty} \epsilon u \left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\right) w'(1-F(\epsilon)) f(\epsilon) d\epsilon < 0$  so that  $\beta < 1$ .

**Point ii)** From (4.71), it follows directly

$$\beta > 1 \quad \iff \quad G(\alpha, \beta) := \int_{-\infty}^{+\infty} \epsilon u \left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \beta\theta\epsilon\right) w'(1-F(\epsilon)) f(\epsilon) d\epsilon > 0 \quad (4.72)$$

**Example:**

Consider that the relationship between output and effort is affected by a shock that follows a logistic distribution with mean 0 and variance  $\frac{\pi^2}{3}$ . The probability density function and cumulative distribution functions are given by

$$f(\epsilon) = \frac{\exp(-\epsilon)}{(1 + \exp(-\epsilon))^2} \quad \text{and} \quad F(\epsilon) = \frac{1}{1 + \exp(-\epsilon)}$$

Assume that the weighting function is the following linear combination of logarithmic and quadratic functions

$$w(p) = a \frac{\ln(\delta p + 1)}{\ln(1 + \delta)} + (1 - a - b)p^2 + bp$$

with  $\delta, a$  and  $b$  being parameters of the weighting function. The derivative of  $w(p)$  is given by

$$w'(p) = a \frac{\delta a}{(\delta p + 1)\ln(1 + \delta)} + 2(1 - a - b)p + b$$

We set  $(\delta, a, b) = (19, 1.25, -2)$ . Figure 4.C.1 plots the density and probability weighting functions. Note that (i) the weighting function is differentiable on  $[0, 1]$ , (ii) the derivative function  $w'(p)$  is U-shaped and (iii) the derivatives of small probabilities are greater than the derivatives of high probabilities (see Figure 4.C.2).

Furthermore, assume a quadratic utility function  $u(x) = x - rx^2$  that is concave (i.e.,  $r > 0$ ).

- **Case 1 (presence of tradeoff with risk-seeking agent):** we set  $(r, \psi, \theta, y_0) = (0.02, 0.5, 0.5, 4)$ , with  $y_0$  being the alternative (outside) outcome. Let  $E = \alpha + \frac{\beta\theta}{4\psi}$ ,  $S_1 = \int_{-\infty}^{+\infty} \epsilon w'(1 - F(\epsilon))f(\epsilon)d\epsilon$  and  $S_2 = \int_{-\infty}^{+\infty} \epsilon^2 w'(1 - F(\epsilon))f(\epsilon)d\epsilon$ , then the optimal contract is given by the following system of two equations

$$\frac{\partial \mathcal{L}}{\partial \mu} = E(1 - rE) + \beta\theta(1 - 2rE)S_1 - r\beta^2\theta^2S_2 - y_0 + ry_0^2 = 0$$

$$\beta = 1 + \frac{2\psi}{\theta} \frac{(1 - 2rE)S_1 - 2r\beta\theta S_2}{1 - 2rE - 2r\beta\theta S_1}$$

The optimal variable pay is  $\beta^* = 0.93$  and the optimal fixed pay is  $\alpha^* = 3.87$ . Recall that in the absence of a shock, the optimal variable pay is  $\beta^* = 1$  and the optimal fixed pay is  $\alpha^* = 3.5$ . Hence, the optimal variable pay in the absence of a shock is greater than the variable pay in presence of the shock. The expected value is  $E[L] = 3.97$  and the certainty equivalent of  $L$  is 4. Hence, the agent exhibits risk-seeking at the optimal contract  $(\alpha^*, \beta^*) = (3.87, 0.93)$  where the tradeoff between risk and incentive is observed.

- **Case 2 (absence of tradeoff with risk-seeking agent):** Consider the calibration of parameters as before with the only change that  $r = 0.01$ . The optimal variable pay is  $\beta^* = 1.08$  and the optimal fixed pay is  $\alpha^* = 3.81$ . The optimal variable pay in the absence of shock is less than the variable pay in the presence of shock. We have the expected value  $E[L] = 3.95$  and the certainty equivalent of  $L$  is 4. Hence, the agent exhibits risk-seeking at the optimal contract  $(\alpha^*, \beta^*) = (3.95, 1.08)$  where the tradeoff between risk and incentive is not observed.

QED.

Figure 4.C.1: Density function and probability weighting function

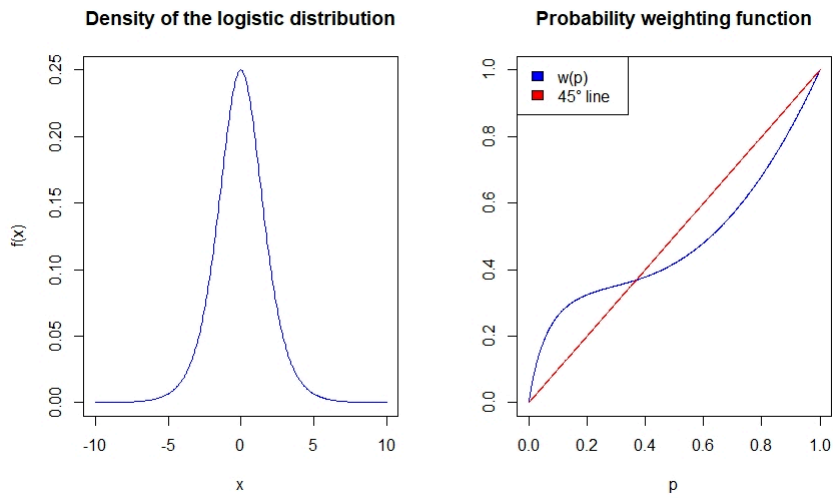
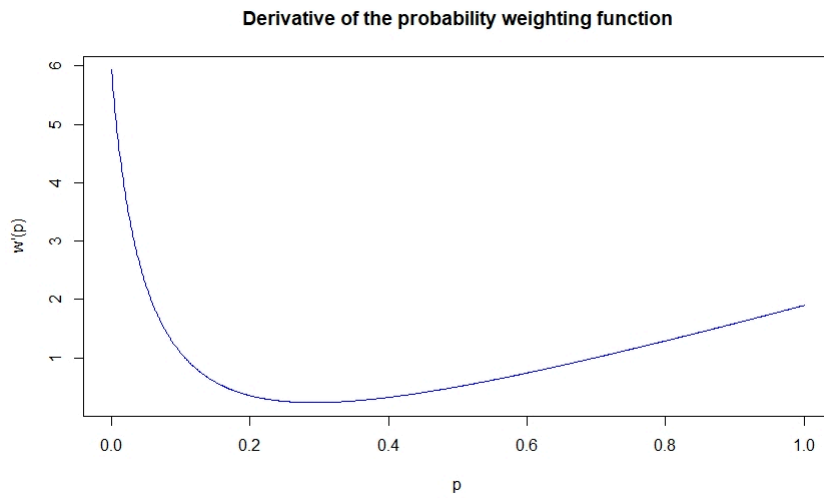


Figure 4.C.2: Derivative of probability weighting function



### 4.C.1 Proofs of propositions in the BB model

#### Proof of Proposition 1

The minimum fixed pay accepted by an agent to work increases with the shock

$\epsilon$ . The expected utility associated with the contract is given by

$$EU(L) = pu\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1-p)u\left(\alpha + \beta\theta(e - \epsilon) - \psi e^2\right)$$

For any given contract  $(\alpha, \beta)$ , the agent's optimal level of effort is given by

$$e = \frac{\beta\theta}{2\psi}$$

Note that this level of effort does not depend on  $\alpha$ . The agent accepts to provide the level of effort if

$$pu\left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right) + (1-p)u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right) \geq u(y_0)$$

Note that the left-hand side of the above inequality is strictly increasing in  $\alpha$ . Hence, there exists a minimum level of fixed pay  $\alpha_m$  such that the participation constraint is binding, that is

$$F(\alpha_m, \epsilon) := pu(e) + (1-p)u\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right) - u(y_0) = 0 \quad (4.73)$$

Denote by  $y_-^* = \alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon$  and  $y_+^* = \alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon$ , then  $y_-^* < y_+^*$ .

**Point i)** The minimum fixed pay increases with the utility (outcome)-risk aversion

Assuming CARA utility function, equation (4.73) becomes

$$\begin{aligned} F(\alpha_m, \epsilon) := & p \exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right)\right) + \\ & (1-p) \exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right)\right) - \exp(-ry_0) = 0 \end{aligned} \quad (4.74)$$

$$\text{sign}\left(\frac{d\alpha_m}{dr}\right) = \text{sign}\left(-py_+^* \exp(-ry_+^*) - (1-p)y_-^* \exp(-ry_-^*) + y_0 \exp(-ry_0)\right)$$

Denote by  $v(x) = x \exp(-rx)$  a utility function over  $[0, \infty)$  with  $rx < 1$  (Assumption A3"). The certainty equivalent  $y_0^*$  of the lottery  $(y_+^*, y_-^*; p, 1-p)$  according to the utility function  $v(\cdot)$  is implicitly defined by

$$y_0^* \exp(-ry_0^*) = py_+^* \exp(-ry_+^*) + (1-p)y_-^* \exp(-ry_-^*)$$

Take the absolute risk aversion index of  $v(\cdot)$ ,

$$-\frac{v''(x)}{v'(x)} = r \frac{2-rx}{1-rx} > r$$

Hence the utility function  $v(\cdot)$  is associated to higher risk-aversion index than  $u(\cdot)$ . By the [Pratt \(1964\)](#) approximation, we have  $y_0^* < y_0$ . Hence,

$$y_0^* \exp(-ry_0^*) = py_+^* \exp(-ry_+^*) + (1-p)y_-^* \exp(-ry_-^*) < y_0 \exp(-ry_0)$$

This yields  $\frac{d\alpha_m}{dr} > 0$ .

**Point ii)** The implicit function theorem yields

$$\frac{d\alpha_m}{d\epsilon} = \beta\theta(1-p) \frac{u'(y_-^*) - u'(y_+^*)}{pu'(y_+^*) + (1-p)u'(y_-^*)} > 0$$

Under Assumption A3', the minimum  $\alpha$  increases with the shock size. Note that if the utility function is instead convex and the second-order condition resulting from the second derivative of  $EU(L)$  with respect to the effort is negative, then  $\frac{d\alpha_m}{d\epsilon} < 0$ .

QED.

### Proof of Proposition 2

The rank dependent utility associated with the contract is given by

$$RDU(L) = w(p)u\left(\alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2\right) + (1-w(p))u\left(\alpha + \beta\theta(e - \epsilon) - \psi e^2\right)$$

For any given contract  $(\alpha, \beta)$ , agent's optimal level of effort under the accepted contract is

$$e = \frac{\beta\theta}{2\psi}$$

Note that this level of effort does not depend on  $\alpha$ . The agent accepts to provide a given level of effort if

$$w(p)u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right) + (1-w(p))u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right) \geq u(y_0)$$

Note that the left-hand side of the above inequality is strictly increasing in  $\alpha$ . Hence, there exists a minimum level of fixed pay  $\alpha_m$  such that the previous participation constraint is binding, that is

$$F(\alpha_m, \epsilon) := w(p)u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right) + (1-w(p))u\left(\alpha + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right) - u(y_0) = 0 \quad (4.75)$$

**Point i)** The minimum fixed pay increases with the utility risk-aversion and probability risk-aversion



Assuming CARA utility function, the equation (4.75) becomes

$$F(\alpha_m, \epsilon) := -\exp(-ry_0) + w(p)\exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right)\right) \\ + (1-w(p))\exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right)\right) = 0 \quad (4.76)$$

$$\text{sign}\left(\frac{d\alpha_m}{dr}\right) = \text{sign}\left(-w(p)y_+^*\exp(-ry_+^*) - (1-w(p))y_-^*\exp(-ry_-^*) + y_0\exp(-ry_0)\right)$$

Denote by  $v(x) = x\exp(-rx)$  a utility function over  $[0, \infty)$  with  $rx < 1$ . The certainty equivalent  $y_0^*$  of the lottery  $(y_+^*, y_-^*; p, 1-p)$  according to the utility function  $v(\cdot)$  is implicitly defined by

$$y_0^*\exp(-ry_0^*) = w(p)y_+^*\exp(-ry_+^*) + (1-w(p))y_-^*\exp(-ry_-^*)$$

Take the absolute risk-aversion index of  $v(\cdot)$ ,

$$-\frac{v''(x)}{v'(x)} = r\frac{2-rx}{1-rx} > r$$

Hence the utility function  $v(\cdot)$  is associated with a higher risk-aversion index than  $u(\cdot)$ . By Lemma 1 (Appendix 4.A) that provides the equivalent of Pratt (1964) approximation in our setting, we have  $y_0^* < y_0$ . Hence,

$$y_0^*\exp(-ry_0^*) = w(p)y_+^*\exp(-ry_+^*) + (1-w(p))y_-^*\exp(-ry_-^*) < y_0\exp(-ry_0)$$

This yields  $\frac{d\alpha_m}{dr} > 0$ .

Also, for a given probability  $p = \bar{p}$  with  $\delta := w(\bar{p})$ , the minimum fixed pay decreases with degree of probability overweighting.

The implicit function theorem applied to (4.75) directly leads to

$$\frac{d\alpha_m}{d\delta} = -\frac{u(y_+^*) - u(y_-^*)}{w(p)u'(y_+^*) + (1-w(p))u'(y_-^*)} < 0$$

Hence, fixed pay increases with probability risk-aversion.

**Point ii)** Implicit function theorem leads to

$$\frac{d\alpha_m}{d\epsilon} = \beta\theta \frac{(1-w(p))u'(y_-^*) - \frac{w(p)}{p}u'(y_+^*)}{w(p)u'(y_+^*) + (1-w(p))u'(y_-^*)}$$

It follows that for  $w(p) \leq p$  (underweighting), we have directly  $\frac{d\alpha_m}{d\epsilon} > 0$ .

Similarly, we find that  $\frac{d\alpha_m}{d\beta} > 0$  under the assumption that  $e = \frac{\beta\theta}{2\psi} > \epsilon$ .

**Point iii)** In contrast, assuming  $w(p) > p$  (overweighting), we have

$$\frac{d\alpha_m}{d\epsilon} < 0 \iff \frac{\frac{w(p)}{p}}{\frac{1-w(p)}{1-p}} > \frac{u'(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon)}{u'(\alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon)}$$

For CARA utility function this implies that

$$\frac{d\alpha_m}{d\epsilon} < 0 \iff r < r_{to}(\beta, \epsilon)$$

with the threshold defined as

$$r_{to}(\beta, \epsilon) := \frac{p}{\beta\theta\epsilon} \left[ \ln\left(\frac{w(p)}{p}\right) - \ln\left(\frac{1-w(p)}{1-p}\right) \right] > 0$$

Hence, under rank dependent utility theory, the minimum accepted  $\alpha$  decreases with the shock size if we have substantial overweighting and moderate utility curvature.

**Point iv)**

The certainty equivalent  $ce = y_0$  of a lottery  $L = (\alpha_m + \beta\theta(e + \frac{1-p}{p}\epsilon), \alpha_m + \beta\theta(e - \epsilon); p, 1 - p)$  with  $e = \frac{\beta\theta}{2\psi}$  is given by

$$u(ce) = \delta \frac{1 - \exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} + \frac{1-p}{p}\beta\theta\epsilon\right)\right)}{r} + (1-\delta) \frac{1 - \exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi} - \beta\theta\epsilon\right)\right)}{r}$$

The utility of the expected value  $E[L] = \alpha_m + \beta\theta e - \psi e^2 = \alpha_m + \frac{\beta^2\theta^2}{4\psi}$  is given by

$$u(E[L]) = \frac{1 - \exp\left(-r\left(\alpha_m + \frac{\beta^2\theta^2}{4\psi}\right)\right)}{r}$$

Define by  $g(\cdot)$  the following differential function over  $[0, \infty)$

$$g(r) = \delta \exp\left[-r\beta\theta\frac{1-p}{p}\epsilon\right] + (1-\delta)\exp[r\beta\theta\epsilon]$$

The absolute risk-aversion  $r_N(\beta)$  for which the equality  $u(ce) = u(E[L])$  holds for a risk-neutral agent is implicitly defined by

$$g(r_N(\beta, \epsilon)) = 1$$

Note that  $g(\cdot)$  has the following three characteristics: (i)  $g(\cdot)$  is convex on  $[0, \infty)$ ; (ii)  $g(0) = 1$  and  $\lim_{r \rightarrow +\infty} g(r) = +\infty$ ; (iii)  $g(\cdot)$  attains its minimum exactly at the thresholds of the tradeoff  $r_{to}(\beta, \epsilon)$

$$r_{to}(\beta, \epsilon) = \frac{p}{\beta\theta\epsilon} \left[ \ln\left(\frac{w(p)}{p}\right) - \ln\left(\frac{1-w(p)}{1-p}\right) \right]$$

These three characteristics yield two solutions for  $r_N(\beta, \epsilon)$  :  $r_1 = 0 < r_{to}(\beta, \epsilon)$  and  $r_2 > r_{to}(\beta, \epsilon)$ .

It is clear that we should rule out the case  $r_1 = 0 < r_{to}(\beta, \epsilon)$ . Indeed, for  $r_1 = 0$  we have a linear utility function. Then, to have risk-neutral agent under linear utility function, we should have also  $\delta = w(p) = p$ . This contradicts our initial assumption  $\delta > p$ .

Ruling out the case  $r_1 = 0$ , it follows that the value of  $r_N(\beta, \epsilon)$  that allows the equality  $u(ce) = u(E[L])$  for a risk-neutral agent (that compensates probability risk-seeking with utility risk aversion) is such that  $r_N(\beta, \epsilon) > r_{to}(\beta, \epsilon)$ .

Finally, note that this result holds for general utility function (see our Proposition B3).

**Point v)** A simple derivative of the expression of  $r_{to}(\beta, \epsilon)$  shows that this threshold decreases with  $\beta$  and  $\epsilon$ .

The CARA coefficient for risk-neutrality is implicitly determined by

$$F(r_N, \beta) := \delta \exp\left[-r\beta\theta\frac{1-p}{p}\epsilon\right] + (1-\delta)\exp[r\beta\theta\epsilon] - 1 = 0$$

The implicit function theorem yields

$$\frac{r_N}{\beta} \frac{dr_N(\beta, \epsilon)}{d\beta} = -1 < 0$$

Hence, the agent becomes risk-seeking for a sufficiently small value of variable pay  $\beta$ . In particular, if the agent is risk-neutral or risk-seeking for a contract involving  $\beta_1$ ; then the agent is risk-seeking for contract involving  $\beta_0 < \beta_1$ .

Similarly,

$$\frac{r_N}{\epsilon} \frac{dr_N(\beta, \epsilon)}{d\epsilon} = -1 < 0$$

QED.

**Proof of Proposition 3:**

The mean-variance-skewness preference associated with the contract is given by

$$MVS(L) = \alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p} \beta^2 \theta^2 \epsilon^2 + a_s \frac{1-p}{p} \frac{1-2p}{p} \beta^3 \theta^3 \epsilon^3$$

For any accepted contract  $(\alpha, \beta)$ , the agent's optimal level of effort is given by

$$e = \frac{\beta\theta}{2\psi}$$

Note that this level of effort does not depend on  $\alpha$ . The agent agrees to provide the level of effort if

$$\alpha + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p} \beta^2 \theta^2 \epsilon^2 + a_s \frac{1-p}{p} \frac{1-2p}{p} \beta^3 \theta^3 \epsilon^3 \geq y_0$$

Note that the left hand side of the above inequality is strictly increasing in  $\alpha$ . Hence, there is a minimum level of fixed pay  $\alpha_m$  such that the previous participation constraint is binding, that is

$$F(\alpha_m, \epsilon) := \alpha_m + \beta\theta e - \psi e^2 + a_v \frac{1-p}{p} \beta^2 \theta^2 \epsilon^2 + a_s \frac{1-p}{p} \frac{1-2p}{p} \beta^3 \theta^3 \epsilon^3 - y_0 = 0 \quad (4.77)$$

**Point i)** The minimum fixed pay increases with the aversion to variance

From (4.77), we have

$$\frac{d\alpha_m}{da_v} = -\frac{1-p}{p} \beta^2 \theta^2 \epsilon^2 < 0$$

Hence, when  $a_v$  decreases (i.e., high aversion to variance), then the minimum fixed pay increases. Moreover

$$\frac{d\alpha_m}{da_s} = -\frac{1-p}{p} \frac{1-2p}{p} \beta^3 \theta^3 \epsilon^3$$

Hence,  $\frac{d\alpha_m}{da_s} < 0$  if  $p < \frac{1}{2}$  and  $\frac{d\alpha_m}{da_s} < 0$  if  $p > \frac{1}{2}$ .

This means that for  $p < \frac{1}{2}$  (resp.  $p > \frac{1}{2}$ ), the minimum fixed pay decreases (resp. increases) with the preference for positively skewed lotteries.

**Point ii)**

The implicit function theorem applied to (4.77) leads to

$$\frac{d\alpha_m}{d\epsilon} = -\frac{1-p}{p}\beta^2\theta^2\epsilon\left(2a_v + 3a_s\frac{1-2p}{p}\beta\theta\epsilon\right)$$

It follows that for  $p > \frac{1}{2}$  (negative skewness), we have  $\frac{d\alpha_m}{d\epsilon} > 0$ .

**Point iii)**

In contrast, for  $p < \frac{1}{2}$  (positive skewness), we have

$$\frac{d\alpha_m}{d\epsilon} > 0 \iff -\frac{a_v}{a_s} > \tau_{to}(\beta, \epsilon)$$

with  $\tau_{to}(\beta, \epsilon) = \frac{3}{2}\frac{1-2p}{p}\beta\theta\epsilon$ .

**Point iv)** Denote by  $\tau_N(\beta, \epsilon) = \frac{S(L)}{V(L)} = \frac{1-2p}{p}\beta\theta\epsilon$ . Hence, the agent exhibits risk-aversion if  $-\frac{a_v}{a_s} > \tau_N(\beta, \epsilon)$ , is risk-neutral if  $-\frac{a_v}{a_s} = \tau_N(\beta, \epsilon)$  and risk-seeking if  $-\frac{a_v}{a_s} < \tau_N(\beta, \epsilon)$ .

Clearly,  $\tau_N(\beta, \epsilon) = \frac{S(L)}{V(L)} = \frac{1-2p}{p}\beta\theta\epsilon < \frac{3}{2}\frac{1-2p}{p}\beta\theta\epsilon = \tau_{to}(\beta, \epsilon)$ .

Hence, for any couple  $(a_v, a_s)$  such that  $-\frac{a_v}{a_s} \in (\tau_N(\beta, \epsilon), \tau_{to}(\beta, \epsilon))$  the agent is risk-averse and the minimum fixed pay accepted  $\alpha$  decreases with shock.

**Point v)**

Clearly,  $\tau_{to}(\beta, \epsilon)$  and  $\tau_N(\beta, \epsilon)$  increase with the shock  $\epsilon$  and  $\beta$ .

QED.

### 4.C.2 Elicitation of risk preferences

We consider binary lotteries denoted by  $L = (x, y; p, 1 - p)$ , with  $x$  being the outcome that occurs with probability  $p$ , and  $y$  being the outcome that occurs with probability  $1 - p$ . We use 15 lotteries presented in the Table 4.C.1. They are a combination of 5 probabilities  $(p_1, p_2, p_3, p_4, p_5) = (0.1, 0.25, 0.33, 0.50, 0.75)$  and three couples of outcomes  $\{(100, 0), (100, 50), (50, 0)\}$ . The elicited certainty equivalents for each lottery using the switching outcomes technique (e.g., [Tversky and Kahneman, 1992a](#); [Gonzalez and Wu, 1999a](#); [Abdellaoui et al., 2008a](#)).

In addition, we utilize the 30 values of the minimum fixed pay elicited in the main experiment to obtain further certainty equivalent data. The insight is that the outside option of 1000 is the certainty equivalent of the lottery  $L = (x, y; p, 1 - p)$  in which

$$x = \alpha_m + \frac{\beta^2 \theta^2}{4\psi} + \frac{1-p}{p} \beta \theta \epsilon \quad \text{and} \quad y = \alpha_m + \frac{\beta^2 \theta^2}{4\psi} - \beta \theta \epsilon$$

We then have in total 45 certainty equivalent data points per individual such that each of the 5 probabilities is presented in 9 binary lotteries. We use this dataset to estimate the parameters of EUT, RDU and MVS at the individual level.

#### RDU and EUT

For RDU, we follow the procedure developed in [Kpegli et al. \(2023\)](#) to estimate probability weights. Denote by  $\mathbf{ce}$ ,  $\mathbf{x}$  and  $\mathbf{y}$  respectively the values of certainty equivalent, the high outcome  $x$  and the small outcome  $y$ . Also, denote by  $\mathbf{I}^k$  the dummy variable for the probability  $p_k$ , that is a variable that takes value 1 if probability is equal to  $p_k$  and 0 otherwise. We assume CARA utility function

so that we have the following empirical equation for certainty equivalent:

$$\mathbf{ce}_l = -\frac{1}{r} \ln \left[ \left( \exp(-r\mathbf{x}_l) - \exp(-r\mathbf{y}_l) \right) \sum_{k=1}^K \delta_k \mathbf{I}_l^k + \exp(-r\mathbf{y}_l) \right] + \mathbf{e}_l \quad (4.78)$$

where  $\mathbf{e}$  is the error term,  $l$  is the  $l$ th line in  $\mathbf{ce}$ ,  $\mathbf{x}$ ,  $\mathbf{y}$  and  $\mathbf{e}$ ;  $r$  the CARA coefficient and  $w(p_k) = \delta_k$  for  $k = 1, 2, \dots, 5$ . We assume that the error term is normally distributed with mean 0 and heteroscedastic variance  $\sigma_l = \sigma|\mathbf{x}_l - \mathbf{y}_l|$ .

We then estimate  $r$ ,  $\delta_k$  and  $\sigma$  by maximum likelihood method.

For the special case of EUT, we assume  $\delta_k = p_k$  and estimate only  $r$  and  $\sigma$ .

### MVS

Under MVS, certainty equivalents satisfy the following empirical equation

$$\mathbf{ce}_l = \mathbf{E}_l + a_v \mathbf{V}_l + a_s \mathbf{S}_l + e_l$$

with  $\mathbf{ce}$ ,  $\mathbf{E}$ ,  $\mathbf{V}$  and  $\mathbf{S}$  denoting respectively values of certainty equivalent, mean, variance and skewness associated with each of the 45 lotteries.

We assume that the error term is normally distributed with mean 0 and heteroscedastic variance  $\sigma_l = \sigma|\mathbf{x}_l - \mathbf{y}_l|$ . We then estimate  $a_v$ ,  $a_s$  and  $\sigma$  by maximum likelihood method.



Table 4.C.1: Lotteries in the experiment

<i>N</i> ° Lottery	<i>x</i>	<i>y</i>	<i>p</i>
1	100	0	0.1
2	100	50	0.1
3	50	0	0.1
4	100	0	0.25
5	100	50	0.25
6	50	0	0.25
7	100	0	0.33
8	100	50	0.33
9	50	0	0.33
10	100	0	0.50
11	100	50	0.50
12	50	0	0.50
13	100	0	0.75
14	100	50	0.75
15	50	0	0.75

Table 4.C.2: Mean of individual estimates<sup>†,‡</sup>

	EU		MVS		RDU	
	Coef.	95% CI	Coef.	95% CI	Coef.	95% CI <sup>(b)</sup>
<i>r</i>	0.0038	[0.0022,0.0055]	-	-	0.0023	[0.0015,0.0031]
<i>a<sub>v</sub></i>	-	-	-0.00097	[-0.0011, -0.0008]	-	-
<i>a<sub>s</sub></i>	-	-	$4.8 \times 10^{-7}$	$[4.0 \times 10^{-7}, 5.6 \times 10^{-7}]$	-	-
<i>w</i> (0.10)	-	-	-	-	0.2231	[0.2034,0.2429]
<i>w</i> (0.25)	-	-	-	-	0.3278	[0.3105,0.3450]
<i>w</i> (0.33)	-	-	-	-	0.3729	[0.3553,0.3904]
<i>w</i> (0.50)	-	-	-	-	0.4856	[0.4685,0.5026]
<i>w</i> (0.75)	-	-	-	-	0.6409	[0.6208,0.6610]

<sup>†</sup> The parameters are computed from regression models controlling for individual heteroscedasticity due to observable individual characteristics (i.e., numeracy test score, cognitive reflection test score, gender and age).

<sup>‡</sup> Standard errors clustered at the individual level when computing 95% CI due to multiple probability weights per subject.

Table 4.C.3: Mean of minimum fixed pay across treatments<sup>†</sup>

$p$	$\beta$	$e^\ddagger$	$\alpha_3^m$	$\alpha_m^A$	$\alpha_4^m - \alpha_3^m$	$\alpha_m^0$	$\alpha_3^3 - \alpha_m^0$	$\alpha_m^4 - \alpha_m^0$
0.1	0.30	3.00	881.3***	901.4***	20.05***	910.00	-28.69***	-8.64
0.1	0.50	5.00	750.0***	792.9***	42.95***	750.00	-0.01	42.95***
0.1	0.70	7.00	579.9***	628.3***	48.49***	510.00	69.86***	118.3***
0.25	0.30	3.00	898.1***	917.6***	19.44***	910.00	-11.87***	7.57
0.25	0.50	5.00	761.7***	803.5***	41.82***	750.00	11.67**	53.49***
0.25	0.70	7.00	582.2***	626.8***	44.57***	510.00	72.22***	116.8***
0.33	0.30	3.00	900.5***	926.1***	25.65***	910.00	-9.505***	16.14***
0.33	0.50	5.00	780.6***	795.1***	14.56***	750.00	30.55***	45.11***
0.33	0.70	7.00	590.7***	620.2***	29.44***	510.00	80.72***	110.2***
0.5	0.30	3.00	919.6***	926.2***	6.597**	910.00	9.642***	16.24***
0.5	0.50	5.00	773.6***	786.4***	12.82***	750.00	23.63***	36.45***
0.5	0.70	7.00	582.5***	615.4***	32.86***	510.00	72.53***	105.4***
0.75	0.30	3.00	916.7***	937.6***	20.94***	910.00	6.685***	27.63***
0.75	0.50	5.00	778.4***	789.5***	11.02**	750.00	28.45***	39.47***
0.75	0.70	7.00	571.5***	607.3***	35.87***	510.00	61.45***	97.32***

Standard errors in parentheses.

\*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  for the significance of coefficient tests.

<sup>†</sup> Mean of fixed pay are computed from regression analyses by allowing heteroscedasticity due to observable individual characteristics (i.e., numeracy skills, cognitive skills, gender and age).

<sup>‡</sup> According to the calibration  $(\psi, \theta) = (2.5, 100)$ , the effort is computed as  $e = \frac{\beta\theta}{2\psi}$ .

### 4.C.3 - Decomposition of the cells in Table 4.4.5 according to the estimated risk attitudes

Table 4.C.4: RIT, risk-attitudes, and curvature of utility under EUT

	Number	Percentage
RIT and Risk-averse		
Concave	14	1.55 %
Convex	891	98.45%
Total	905	100%
RIT and Risk-neutral		
	Number	Percentage
Concave	23	9.96%
Convex	208	90.04%
Total	231	100%
RIT and Risk-seeking		
	Number	Percentage
Concave	229	36.12%
Convex	405	63.88%
Total	634	100%
No-RIT and Risk-averse		
	Number	Percentage
Concave	24	5.06%
Convex	450	94.94%
Total	474	100%
No-RIT and Risk-neutral		
	Number	Percentage
Concave	40	10.55%
Convex	339	89.45%
Total	379	100%
No-RIT and Risk-seeking		
	Number	Percentage
Concave	112	47.06%
Convex	126	52.94%
Total	238	100%
Reversed RIT and Risk-averse		
Continued on next page		

**Table 4.C.5 – continued from previous page**

	Number	Percentage
	Number	Percentage
Concave	77	19.40%
Convex	320	80.60%
Total	397	100%
Reversed RIT and Risk-neutral		
	Number	Percentage
Concave	32	28.32%
Convex	81	71.68%
Total	113	100%
Reversed RIT and Risk-seeking		
	Number	Percentage
Concave	124	67.39%
Convex	60	32.61%
Total	184	100%

Table 4.C.6: RIT, risk attitudes, utility curvature and probability weighting under RDU

Number (%)	Underweighting	Overweighting	Total
RIT and Risk-averse			
Convex	18 (1.99 %)	0 (0.00 %)	18 (1.99%)
Concave	404 (44.64%)	484 (53.37%)	887 (98.01%)
Total	422 (46.63%)	483 (53.37%)	905 (100%)
RIT and Risk-neutral			
Convex	8 (19.41%)	2 (68.78%)	10 (4.33%)
Concave	105 (45.45%)	116 (50.22%)	221 (95.67%)
Total	113 (48.92%)	118 (51.08%)	231 (100%)

Continued on next page

**Table 4.C.7 – continued from previous page**

Number (%)	Underweighting	Overweighting	Total
RIT and Risk-seeking			
Convex	72 (11.36%)	51 (8.04%)	123 (19.40%)
Concave	123 (19.40%)	388 (61.20%)	511 (80.60%)
Total	195 (40.08%)	439 (69.24%)	634 (100%)
No RIT and Risk-averse			
Convex	48 (10.13%)	2 (0.42%)	50 (10.55%)
Concave	206 (43.46%)	218 (45.99%)	424 (89.45%)
Total	254 (53.59%)	220 (46.41%)	474 (100%)
No RIT and Risk-neutral			
Convex	46 (12.14%)	8 (2.11%)	54 (14.25%)
Concave	180 (47.49%)	145 (38.26%)	325 (85.75%)
Total	226 (59.63%)	153 (40.37%)	379 (100%)
No RIT and Risk-seeking			
Convex	28 (11.76%)	31 (13.03%)	59 (24.79%)
Concave	31 (13.03%)	148 (62.18%)	179 (75.21%)
Total	59 (24.79%)	179 (75.21%)	238 (100%)
Reversed RIT and Risk-aversion			
Convex	30 (7.56%)	9 (2.27%)	39 (9.82%)
Concave	168 (42.32%)	190 (47.86%)	358 (90.18%)
Total	198 (49.87%)	199 (50.13%)	397 (100%)
Reversed RIT and Risk-neutral			
Convex	10	6	16
Continued on next page			

**Table 4.C.7 – continued from previous page**

Number (%)	Underweighting	Overweighting	Total
	(8.85%)	(5.31 %)	(14.16%)
Concave	29 (25.66%)	68 (60.18%)	97 (85.84%)
Total	39 (34.51%)	74 (65.49%)	113 (100%)
Reversed RIT and Risk-seeking			
Convex	16 (8.7%)	35 (19.02%)	51 (27.72%)
Concave	14 (7.61%)	119 (64.67%)	133 (72.28%)
Total	30 (16.3%)	154 (83.7%)	184 (100%)

Table 4.C.8: RIT, risk-attitudes, and preference/aversion for skewness and variance under MVS

Number (%)	Aversion for skewness	Preference for skewness	Total
RIT and Risk-averse			
Preference for variance	13 (1.44%)	1 (0.11%)	14 (1.55%)
Aversion to variance	20 (2.21%)	871 (96.24 %)	891 (98.45%)
Total	33 (3.65%)	872 (96.35 %)	905 (100.00 %)
RIT and Risk-neutral			
Preference for variance	19 (8.23%)	1 (0.43%)	20 (8.66%)
Aversion to variance	3 (1.30%)	208 (90.04%)	211 (91.34%)
Total	22 (9.52%)	209 (90.48%)	231 (100.00%)
RIT and Risk-seeking			
Preference for variance	213	13	226

Continued on next page

Table 4.C.9 – continued from previous page

Number (%)	Aversion for skewness	Preference for skewness	Total
	(33.60%)	(2.05%)	(35.65%)
Aversion for variance	17 (2.68%)	391 (61.67%)	408 (64.35%)
Total	230 (36.28%)	404 (63.72%)	634 (100.00%)
No RIT and Risk-averse			
Preference for variance	21 (4.43%)	4 (0.84%)	25 (5.27%)
Aversion for variance	10 (2.11%)	439 (92.62%)	449 (94.73%)
Total	31 (6.54%)	443 (93.46%)	474 (100.00%)
No RIT and Risk-neutral			
Preference for variance	27 (7.12%)	11 (2.90%)	38 (10.03%)
Aversion for variance	9 (2.37%)	332 (87.60%)	341 (89.97%)
Total	36 (9.50%)	343 (90.50%)	379 (100.00%)
No RIT and Risk-seeking			
Preference for variance	100 (42.02%)	11 (4.62%)	111 (46.64%)
Aversion for variance	10 (4.20%)	117 (49.16%)	127 (53.36%)
Total	110 (46.22%)	128 (53.78%)	238 (100.00%)
Reversed RIT and Risk-aversion			
Preference for variance	66 (16.62%)	6 (1.51%)	72 (18.14%)
Aversion for variance	12 (3.02%)	313 (78.84%)	325 (81.86%)
Total	78 (19.65%)	319 (80.35%)	397 (100.00%)
Reversed RIT and Risk-neutral			
Preference for variance	29 (25.66%)	2 (1.77%)	31 (27.43%)
Aversion for variance	4	78	82

Continued on next page

**Table 4.C.9 – continued from previous page**

Number (%)	Aversion for skewness	Preference for skewness	Total
	(3.54%)	(69.03%)	(72.57%)
Total	33 (29.20%)	80 (70.80%)	113 (100.00%)
Reversed RIT and Risk-seeking			
Preference for variance	112 (60.87%)	11 (5.98%)	123 (66.85%)
Aversion for variance	5 (2.72%)	56 (30.43%)	61 (33.15%)
Total	117 (63.59%)	67 (36.41%)	184 (100.00%)

## 4.D Prospect theory (PT) analysis

In this section, we assume the agent is endowed with a reference-dependence utility function of the following form:

$$u^R(x, R) = x + v(x - R) \quad (4.79)$$

where  $x$  is the absolute outcome,  $R$  the reference point and  $v(\cdot)$  is a value function à la [Tversky and Kahneman \(1992a\)](#), that is assumed to be continuous and strictly increasing with  $v(0)=0$ . Following [Tversky and Kahneman \(1992a\)](#) and [Abdellaoui et al. \(2008a\)](#), we specify the value function as follows:

$$v(x - R) = \begin{cases} u(x - R) & \text{if } x \geq R \\ \lambda u(x - R) & \text{if } x < R \end{cases} \quad (4.80)$$



where  $\lambda > 0$  is the loss-aversion index and  $u(\cdot)$  is the basic utility function. Following the LEN model, we assume the following exponential utility function:

$$v(x - R) = \begin{cases} \frac{1 - \exp(-r^+(x - R))}{r^+} & \text{if } x \geq R \\ -\lambda \frac{\exp(r^-(x - R)) - 1}{r^-} & \text{if } x < R \end{cases} \quad (4.81)$$

with  $r^+$  and  $r^-$  representing the index of absolute risk-aversion in the gain and loss domains respectively.

We denote the probability weighting function in the gain ( $x \geq R$ ) and loss ( $x < R$ ) domains by  $w^+(\cdot)$  and  $w^-(\cdot)$ . We refer to probability risk-aversion [risk-seeking] as the case in which  $w^+(p) \leq p$  and  $w^-(1 - p) \geq 1 - p$  [ $w^+(p) > p$  and  $w^-(1 - p) < 1 - p$ ]

We consider the mixed lottery  $L = (x_1, x_2; p, 1 - p)$  with  $x_1 \geq R \geq x_2$ , which is valued as follows:

$$V(L) = w^+(p)u^R(x_1, R) + w^-(1 - p)u^R(x_2, R) \quad (4.82)$$

In our principal-agent setup (see Section 2.1), the agent is facing a lottery with  $x_1 = \alpha + \beta\theta\left(e + \frac{1-p}{p}\epsilon\right) - \psi e^2$  and  $x_2 = \alpha + \beta\theta\left(e - \epsilon\right) - \psi e^2$ . We further assume that the agent's reference point is given by the expected value of the lottery:

$$R = \alpha + \beta\theta e - \psi e^2 \quad (4.83)$$

The risk-free reference point ensures that the agent is systematically in the gain domain when the random shock yields a positive outcome (i.e.,  $\frac{1-p}{p}\epsilon$ ) and in the loss domain otherwise (i.e.,  $-\epsilon$ ).

Based on the previous assumptions, the following proposition summarizes the results regarding the optimal behavior of the agent and the principal.

**Proposition E1 (Risk-incentives tradeoff with PT).** Under A0, A1, A2, A3', A3'', A4, A5 and assuming a PT agent as specified in (4.82):

- i) For a given contract  $(\alpha, \beta)$ , the optimal level of effort increases with  $\theta$ , decreases with  $\psi$  and does not depend on the fixed pay  $\alpha$ , the utility curvature in loss domain  $r^-$ , the utility curvature in gain domain  $r^+$ , the loss aversion index  $\lambda$  and the shock.
- ii)  $\beta^*(\epsilon, r, \psi, \theta)$  and  $e^*(\epsilon, r, \psi, \theta)$  decrease with  $\lambda$ ,  $r^+$  (the utility risk-aversion in the gain domain), probability risk-aversion (i.e., overweighting in loss domain and underweighting in gain domain), while increases with  $r^-$  (the utility risk-aversion in the loss domain).
- iii)  $\beta^*(\epsilon, r, \psi, \theta)$  and  $e^*(\epsilon, r, \psi, \theta)$  are higher in the presence of shock than in its absence if the agent exhibits sufficient probability risk-seeking, moderate utility curvature and loss-aversion.

**Proof of Proposition E1:**

Given the linear contract  $(\alpha, \beta)$ , the objective function of agent with a cost function  $C(e) = \psi e^2$  is given by

$$PT(L) = w^+(p) \left[ x_1 + \frac{1 - \exp\left(-r^+ \beta \theta \frac{1-p}{p} \epsilon\right)}{r^+} \right] + w^-(1-p) \left[ x_2 + \lambda \frac{\exp\left(-r^- \beta \theta \epsilon\right) - 1}{r^-} \right] \quad (4.84)$$

with

$$x_1 = \alpha + \beta \theta \left( e + \frac{1-p}{p} \epsilon \right) - \psi e^2 \text{ and } x_2 = \alpha + \beta \theta (e - \epsilon) - \psi e^2.$$

The first-order condition of the agent's maximization problem is given by

$$(\beta\theta - 2\psi e)[w^+(p) + w^-(1-p)] = 0$$

Since  $w^+(p) + w^-(1-p) \neq 0$ , it follows that the optimal effort function is given by

$$e = \frac{\beta\theta}{2\psi}$$

**Point i)**

The optimization problem of the principal is to maximize the expected value of  $\theta z - y$  by accounting for the agent's incentive compatibility constraint (IC) and participation constraint (PC):

$$\left\{ \begin{array}{l} \max_{\alpha, \beta} \pi = \theta e - (\alpha + \beta\theta e) \\ s.t. : \\ e = \frac{\beta\theta}{2\psi} \\ w^+(p) \left[ x_1 + \frac{1 - \exp\left(-r^+ \beta\theta \frac{1-p}{p} \epsilon\right)}{r^+} \right] + w^-(1-p) \left[ x_2 + \lambda \frac{\exp\left(-r^- \beta\theta \epsilon\right) - 1}{r^-} \right] = y_0 \end{array} \right.$$

which is equivalent to

$$\max_{\beta} \frac{\theta^2}{2\psi} (\beta - 0.5\beta^2) + \left[ w^+(p) \frac{1 - \exp\left(-r^+ \beta\theta \frac{1-p}{p} \epsilon\right)}{r^+} + \lambda w^-(1-p) \times \frac{\exp\left(-r^- \beta\theta \epsilon\right) - 1}{r^-} + \beta\theta \epsilon \left( w^+(p) \frac{1-p}{p} - w^-(1-p) \right) - y_0 \right] \times \frac{1}{w^+(p) + w^-(1-p)} \quad (4.85)$$

The first-order conditions are given by

$$\frac{\theta^2}{2\psi}(1-\beta) + \frac{\theta\epsilon}{w^+(p) + w^-(1-p)} \left[ w^+(p) \frac{1-p}{p} \exp\left(-r^+ \beta \theta \frac{1-p}{p} \epsilon\right) - \lambda w^-(1-p) \exp\left(-r^- \beta \theta \epsilon\right) + w^+(p) \frac{1-p}{p} - w^-(1-p) \right] = 0 \quad (4.86)$$

Equation (4.86) defines the optimal variable pay  $\beta^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$ . The optimal variable pay in the absence of shock ( $\epsilon = 0$ ) is given by  $\lim_{\epsilon \rightarrow 0} \beta^*(.) = 1$ .

The implicit function theorem applied to (4.86) leads to

$$\frac{\partial \beta^*}{\partial \lambda} < 0 \quad (4.87)$$

$$\frac{\partial \beta^*}{\partial r^+} < 0 \quad (4.88)$$

$$\frac{\partial \beta^*}{\partial r^-} > 0 \quad (4.89)$$

Since  $e^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta) = \frac{\theta}{2\psi} \beta^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$ , it also follows that  $\frac{\partial e^*}{\partial \lambda} < 0$ ,  $\frac{\partial e^*}{\partial r^+} < 0$ ,  $\frac{\partial e^*}{\partial r^-} > 0$ .

For given probability  $p = \bar{p}$ , denote by  $\delta^+ = w^+(\bar{p})$  and  $\delta^- = w^+(1-\bar{p})$ ; then implicit function theorem applied to (4.86) leads to

$$\frac{\partial \beta^*}{\partial \delta^+} > 0$$

$$\frac{\partial \beta^*}{\partial \delta^-} < 0$$

Since  $e^*(\alpha, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta) = \frac{\theta}{2\psi} \beta^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$ , it also follows that  $\frac{\partial e^*}{\partial \delta^+} > 0$ ,  $\frac{\partial e^*}{\partial \delta^-} < 0$ .

**Point iii)**

From (4.86) we have

$$\frac{\frac{w^+(p)}{p}}{\frac{w^-(1-p)}{1-p}} > \frac{1 + \lambda \exp(-r^- \beta^* \theta \epsilon)}{1 + \exp\left(-r^+ \beta^* \theta \frac{1-p}{p} \epsilon\right)} \iff \beta^* > 1 = \lim_{\epsilon \rightarrow 0} \beta^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$$

Since  $e^*(\alpha, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta) = \frac{\theta}{2\psi} \beta^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$ , it also follows that

$$\frac{\frac{w^+(p)}{p}}{\frac{w^-(1-p)}{1-p}} > \frac{1 + \lambda \exp(-r^- \beta^* \theta \epsilon)}{1 + \exp\left(-r^+ \beta^* \theta \frac{1-p}{p} \epsilon\right)} \iff e^* > \frac{\theta}{2\psi} = \lim_{\epsilon \rightarrow 0} e^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$$

Hence,  $\beta^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$  and  $e^*(\alpha, \beta, \epsilon, r^+, r^-, \lambda, w^+, w^-, \psi, \theta)$  are higher in the presence of shock than in its absence if the agent exhibits sufficient probability risk-seeking, moderate utility curvature and loss-aversion.

QED.

## 4.E H-Experimental instructions

## H1- Instruction for Day 1

### H1-1: Numeracy Test

Thank you for participating in this experiment. This experiment is composed of two parts. In the first part that you will perform today, you will answer a series of questions. The duration of this first part of the experiment will be approximately 30 minutes. After completing the first part, you will be invited to participate in a second part in the next few days. By participating in this first part, you agree to complete the second part.

Payments for both parts will be made early next week once you have completed the second part of the experience. A participation bonus of 4 euros will be added to your payments for your participation in both parts.

The experience will be done entirely online. All the information you need to make your decisions will be visible on the screen. You will not need to consult any other documents, so we ask you to stay focused on the instructions and on your decisions during the experiment.

Please answer the following questions carefully.

Each question has one and only one correct solution.

If you are ready, please proceed to the next page.

Imagine that we toss an undamaged coin 1,000 times. What is your best estimate of the number of times the coin will land on the face side over 1,000 tosses?

Indicate your answer (integer between 0 and 1,000) below:

A lottery ticket has a 1% chance of winning a \$10 prize. Suppose 1,000 people buy a ticket, what is your best estimate of the number of people who would win the \$10 prize?

Indicate your answer (integer between 0 and 1,000) below:

In a television show, the probability of winning a car is 1 in 1,000. What percentage of the contestants on the television show win a car?

State your answer (in percentages, use the comma ", " if necessary) below:

Out of 1,000 students at a university, 500 are enrolled in the economics-management field. Of these 500 economics and management students, 100 are male students. Out of the 500 students who are not in economics and management, 300 are male students. What is the probability that a randomly drawn male student will be enrolled in the economics-management major? Please state the probability as a percentage.

Indicate your answer (whole number between 0 and 100) below:

Imagine that we roll a five-sided die 50 times. On average, out of these 50 throws, how many times will this five-sided die show an odd number (1, 3 or 5)?

Indicate your answer (integer between 0 and 50) below:

## H1-2: Probability training

In the next screen, we will show you a table with a certain number of cells. The cells with the same number will be represented with the same color. The computer will choose a cell at random and repeat this operation a large number of times. Each time the computer chooses a square, it will appear dark. The percentage of times a number was chosen by the computer during the simulation will appear at the bottom of the table.

So a number that appears in more boxes will be selected by the computer more often. For example, if the number 400 appears in 7 out of 9 cells, it will be chosen 7 times out of 9 if the simulation is long enough, that is, 78% of the time ( $7/9=78\%$ ).

Here is an example of a table. You can finish the simulation performed by the computer by clicking on the 'Finish Simulation' button.

100	100	400	400	400	400	400	400	400
23%		77%						

**Terminer Simulation**

Below each table, you will be asked to enter an estimate of the percentage of times the computer will choose a number represented in the table in the case of a simulation of 100,000 numbers.

You will earn 10 cents for each correct answer, i.e., an answer that does not differ from the simulation result by more than 5%.

TABLEAU #1

300	300	300	300	300	300	400	400	400
0%						0%		

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 400 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

TABLEAU #2

500	500	500	500	500	500	600	600
0%						0%	

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 600 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

TABLEAU #3

200	200	200	200	200	300	300	300	300	300
0%					0%				

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 300 on a simulation of 100 000 numbers?



%

(Enter an integer between 0 and 100)

**TABLEAU #4**

400	400	400	900	900	900	900	900	900
0%			0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

**TABLEAU #5**

600	600	700	700	700	700	700	700
0%		0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 700 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

**TABLEAU #6**

100	100	100	100	100	100	100	100	100	800
0%									0%

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 800 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

**TABLEAU #7**

700	900	900	900	900	900	900	900	900	900
0%	0%								

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

### **H1-3: Probability weighting**

In this task you will be asked to make a series of choices. You will see 15 tables, each consisting of 11 rows. Each row has two options; of which you must choose one: 'Option A' or 'Option B'.

Option A gives you a sure win.

Option B is a lottery that gives you a certain win with a 33% chance and another win with a 67% chance. Option B changes from table to table, but it is the same for all 11 rows in a given table.

All amounts in the tables are in euro cents.

When the experiment is over, only one row from all the rows in all the tables will be randomly selected for payment. Thus, each line has the same probability of being chosen for the payouts, so you should pay equal attention to all your choices.

Example of a table:

Option A		Option B	
100	A1	B1	33% de chances pour gagner 100 67% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

In each line, you will be asked to indicate whether you prefer option A or option B.

Both options are initially displayed in gray. Click on either option to select it. Your selection will be highlighted in orange. You can change your selection at any time by clicking on the box that corresponds to the desired option.

The computer will help you make your choices by avoiding mistakes. For example, if you select 'Option A' for a given line, the computer will mark 'Option A' for all previous lines (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Let's assume that the following line has been chosen for the payment calculation:

70	A4	B4	33% de chances pour gagner 100 67% de chances pour gagner 50
----	----	----	---

- If you selected 'Option A' for this line, you will win 70 cents.
- If you selected 'Option B' for this line, the computer will randomly choose a number between 1 and 3 to determine your winnings.
  - If the randomly selected number is 1 (33% chance), you will win 100 cents.
  - If the randomly chosen number is 2 or 3 (67% chance), you will win 50 cents.

If you are ready, click on '>>' to start.

**TABLEAU #1**

Option A		Option B	
100	A1	B1	10% de chances pour gagner 100 90% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#1

**TABLEAU #2**

Option A		Option B	
100	A1	B1	10% de chances pour gagner 50 90% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#2

**TABLEAU #3**

Option A		Option B	
100	A1	B1	10% de chances pour gagner 100 90% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#3

**TABLEAU #4**

Option A		Option B	
100	A1	B1	25% de chances pour gagner 100 75% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#4

**TABLEAU #5**

Option A		Option B	
100	A1	B1	25% de chances pour gagner 50 75% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#5

**TABLEAU #6**

Option A		Option B	
100	A1	B1	25% de chances pour gagner 100 75% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#6

TABLEAU #7

Option A		Option B	
100	A1	B1	33% de chances pour gagner 100 67% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#7

TABLEAU #8

Option A		Option B	
100	A1	B1	33% de chances pour gagner 50 67% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#8

**TABLEAU #9**

Option A		Option B	
100	A1	B1	33% de chances pour gagner 100 67% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#9

**TABLEAU #10**

Option A		Option B	
100	A1	B1	50% de chances pour gagner 100 50% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#10



**TABLEAU #11**

Option A		Option B	
100	A1	B1	50% de chances pour gagner 50 50% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#11

**TABLEAU #12**

Option A		Option B	
100	A1	B1	50% de chances pour gagner 100 50% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#12

**TABLEAU #13**

Option A		Option B	
100	A1	B1	75% de chances pour gagner 100 25% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#13

**TABLEAU #14**

Option A		Option B	
100	A1	B1	75% de chances pour gagner 50 25% de chances pour gagner 0
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#14

**TABLEAU #15**

Option A		Option B	
100	A1	B1	75% de chances pour gagner 100 25% de chances pour gagner 50
90	A2	B2	
80	A3	B3	
70	A4	B4	
60	A5	B5	
50	A6	B6	
40	A7	B7	
30	A8	B8	
20	A9	B9	
10	A10	B10	
0	A11	B11	

Select an option for TABLEAU#15

**H1-4: : Holt&Laury\_1Switch**

In the next screen, you will be asked to make ten choices (one choice for each row of the table). Each time, you will be asked to indicate whether you prefer 'Option A' or 'Option B'. When the experiment is complete, one row of the table will be randomly selected for payment. This means that each row has the same probability of being selected for the payout, so you should pay equal attention to all your choices.

Your winnings will depend on whether you choose 'Option A' or 'Option B'. To determine your winnings, a number between 1 and 10 will be randomly selected by the computer.

All amounts in the tables are in cents.

For each of the 10 rows in the table, you will be asked to indicate whether you prefer 'Option A' or 'Option B'.

Both options are initially displayed in gray. Click on one of the two options to select it. Your selection will be highlighted in orange. You can change your selection at any time by clicking on the box that corresponds to the desired option.

The computer will help you make your selection without errors. For example, if you select 'Option A' for a given line, the computer will mark 'Option A' for all previous lines (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Suppose the following line was randomly selected for payment:

Option A		Nombre au hasard										Option B		
100	80												190	5
A4		1	2	3	4	5	6	7	8	9	10	B4		

- If you selected 'Option A' (by clicking on the box 'A4') and the computer randomly selected the number :
  - 1, 2, 3 or 4 you win 100 euro cents
  - 5, 6, 7, 8, 9 or 10 you win 80 cents
- If you have selected 'Option B' (by clicking on the box 'B4') and the second number is :
  - 1, 2, 3 or 4 you win 190 cents
  - 5, 6, 7, 8, 9 or 10 you win 5 euro cents

You can click on the 'A4' or 'B4' boxes now to practice selecting an option (it will be highlighted in orange).

Therefore, the color of the numbers in the 'Random Number' column represents your chances of getting each possible payout.

The more purple numbers in a row, the more likely you are to get 100 or 190 cents, depending on whether you select 'Option A' or 'Option B', and the less likely you are to get the green amounts if that row is selected at random for payment.

The more numbers colored green on a line, the more likely you are to get 80 or 5 cents, depending on whether you select 'Option A' or 'Option B', and the less likely you are to get the purple amounts if that line is randomly selected for payment.

In summary, you will have ten choices: in each row of the table, you will have to choose between Option A and Option B. You can choose option A in some rows and option B in others, and you can change your choices and take them in any order.

If you are ready, click on '>>' to begin.

In each of the following 10 lines, indicate whether you prefer 'Option A' or 'Option B'.

Option A		Nombre au hasard										Option B	
100	80											190	5
A1		1	2	3	4	5	6	7	8	9	10	B1	
A2		1	2	3	4	5	6	7	8	9	10	B2	
A3		1	2	3	4	5	6	7	8	9	10	B3	
A4		1	2	3	4	5	6	7	8	9	10	B4	
A5		1	2	3	4	5	6	7	8	9	10	B5	
A6		1	2	3	4	5	6	7	8	9	10	B6	
A7		1	2	3	4	5	6	7	8	9	10	B7	
A8		1	2	3	4	5	6	7	8	9	10	B8	
A9		1	2	3	4	5	6	7	8	9	10	B9	
A10		1	2	3	4	5	6	7	8	9	10	B10	

Select 'Option A' or 'Option B' for line #1 by clicking on box 'A1' or box 'B1'.

### H1-5: Loss aversion

In the next screen, you will be asked to make ten choices (one choice for each row of the table). Each time, you will be asked to indicate whether you prefer 'Option A' or 'Option B'. When the experiment is complete, one row of the table will be randomly selected for payment. This means that each row has the same probability of being selected for the payout, so you should pay equal attention to all your choices. Your winnings will depend on whether you choose 'Option A' or 'Option B'. To determine your winnings, a number between 1 and 10 will be randomly selected by the computer.

In each case, 'Option A' and 'Option B' are such that they generate losses with a 50% probability and wins with a 50% probability.

In the table, option A is different in each row, while option B remains the same in all rows: 'lose 100 cents with 50% chance, win 100 cents with 50% chance'.

All the amounts that appear in the tables are in euro cents.

In this part of the experiment, any winnings you make will be added to your total winnings and any losses you suffer will be subtracted from your total winnings.

For each of the 10 rows in the table, you will be asked to indicate whether you prefer 'Option A' or 'Option B'.

Both options are initially displayed in gray. Click on one of the two options to select it. Your selection will be highlighted in orange. You can change your selection at any time by clicking on the box that corresponds to the desired option.

The computer will help you make your choices by avoiding mistakes. For example, if you select 'Option A' for a given line, the computer will mark 'Option A' for all previous lines (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Example:

Suppose the following line was randomly selected for payment:

#	Option A	Option B
4	perdre <b>175</b> avec 50% de chances gagner <b>500</b> avec 50% de chances	perdre <b>100</b> avec 50% de chances gagner <b>100</b> avec 50% de chances

- If you selected 'Option A', you have a 50% chance of losing 175 cents and a 50% chance of winning 500 cents
- If you selected 'Option B', you will have a 50% chance of losing 100 cents and a 50% chance of winning 100 cents

Now you can click on the boxes corresponding to 'Option A' or 'Option B' to practice selecting an option (it will be highlighted in orange).

In summary, 1 of the 10 rows in the table will be selected at random, and your choice ('Option A' or 'Option B') will determine how much money you can receive in that part of the experiment.

- If you chose 'Option A' for the randomly selected row, you will either win the corresponding amount of money (with a 50% chance) or lose the corresponding amount of money (with a 50% chance).
- If you chose 'Option B' for the randomly selected line, you will either win 100 cents (with a 50% chance) or lose 100 cents (with a 50% chance).

If you are ready, click on '>>' to start.

In each of the following 10 lines, indicate whether you prefer 'Option A' or 'Option B'.

#	Option A	Option B
1	perdre 140 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
2	perdre 150 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
3	perdre 160 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
4	perdre 175 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
5	perdre 190 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
6	perdre 210 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
7	perdre 240 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
8	perdre 290 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
9	perdre 395 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances
10	perdre 700 avec 50% de chances gagner 500 avec 50% de chances	perdre 100 avec 50% de chances gagner 100 avec 50% de chances

Select 'Option A' or 'Option B' for line #1 by clicking on box 'A1' or box 'B1'.

### **H1-6: Cognitive reflection test - Problems**

Please answer the following questions carefully.

Each question has only one solution.

You will have exactly 5 minutes to answer all the questions.

If you are ready, click on '>>' to begin.

A table and a chair cost 150 euros in total. The table costs 100 euros more than the chair. How much does the chair cost?

(answer below in euros)

If it takes 10 hours for 10 mechanics to repair 10 cars, how long would it take 80 mechanics to repair 80 cars?

(answer below in hours)

A new library buys books for its collection. Each week the number of books purchased doubles. If it takes 36 weeks to buy all the books they need, how long would it take the library to buy half the books they need?

(answer below in weeks)

In the zoo, the lions eat a ton of meat every 6 weeks, and the tigers eat a ton of meat every 12 weeks, how long would it take the lions and tigers together to eat a ton of meat?

(answer below in weeks)



John had the 25th fastest time and the 25th slowest time in a race. How many people participated in the race?

(answer below)

An art collector buys a famous painting for 50 million and sells it for 60 million. A few years later, the collector buys it back for 70 million and sells it for 80 million. How much money did the collector make in the end?

(answer below in millions)

Marie invested 12,000 euros in the stock market in November 2013. Six months later, in May 2014, the shares she had bought had fallen by 50%. Fortunately for Marie, from May 2014 to August 2014, the shares she had purchased had increased by 75%. At this point, Mary:

- earned money
- lost money
- did not make or lose any money

### **H1-7: Demographics**

Please answer the following sociodemographic questions:

Gender:

- Male
- Female
- Other

Age (in years):

Nationality:

What was the size of the community where you lived the most time in your life?

- Less than 2000 inhabitants
- Between 2000 and 10000 inhabitants
- Between 10000 and 100000 inhabitants
- More than 10000 inhabitants

How many brothers and sisters do you have?

What is your position among your siblings?

(Please answer with a number. 1 = oldest)

To what extent have you been involved in other studies like this?

1 - Jamais	2	3	4	5 - Souvent
------------	---	---	---	-------------

How do you see yourself: are you generally a person who is fully willing to take risks or do you try to avoid taking risks?

Please select a number on the scale, where 0 means 'not at all willing to take risks' and 10 means 'very willing to take risks'.

0 - pas du tout disposé à prendre des risques	1	2	3	4	5	6	7	8	9	10 - très disposé à prendre des risques
---	---	---	---	---	---	---	---	---	---	---

## H2- Instruction for Day 2

Welcome to the second part of the experiment!

We remind you that this experiment will take place entirely online. All the information you need to make your decisions will be visible on the screen. You will not need to consult any other documents, so we ask you to stay focused on the instructions and your decisions during the experiment.

A participation bonus of €4 will be added to your winnings from the experiment and will be paid to you at the end of this part of the experiment.

Pour commencer, veuillez saisir votre IDENTIFIANT ci-dessous.

Cet IDENTIFIANT vous a été donné lors de votre participation à la première partie de l'expérience. Vous ne pourrez pas participer et être rémunéré pour cette deuxième partie si vous n'avez pas effectué la première partie.

En général, votre IDENTIFIANT est composé des trois premières lettres de votre nom de famille et des six derniers chiffres de votre IBAN.

Si vous ne vous souvenez pas de votre IDENTIFIANT et avez des difficultés à vous connecter, veuillez contacter [kpegli@gate.cnrs.fr](mailto:kpegli@gate.cnrs.fr)

### H2-1 : Probability training

In the next screen we will show you a table with a number of cells. Identical numbers will be shown in the same colour. The computer will choose a square at random and repeat this operation a large number of times. Each time the computer chooses a square, it will appear dark. The percentage of times that a number has been chosen by the computer during the simulation will appear at the bottom of the table.

Therefore, a number that appears in more boxes will be selected by the computer more often. For example, if the number 400 appears in 7 out of 9 cells, it will be chosen 7 times out of 9 if the simulation is long enough, i.e., 78% of the time ( $7/9=78\%$ ).

### **Example:**

Here is an example of a table. You can end the computer simulation by clicking on the 'End Simulation' button.

100	100	400	400	400	400	400	400	400
21%		79%						

**Terminer Simulation**

Please click on '>>' to continue.

Below each table, you will be asked to enter an estimate of the percentage of times the computer will choose a number represented in the table in the case of a simulation of 100,000 numbers.

You will earn 10 cents for each correct answer, i.e., an answer that does not differ from the simulation result by more than 5%.

TABLEAU #1

100	100	100	100	100	100	100	100	100	800
0%									0%

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 800 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #2

500	500	500	500	500	500	600	600
0%						0%	

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 600 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

TABLEAU #3

300	300	300	300	300	300	400	400	400
0%						0%		

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 400 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

TABLEAU #4

200	200	200	200	200	300	300	300	300	300
0%					0%				

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 300 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

TABLEAU #5

600	600	700	700	700	700	700	700
0%		0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 500 on a simulation of 100 000 numbers?

%

(Enter an integer between 0 and 100)

**TABLEAU #6**

700	900	900	900	900	900	900	900	900	900
0%	0%								

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

**TABLEAU #7**

400	400	400	900	900	900	900	900	900
0%			0%					

Given the numbers in the table, what do you think will be the percentage of cases where the result obtained by the computer will be 900 on a simulation of 100 000 numbers?

 %

(Enter an integer between 0 and 100)

## H2-2: Main task

In this task, you will be asked to make a series of choices. You will see several tables displayed one by one, each consisting of several rows. Each row has two options, of which you must choose one: either Option A or Option B.

Option A gives you a sure win. This option will remain the same throughout this part of the experience. This option will not change within a table or between tables.

Option B is a lottery where only one amount is drawn from two possible amounts. One of the two amounts is coloured green and the other blue, and each has its own probability of being drawn at random. These probabilities are represented by the number of boxes of a certain colour (either green or blue) among all the coloured boxes (green or blue) in a row. This means that a number that appears on more squares has a higher chance of being chosen. The amounts and the distribution of the colours of the boxes change between the rows within each table, but also from one table to another.

For each table, the computer will help you to make your choices without making mistakes. For example, if you select 'Option A' for a given row, the computer will mark 'Option A' for all the preceding rows (up to the first). Similarly, if you select 'Option B' for a line, the computer will mark 'Option B' for all subsequent lines (up to the last one).

Once the experiment is complete, 1 table will be drawn from the 30 tables. For each of these boards, a line will be randomly selected for payment. Depending on your decisions, your payout for the board will be either the amount (in euro cents) of option A or the result (in euro cents) of the lottery for option B.

Since each table has the same probability of being chosen for the payments, you should therefore pay the same attention to all your choices. All amounts that appear in the tables are in euro cents. For example, the amount 1000 corresponds to 10 euros.

Example:

Let's imagine that we have a table with a total of 7 possible payments associated with option B, and the following row of this table has been chosen for the calculation of the payments:

If you selected 'Option A' for this line, you will win 1,000 cents.

- If you selected 'Option B' for this line, the computer will randomly choose a number between 1 and 7 to determine your winnings.
  - If the randomly chosen number is 1 or 2 ( $2/7=29\%$  chance), you will win 250 cents.
  - If the randomly chosen number is 3, 4, 5, 6 or 7 ( $5/7=71\%$  chance), you will win 1,150 euro cents.

If you are ready, click on '>>' to start.

**TABLEAU #1**

Option A		Option B										
1000	A1	B1	50	50	50	50	50	450	450	450	450	450
1000	A2	B2	100	100	100	100	100	500	500	500	500	500
1000	A3	B3	150	150	150	150	150	550	550	550	550	550
1000	A4	B4	200	200	200	200	200	600	600	600	600	600
1000	A5	B5	250	250	250	250	250	650	650	650	650	650
1000	A6	B6	300	300	300	300	300	700	700	700	700	700
1000	A7	B7	350	350	350	350	350	750	750	750	750	750
1000	A8	B8	400	400	400	400	400	800	800	800	800	800
1000	A9	B9	450	450	450	450	450	850	850	850	850	850
1000	A10	B10	500	500	500	500	500	900	900	900	900	900
1000	A11	B11	550	550	550	550	550	950	950	950	950	950
1000	A12	B12	600	600	600	600	600	1000	1000	1000	1000	1000
1000	A13	B13	650	650	650	650	650	1050	1050	1050	1050	1050
1000	A14	B14	700	700	700	700	700	1100	1100	1100	1100	1100
1000	A15	B15	750	750	750	750	750	1150	1150	1150	1150	1150
1000	A16	B16	800	800	800	800	800	1200	1200	1200	1200	1200
1000	A17	B17	850	850	850	850	850	1250	1250	1250	1250	1250
1000	A18	B18	900	900	900	900	900	1300	1300	1300	1300	1300
1000	A19	B19	950	950	950	950	950	1350	1350	1350	1350	1350
1000	A20	B20	1000	1000	1000	1000	1000	1400	1400	1400	1400	1400
1000	A21	B21	1050	1050	1050	1050	1050	1450	1450	1450	1450	1450

Select an option for TABLEAU #1



**TABLEAU #2**

Option A		Option B										
1000	A1	B1	50	50	50	50	50	50	50	50	50	2050
1000	A2	B2	100	100	100	100	100	100	100	100	100	2100
1000	A3	B3	150	150	150	150	150	150	150	150	150	2150
1000	A4	B4	200	200	200	200	200	200	200	200	200	2200
1000	A5	B5	250	250	250	250	250	250	250	250	250	2250
1000	A6	B6	300	300	300	300	300	300	300	300	300	2300
1000	A7	B7	350	350	350	350	350	350	350	350	350	2350
1000	A8	B8	400	400	400	400	400	400	400	400	400	2400
1000	A9	B9	450	450	450	450	450	450	450	450	450	2450
1000	A10	B10	500	500	500	500	500	500	500	500	500	2500
1000	A11	B11	550	550	550	550	550	550	550	550	550	2550
1000	A12	B12	600	600	600	600	600	600	600	600	600	2600
1000	A13	B13	650	650	650	650	650	650	650	650	650	2650
1000	A14	B14	700	700	700	700	700	700	700	700	700	2700
1000	A15	B15	750	750	750	750	750	750	750	750	750	2750
1000	A16	B16	800	800	800	800	800	800	800	800	800	2800
1000	A17	B17	850	850	850	850	850	850	850	850	850	2850
1000	A18	B18	900	900	900	900	900	900	900	900	900	2900
1000	A19	B19	950	950	950	950	950	950	950	950	950	2950
1000	A20	B20	1000	1000	1000	1000	1000	1000	1000	1000	1000	3000
1000	A21	B21	1050	1050	1050	1050	1050	1050	1050	1050	1050	3050

Select an option for TABLEAU #2

**TABLEAU #3**

Option A		Option B										
1000	A1	B1	0	0	0	0	0	180	180	180	180	180
1000	A2	B2	50	50	50	50	50	230	230	230	230	230
1000	A3	B3	100	100	100	100	100	280	280	280	280	280
1000	A4	B4	150	150	150	150	150	330	330	330	330	330
1000	A5	B5	200	200	200	200	200	380	380	380	380	380
1000	A6	B6	250	250	250	250	250	430	430	430	430	430
1000	A7	B7	300	300	300	300	300	480	480	480	480	480
1000	A8	B8	350	350	350	350	350	530	530	530	530	530
1000	A9	B9	400	400	400	400	400	580	580	580	580	580
1000	A10	B10	450	450	450	450	450	630	630	630	630	630
1000	A11	B11	500	500	500	500	500	680	680	680	680	680
1000	A12	B12	550	550	550	550	550	730	730	730	730	730
1000	A13	B13	600	600	600	600	600	780	780	780	780	780
1000	A14	B14	650	650	650	650	650	830	830	830	830	830
1000	A15	B15	700	700	700	700	700	880	880	880	880	880
1000	A16	B16	750	750	750	750	750	930	930	930	930	930
1000	A17	B17	800	800	800	800	800	980	980	980	980	980
1000	A18	B18	850	850	850	850	850	1030	1030	1030	1030	1030
1000	A19	B19	900	900	900	900	900	1080	1080	1080	1080	1080
1000	A20	B20	950	950	950	950	950	1130	1130	1130	1130	1130
1000	A21	B21	1000	1000	1000	1000	1000	1180	1180	1180	1180	1180

Select an option for TABLEAU #3

**TABLEAU #4**

Option A		Option B											
1000	A1	B1	0	0	0	0	0	0	0	0	0	0	900
1000	A2	B2	50	50	50	50	50	50	50	50	50	50	950
1000	A3	B3	100	100	100	100	100	100	100	100	100	100	1000
1000	A4	B4	150	150	150	150	150	150	150	150	150	150	1050
1000	A5	B5	200	200	200	200	200	200	200	200	200	200	1100
1000	A6	B6	250	250	250	250	250	250	250	250	250	250	1150
1000	A7	B7	300	300	300	300	300	300	300	300	300	300	1200
1000	A8	B8	350	350	350	350	350	350	350	350	350	350	1250
1000	A9	B9	400	400	400	400	400	400	400	400	400	400	1300
1000	A10	B10	450	450	450	450	450	450	450	450	450	450	1350
1000	A11	B11	500	500	500	500	500	500	500	500	500	500	1400
1000	A12	B12	550	550	550	550	550	550	550	550	550	550	1450
1000	A13	B13	600	600	600	600	600	600	600	600	600	600	1500
1000	A14	B14	650	650	650	650	650	650	650	650	650	650	1550
1000	A15	B15	700	700	700	700	700	700	700	700	700	700	1600
1000	A16	B16	750	750	750	750	750	750	750	750	750	750	1650
1000	A17	B17	800	800	800	800	800	800	800	800	800	800	1700
1000	A18	B18	850	850	850	850	850	850	850	850	850	850	1750
1000	A19	B19	900	900	900	900	900	900	900	900	900	900	1800
1000	A20	B20	950	950	950	950	950	950	950	950	950	950	1850
1000	A21	B21	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1900

Select an option for TABLEAU #4

**TABLEAU #5**

Option A		Option B											
1000	A1	B1	210	210	210	210	210	210	210	1050	1050	1050	
1000	A2	B2	260	260	260	260	260	260	260	1100	1100	1100	
1000	A3	B3	310	310	310	310	310	310	310	1150	1150	1150	
1000	A4	B4	360	360	360	360	360	360	360	1200	1200	1200	
1000	A5	B5	410	410	410	410	410	410	410	1250	1250	1250	
1000	A6	B6	460	460	460	460	460	460	460	1300	1300	1300	
1000	A7	B7	510	510	510	510	510	510	510	1350	1350	1350	
1000	A8	B8	560	560	560	560	560	560	560	1400	1400	1400	
1000	A9	B9	610	610	610	610	610	610	610	1450	1450	1450	
1000	A10	B10	660	660	660	660	660	660	660	1500	1500	1500	
1000	A11	B11	710	710	710	710	710	710	710	1550	1550	1550	
1000	A12	B12	760	760	760	760	760	760	760	1600	1600	1600	
1000	A13	B13	810	810	810	810	810	810	810	1650	1650	1650	
1000	A14	B14	860	860	860	860	860	860	860	1700	1700	1700	
1000	A15	B15	910	910	910	910	910	910	910	1750	1750	1750	
1000	A16	B16	960	960	960	960	960	960	960	1800	1800	1800	
1000	A17	B17	1010	1010	1010	1010	1010	1010	1010	1850	1850	1850	
1000	A18	B18	1060	1060	1060	1060	1060	1060	1060	1900	1900	1900	
1000	A19	B19	1110	1110	1110	1110	1110	1110	1110	1950	1950	1950	
1000	A20	B20	1160	1160	1160	1160	1160	1160	1160	2000	2000	2000	
1000	A21	B21	1210	1210	1210	1210	1210	1210	1210	2050	2050	2050	

Select an option for TABLEAU #5

**TABLEAU #6**

Option A		Option B										
1000	A1	B1	100	100	100	100	100	100	700	700		
1000	A2	B2	150	150	150	150	150	150	750	750		
1000	A3	B3	200	200	200	200	200	200	800	800		
1000	A4	B4	250	250	250	250	250	250	850	850		
1000	A5	B5	300	300	300	300	300	300	900	900		
1000	A6	B6	350	350	350	350	350	350	950	950		
1000	A7	B7	400	400	400	400	400	400	1000	1000		
1000	A8	B8	450	450	450	450	450	450	1050	1050		
1000	A9	B9	500	500	500	500	500	500	1100	1100		
1000	A10	B10	550	550	550	550	550	550	1150	1150		
1000	A11	B11	600	600	600	600	600	600	1200	1200		
1000	A12	B12	650	650	650	650	650	650	1250	1250		
1000	A13	B13	700	700	700	700	700	700	1300	1300		
1000	A14	B14	750	750	750	750	750	750	1350	1350		
1000	A15	B15	800	800	800	800	800	800	1400	1400		
1000	A16	B16	850	850	850	850	850	850	1450	1450		
1000	A17	B17	900	900	900	900	900	900	1500	1500		
1000	A18	B18	950	950	950	950	950	950	1550	1550		
1000	A19	B19	1000	1000	1000	1000	1000	1000	1600	1600		
1000	A20	B20	1050	1050	1050	1050	1050	1050	1650	1650		
1000	A21	B21	1100	1100	1100	1100	1100	1100	1700	1700		

Select an option for TABLEAU #6

**TABLEAU #7**

Option A		Option B										
1000	A1	B1	100	100	100	100	100	100	100	100	100	1600
1000	A2	B2	150	150	150	150	150	150	150	150	150	1650
1000	A3	B3	200	200	200	200	200	200	200	200	200	1700
1000	A4	B4	250	250	250	250	250	250	250	250	250	1750
1000	A5	B5	300	300	300	300	300	300	300	300	300	1800
1000	A6	B6	350	350	350	350	350	350	350	350	350	1850
1000	A7	B7	400	400	400	400	400	400	400	400	400	1900
1000	A8	B8	450	450	450	450	450	450	450	450	450	1950
1000	A9	B9	500	500	500	500	500	500	500	500	500	2000
1000	A10	B10	550	550	550	550	550	550	550	550	550	2050
1000	A11	B11	600	600	600	600	600	600	600	600	600	2100
1000	A12	B12	650	650	650	650	650	650	650	650	650	2150
1000	A13	B13	700	700	700	700	700	700	700	700	700	2200
1000	A14	B14	750	750	750	750	750	750	750	750	750	2250
1000	A15	B15	800	800	800	800	800	800	800	800	800	2300
1000	A16	B16	850	850	850	850	850	850	850	850	850	2350
1000	A17	B17	900	900	900	900	900	900	900	900	900	2400
1000	A18	B18	950	950	950	950	950	950	950	950	950	2450
1000	A19	B19	1000	1000	1000	1000	1000	1000	1000	1000	1000	2500
1000	A20	B20	1050	1050	1050	1050	1050	1050	1050	1050	1050	2550
1000	A21	B21	1100	1100	1100	1100	1100	1100	1100	1100	1100	2600

Select an option for TABLEAU #7

**TABLEAU #8**

Option A		Option B										
1000	A1	B1	210	210	583	583	583	583	583	583		
1000	A2	B2	260	260	633	633	633	633	633	633		
1000	A3	B3	310	310	683	683	683	683	683	683		
1000	A4	B4	360	360	733	733	733	733	733	733		
1000	A5	B5	410	410	783	783	783	783	783	783		
1000	A6	B6	460	460	833	833	833	833	833	833		
1000	A7	B7	510	510	883	883	883	883	883	883		
1000	A8	B8	560	560	933	933	933	933	933	933		
1000	A9	B9	610	610	983	983	983	983	983	983		
1000	A10	B10	660	660	1033	1033	1033	1033	1033	1033		
1000	A11	B11	710	710	1083	1083	1083	1083	1083	1083		
1000	A12	B12	760	760	1133	1133	1133	1133	1133	1133		
1000	A13	B13	810	810	1183	1183	1183	1183	1183	1183		
1000	A14	B14	860	860	1233	1233	1233	1233	1233	1233		
1000	A15	B15	910	910	1283	1283	1283	1283	1283	1283		
1000	A16	B16	960	960	1333	1333	1333	1333	1333	1333		
1000	A17	B17	1010	1010	1383	1383	1383	1383	1383	1383		
1000	A18	B18	1060	1060	1433	1433	1433	1433	1433	1433		
1000	A19	B19	1110	1110	1483	1483	1483	1483	1483	1483		
1000	A20	B20	1160	1160	1533	1533	1533	1533	1533	1533		
1000	A21	B21	1210	1210	1583	1583	1583	1583	1583	1583		

Select an option for TABLEAU #8

**TABLEAU #9**

Option A		Option B										
1000	A1	B1	280	280	560	560	560	560	560	560		
1000	A2	B2	330	330	610	610	610	610	610	610		
1000	A3	B3	380	380	660	660	660	660	660	660		
1000	A4	B4	430	430	710	710	710	710	710	710		
1000	A5	B5	480	480	760	760	760	760	760	760		
1000	A6	B6	530	530	810	810	810	810	810	810		
1000	A7	B7	580	580	860	860	860	860	860	860		
1000	A8	B8	630	630	910	910	910	910	910	910		
1000	A9	B9	680	680	960	960	960	960	960	960		
1000	A10	B10	730	730	1010	1010	1010	1010	1010	1010		
1000	A11	B11	780	780	1060	1060	1060	1060	1060	1060		
1000	A12	B12	830	830	1110	1110	1110	1110	1110	1110		
1000	A13	B13	880	880	1160	1160	1160	1160	1160	1160		
1000	A14	B14	930	930	1210	1210	1210	1210	1210	1210		
1000	A15	B15	980	980	1260	1260	1260	1260	1260	1260		
1000	A16	B16	1030	1030	1310	1310	1310	1310	1310	1310		
1000	A17	B17	1080	1080	1360	1360	1360	1360	1360	1360		
1000	A18	B18	1130	1130	1410	1410	1410	1410	1410	1410		
1000	A19	B19	1180	1180	1460	1460	1460	1460	1460	1460		
1000	A20	B20	1230	1230	1510	1510	1510	1510	1510	1510		
1000	A21	B21	1280	1280	1560	1560	1560	1560	1560	1560		

Select an option for TABLEAU #9



**TABLEAU #10**

Option A		Option B											
1000	A1	B1	210	210	210	210	210	210	210	210	210	210	3010
1000	A2	B2	260	260	260	260	260	260	260	260	260	260	3060
1000	A3	B3	310	310	310	310	310	310	310	310	310	310	3110
1000	A4	B4	360	360	360	360	360	360	360	360	360	360	3160
1000	A5	B5	410	410	410	410	410	410	410	410	410	410	3210
1000	A6	B6	460	460	460	460	460	460	460	460	460	460	3260
1000	A7	B7	510	510	510	510	510	510	510	510	510	510	3310
1000	A8	B8	560	560	560	560	560	560	560	560	560	560	3360
1000	A9	B9	610	610	610	610	610	610	610	610	610	610	3410
1000	A10	B10	660	660	660	660	660	660	660	660	660	660	3460
1000	A11	B11	710	710	710	710	710	710	710	710	710	710	3510
1000	A12	B12	760	760	760	760	760	760	760	760	760	760	3560
1000	A13	B13	810	810	810	810	810	810	810	810	810	810	3610
1000	A14	B14	860	860	860	860	860	860	860	860	860	860	3660
1000	A15	B15	910	910	910	910	910	910	910	910	910	910	3710
1000	A16	B16	960	960	960	960	960	960	960	960	960	960	3760
1000	A17	B17	1010	1010	1010	1010	1010	1010	1010	1010	1010	1010	3810
1000	A18	B18	1060	1060	1060	1060	1060	1060	1060	1060	1060	1060	3860
1000	A19	B19	1110	1110	1110	1110	1110	1110	1110	1110	1110	1110	3910
1000	A20	B20	1160	1160	1160	1160	1160	1160	1160	1160	1160	1160	3960
1000	A21	B21	1210	1210	1210	1210	1210	1210	1210	1210	1210	1210	4010

Select an option for TABLEAU #10

**TABLEAU #11**

Option A		Option B											
1000	A1	B1	280	280	280	280	280	280	280	910	910	910	
1000	A2	B2	330	330	330	330	330	330	330	960	960	960	
1000	A3	B3	380	380	380	380	380	380	380	1010	1010	1010	
1000	A4	B4	430	430	430	430	430	430	430	1060	1060	1060	
1000	A5	B5	480	480	480	480	480	480	480	1110	1110	1110	
1000	A6	B6	530	530	530	530	530	530	530	1160	1160	1160	
1000	A7	B7	580	580	580	580	580	580	580	1210	1210	1210	
1000	A8	B8	630	630	630	630	630	630	630	1260	1260	1260	
1000	A9	B9	680	680	680	680	680	680	680	1310	1310	1310	
1000	A10	B10	730	730	730	730	730	730	730	1360	1360	1360	
1000	A11	B11	780	780	780	780	780	780	780	1410	1410	1410	
1000	A12	B12	830	830	830	830	830	830	830	1460	1460	1460	
1000	A13	B13	880	880	880	880	880	880	880	1510	1510	1510	
1000	A14	B14	930	930	930	930	930	930	930	1560	1560	1560	
1000	A15	B15	980	980	980	980	980	980	980	1610	1610	1610	
1000	A16	B16	1030	1030	1030	1030	1030	1030	1030	1660	1660	1660	
1000	A17	B17	1080	1080	1080	1080	1080	1080	1080	1710	1710	1710	
1000	A18	B18	1130	1130	1130	1130	1130	1130	1130	1760	1760	1760	
1000	A19	B19	1180	1180	1180	1180	1180	1180	1180	1810	1810	1810	
1000	A20	B20	1230	1230	1230	1230	1230	1230	1230	1860	1860	1860	
1000	A21	B21	1280	1280	1280	1280	1280	1280	1280	1910	1910	1910	

Select an option for TABLEAU #11

**TABLEAU #12**

Option A		Option B										
1000	A1	B1	-30	-30	130	130	130	130	130	130		
1000	A2	B2	20	20	180	180	180	180	180	180		
1000	A3	B3	70	70	230	230	230	230	230	230		
1000	A4	B4	120	120	280	280	280	280	280	280		
1000	A5	B5	170	170	330	330	330	330	330	330		
1000	A6	B6	220	220	380	380	380	380	380	380		
1000	A7	B7	270	270	430	430	430	430	430	430		
1000	A8	B8	320	320	480	480	480	480	480	480		
1000	A9	B9	370	370	530	530	530	530	530	530		
1000	A10	B10	420	420	580	580	580	580	580	580		
1000	A11	B11	470	470	630	630	630	630	630	630		
1000	A12	B12	520	520	680	680	680	680	680	680		
1000	A13	B13	570	570	730	730	730	730	730	730		
1000	A14	B14	620	620	780	780	780	780	780	780		
1000	A15	B15	670	670	830	830	830	830	830	830		
1000	A16	B16	720	720	880	880	880	880	880	880		
1000	A17	B17	770	770	930	930	930	930	930	930		
1000	A18	B18	820	820	980	980	980	980	980	980		
1000	A19	B19	870	870	1030	1030	1030	1030	1030	1030		
1000	A20	B20	920	920	1080	1080	1080	1080	1080	1080		
1000	A21	B21	970	970	1130	1130	1130	1130	1130	1130		

Select an option for TABLEAU #12

**TABLEAU #13**

Option A		Option B											
1000	A1	B1	280	280	280	280	280	280	280	1120	1120		
1000	A2	B2	330	330	330	330	330	330	330	1170	1170		
1000	A3	B3	380	380	380	380	380	380	380	1220	1220		
1000	A4	B4	430	430	430	430	430	430	430	1270	1270		
1000	A5	B5	480	480	480	480	480	480	480	1320	1320		
1000	A6	B6	530	530	530	530	530	530	530	1370	1370		
1000	A7	B7	580	580	580	580	580	580	580	1420	1420		
1000	A8	B8	630	630	630	630	630	630	630	1470	1470		
1000	A9	B9	680	680	680	680	680	680	680	1520	1520		
1000	A10	B10	730	730	730	730	730	730	730	1570	1570		
1000	A11	B11	780	780	780	780	780	780	780	1620	1620		
1000	A12	B12	830	830	830	830	830	830	830	1670	1670		
1000	A13	B13	880	880	880	880	880	880	880	1720	1720		
1000	A14	B14	930	930	930	930	930	930	930	1770	1770		
1000	A15	B15	980	980	980	980	980	980	980	1820	1820		
1000	A16	B16	1030	1030	1030	1030	1030	1030	1030	1870	1870		
1000	A17	B17	1080	1080	1080	1080	1080	1080	1080	1920	1920		
1000	A18	B18	1130	1130	1130	1130	1130	1130	1130	1970	1970		
1000	A19	B19	1180	1180	1180	1180	1180	1180	1180	2020	2020		
1000	A20	B20	1230	1230	1230	1230	1230	1230	1230	2070	2070		
1000	A21	B21	1280	1280	1280	1280	1280	1280	1280	2120	2120		

Select an option for TABLEAU #13

TABLEAU #14

Option A		Option B											
1000	A1	B1	-30	-30	-30	-30	-30	-30	-30	450	450		
1000	A2	B2	20	20	20	20	20	20	20	500	500		
1000	A3	B3	70	70	70	70	70	70	70	550	550		
1000	A4	B4	120	120	120	120	120	120	120	600	600		
1000	A5	B5	170	170	170	170	170	170	170	650	650		
1000	A6	B6	220	220	220	220	220	220	220	700	700		
1000	A7	B7	270	270	270	270	270	270	270	750	750		
1000	A8	B8	320	320	320	320	320	320	320	800	800		
1000	A9	B9	370	370	370	370	370	370	370	850	850		
1000	A10	B10	420	420	420	420	420	420	420	900	900		
1000	A11	B11	470	470	470	470	470	470	470	950	950		
1000	A12	B12	520	520	520	520	520	520	520	1000	1000		
1000	A13	B13	570	570	570	570	570	570	570	1050	1050		
1000	A14	B14	620	620	620	620	620	620	620	1100	1100		
1000	A15	B15	670	670	670	670	670	670	670	1150	1150		
1000	A16	B16	720	720	720	720	720	720	720	1200	1200		
1000	A17	B17	770	770	770	770	770	770	770	1250	1250		
1000	A18	B18	820	820	820	820	820	820	820	1300	1300		
1000	A19	B19	870	870	870	870	870	870	870	1350	1350		
1000	A20	B20	920	920	920	920	920	920	920	1400	1400		
1000	A21	B21	970	970	970	970	970	970	970	1450	1450		

Select an option for TABLEAU #14

**TABLEAU #15**

Option A		Option B										
1000	A1	B1	280	280	280	280	280	700	700	700	700	700
1000	A2	B2	330	330	330	330	330	750	750	750	750	750
1000	A3	B3	380	380	380	380	380	800	800	800	800	800
1000	A4	B4	430	430	430	430	430	850	850	850	850	850
1000	A5	B5	480	480	480	480	480	900	900	900	900	900
1000	A6	B6	530	530	530	530	530	950	950	950	950	950
1000	A7	B7	580	580	580	580	580	1000	1000	1000	1000	1000
1000	A8	B8	630	630	630	630	630	1050	1050	1050	1050	1050
1000	A9	B9	680	680	680	680	680	1100	1100	1100	1100	1100
1000	A10	B10	730	730	730	730	730	1150	1150	1150	1150	1150
1000	A11	B11	780	780	780	780	780	1200	1200	1200	1200	1200
1000	A12	B12	830	830	830	830	830	1250	1250	1250	1250	1250
1000	A13	B13	880	880	880	880	880	1300	1300	1300	1300	1300
1000	A14	B14	930	930	930	930	930	1350	1350	1350	1350	1350
1000	A15	B15	980	980	980	980	980	1400	1400	1400	1400	1400
1000	A16	B16	1030	1030	1030	1030	1030	1450	1450	1450	1450	1450
1000	A17	B17	1080	1080	1080	1080	1080	1500	1500	1500	1500	1500
1000	A18	B18	1130	1130	1130	1130	1130	1550	1550	1550	1550	1550
1000	A19	B19	1180	1180	1180	1180	1180	1600	1600	1600	1600	1600
1000	A20	B20	1230	1230	1230	1230	1230	1650	1650	1650	1650	1650
1000	A21	B21	1280	1280	1280	1280	1280	1700	1700	1700	1700	1700

Select an option for TABLEAU #15

**TABLEAU #16**

Option A		Option B											
1000	A1	B1	280	280	280	280	280	280	280	280	280	280	2380
1000	A2	B2	330	330	330	330	330	330	330	330	330	330	2430
1000	A3	B3	380	380	380	380	380	380	380	380	380	380	2480
1000	A4	B4	430	430	430	430	430	430	430	430	430	430	2530
1000	A5	B5	480	480	480	480	480	480	480	480	480	480	2580
1000	A6	B6	530	530	530	530	530	530	530	530	530	530	2630
1000	A7	B7	580	580	580	580	580	580	580	580	580	580	2680
1000	A8	B8	630	630	630	630	630	630	630	630	630	630	2730
1000	A9	B9	680	680	680	680	680	680	680	680	680	680	2780
1000	A10	B10	730	730	730	730	730	730	730	730	730	730	2830
1000	A11	B11	780	780	780	780	780	780	780	780	780	780	2880
1000	A12	B12	830	830	830	830	830	830	830	830	830	830	2930
1000	A13	B13	880	880	880	880	880	880	880	880	880	880	2980
1000	A14	B14	930	930	930	930	930	930	930	930	930	930	3030
1000	A15	B15	980	980	980	980	980	980	980	980	980	980	3080
1000	A16	B16	1030	1030	1030	1030	1030	1030	1030	1030	1030	1030	3130
1000	A17	B17	1080	1080	1080	1080	1080	1080	1080	1080	1080	1080	3180
1000	A18	B18	1130	1130	1130	1130	1130	1130	1130	1130	1130	1130	3230
1000	A19	B19	1180	1180	1180	1180	1180	1180	1180	1180	1180	1180	3280
1000	A20	B20	1230	1230	1230	1230	1230	1230	1230	1230	1230	1230	3330
1000	A21	B21	1280	1280	1280	1280	1280	1280	1280	1280	1280	1280	3380

Select an option for TABLEAU #16

**TABLEAU #17**

Option A		Option B											
1000	A1	B1	210	210	210	210	210	210	210	1330	1330		
1000	A2	B2	260	260	260	260	260	260	260	1380	1380		
1000	A3	B3	310	310	310	310	310	310	310	1430	1430		
1000	A4	B4	360	360	360	360	360	360	360	1480	1480		
1000	A5	B5	410	410	410	410	410	410	410	1530	1530		
1000	A6	B6	460	460	460	460	460	460	460	1580	1580		
1000	A7	B7	510	510	510	510	510	510	510	1630	1630		
1000	A8	B8	560	560	560	560	560	560	560	1680	1680		
1000	A9	B9	610	610	610	610	610	610	610	1730	1730		
1000	A10	B10	660	660	660	660	660	660	660	1780	1780		
1000	A11	B11	710	710	710	710	710	710	710	1830	1830		
1000	A12	B12	760	760	760	760	760	760	760	1880	1880		
1000	A13	B13	810	810	810	810	810	810	810	1930	1930		
1000	A14	B14	860	860	860	860	860	860	860	1980	1980		
1000	A15	B15	910	910	910	910	910	910	910	2030	2030		
1000	A16	B16	960	960	960	960	960	960	960	2080	2080		
1000	A17	B17	1010	1010	1010	1010	1010	1010	1010	2130	2130		
1000	A18	B18	1060	1060	1060	1060	1060	1060	1060	2180	2180		
1000	A19	B19	1110	1110	1110	1110	1110	1110	1110	2230	2230		
1000	A20	B20	1160	1160	1160	1160	1160	1160	1160	2280	2280		
1000	A21	B21	1210	1210	1210	1210	1210	1210	1210	2330	2330		

Select an option for TABLEAU #17



**TABLEAU #18**

Option A		Option B											
1000	A1	B1	100	100	100	100	100	100	100	550	550	550	
1000	A2	B2	150	150	150	150	150	150	150	600	600	600	
1000	A3	B3	200	200	200	200	200	200	200	650	650	650	
1000	A4	B4	250	250	250	250	250	250	250	700	700	700	
1000	A5	B5	300	300	300	300	300	300	300	750	750	750	
1000	A6	B6	350	350	350	350	350	350	350	800	800	800	
1000	A7	B7	400	400	400	400	400	400	400	850	850	850	
1000	A8	B8	450	450	450	450	450	450	450	900	900	900	
1000	A9	B9	500	500	500	500	500	500	500	950	950	950	
1000	A10	B10	550	550	550	550	550	550	550	1000	1000	1000	
1000	A11	B11	600	600	600	600	600	600	600	1050	1050	1050	
1000	A12	B12	650	650	650	650	650	650	650	1100	1100	1100	
1000	A13	B13	700	700	700	700	700	700	700	1150	1150	1150	
1000	A14	B14	750	750	750	750	750	750	750	1200	1200	1200	
1000	A15	B15	800	800	800	800	800	800	800	1250	1250	1250	
1000	A16	B16	850	850	850	850	850	850	850	1300	1300	1300	
1000	A17	B17	900	900	900	900	900	900	900	1350	1350	1350	
1000	A18	B18	950	950	950	950	950	950	950	1400	1400	1400	
1000	A19	B19	1000	1000	1000	1000	1000	1000	1000	1450	1450	1450	
1000	A20	B20	1050	1050	1050	1050	1050	1050	1050	1500	1500	1500	
1000	A21	B21	1100	1100	1100	1100	1100	1100	1100	1550	1550	1550	

Select an option for TABLEAU #18

**TABLEAU #19**

Option A		Option B										
1000	A1	B1	100	100	100	100	100	400	400	400	400	400
1000	A2	B2	150	150	150	150	150	450	450	450	450	450
1000	A3	B3	200	200	200	200	200	500	500	500	500	500
1000	A4	B4	250	250	250	250	250	550	550	550	550	550
1000	A5	B5	300	300	300	300	300	600	600	600	600	600
1000	A6	B6	350	350	350	350	350	650	650	650	650	650
1000	A7	B7	400	400	400	400	400	700	700	700	700	700
1000	A8	B8	450	450	450	450	450	750	750	750	750	750
1000	A9	B9	500	500	500	500	500	800	800	800	800	800
1000	A10	B10	550	550	550	550	550	850	850	850	850	850
1000	A11	B11	600	600	600	600	600	900	900	900	900	900
1000	A12	B12	650	650	650	650	650	950	950	950	950	950
1000	A13	B13	700	700	700	700	700	1000	1000	1000	1000	1000
1000	A14	B14	750	750	750	750	750	1050	1050	1050	1050	1050
1000	A15	B15	800	800	800	800	800	1100	1100	1100	1100	1100
1000	A16	B16	850	850	850	850	850	1150	1150	1150	1150	1150
1000	A17	B17	900	900	900	900	900	1200	1200	1200	1200	1200
1000	A18	B18	950	950	950	950	950	1250	1250	1250	1250	1250
1000	A19	B19	1000	1000	1000	1000	1000	1300	1300	1300	1300	1300
1000	A20	B20	1050	1050	1050	1050	1050	1350	1350	1350	1350	1350
1000	A21	B21	1100	1100	1100	1100	1100	1400	1400	1400	1400	1400

Select an option for TABLEAU #19

**TABLEAU #20**

Option A		Option B										
1000	A1	B1	50	50	50	50	50	50	850	850		
1000	A2	B2	100	100	100	100	100	100	900	900		
1000	A3	B3	150	150	150	150	150	150	950	950		
1000	A4	B4	200	200	200	200	200	200	1000	1000		
1000	A5	B5	250	250	250	250	250	250	1050	1050		
1000	A6	B6	300	300	300	300	300	300	1100	1100		
1000	A7	B7	350	350	350	350	350	350	1150	1150		
1000	A8	B8	400	400	400	400	400	400	1200	1200		
1000	A9	B9	450	450	450	450	450	450	1250	1250		
1000	A10	B10	500	500	500	500	500	500	1300	1300		
1000	A11	B11	550	550	550	550	550	550	1350	1350		
1000	A12	B12	600	600	600	600	600	600	1400	1400		
1000	A13	B13	650	650	650	650	650	650	1450	1450		
1000	A14	B14	700	700	700	700	700	700	1500	1500		
1000	A15	B15	750	750	750	750	750	750	1550	1550		
1000	A16	B16	800	800	800	800	800	800	1600	1600		
1000	A17	B17	850	850	850	850	850	850	1650	1650		
1000	A18	B18	900	900	900	900	900	900	1700	1700		
1000	A19	B19	950	950	950	950	950	950	1750	1750		
1000	A20	B20	1000	1000	1000	1000	1000	1000	1800	1800		
1000	A21	B21	1050	1050	1050	1050	1050	1050	1850	1850		

Select an option for TABLEAU #20

**TABLEAU #21**

Option A		Option B											
1000	A1	B1	0	0	0	0	0	0	0	270	270	270	
1000	A2	B2	50	50	50	50	50	50	50	320	320	320	
1000	A3	B3	100	100	100	100	100	100	100	370	370	370	
1000	A4	B4	150	150	150	150	150	150	150	420	420	420	
1000	A5	B5	200	200	200	200	200	200	200	470	470	470	
1000	A6	B6	250	250	250	250	250	250	250	520	520	520	
1000	A7	B7	300	300	300	300	300	300	300	570	570	570	
1000	A8	B8	350	350	350	350	350	350	350	620	620	620	
1000	A9	B9	400	400	400	400	400	400	400	670	670	670	
1000	A10	B10	450	450	450	450	450	450	450	720	720	720	
1000	A11	B11	500	500	500	500	500	500	500	770	770	770	
1000	A12	B12	550	550	550	550	550	550	550	820	820	820	
1000	A13	B13	600	600	600	600	600	600	600	870	870	870	
1000	A14	B14	650	650	650	650	650	650	650	920	920	920	
1000	A15	B15	700	700	700	700	700	700	700	970	970	970	
1000	A16	B16	750	750	750	750	750	750	750	1020	1020	1020	
1000	A17	B17	800	800	800	800	800	800	800	1070	1070	1070	
1000	A18	B18	850	850	850	850	850	850	850	1120	1120	1120	
1000	A19	B19	900	900	900	900	900	900	900	1170	1170	1170	
1000	A20	B20	950	950	950	950	950	950	950	1220	1220	1220	
1000	A21	B21	1000	1000	1000	1000	1000	1000	1000	1270	1270	1270	

Select an option for TABLEAU #21

**TABLEAU #22**

Option A		Option B											
1000	A1	B1	0	0	0	0	0	0	0	360	360		
1000	A2	B2	50	50	50	50	50	50	50	410	410		
1000	A3	B3	100	100	100	100	100	100	100	460	460		
1000	A4	B4	150	150	150	150	150	150	150	510	510		
1000	A5	B5	200	200	200	200	200	200	200	560	560		
1000	A6	B6	250	250	250	250	250	250	250	610	610		
1000	A7	B7	300	300	300	300	300	300	300	660	660		
1000	A8	B8	350	350	350	350	350	350	350	710	710		
1000	A9	B9	400	400	400	400	400	400	400	760	760		
1000	A10	B10	450	450	450	450	450	450	450	810	810		
1000	A11	B11	500	500	500	500	500	500	500	860	860		
1000	A12	B12	550	550	550	550	550	550	550	910	910		
1000	A13	B13	600	600	600	600	600	600	600	960	960		
1000	A14	B14	650	650	650	650	650	650	650	1010	1010		
1000	A15	B15	700	700	700	700	700	700	700	1060	1060		
1000	A16	B16	750	750	750	750	750	750	750	1110	1110		
1000	A17	B17	800	800	800	800	800	800	800	1160	1160		
1000	A18	B18	850	850	850	850	850	850	850	1210	1210		
1000	A19	B19	900	900	900	900	900	900	900	1260	1260		
1000	A20	B20	950	950	950	950	950	950	950	1310	1310		
1000	A21	B21	1000	1000	1000	1000	1000	1000	1000	1360	1360		

Select an option for TABLEAU #22

**TABLEAU #23**

Option A		Option B										
1000	A1	B1	100	100	300	300	300	300	300	300		
1000	A2	B2	150	150	350	350	350	350	350	350		
1000	A3	B3	200	200	400	400	400	400	400	400		
1000	A4	B4	250	250	450	450	450	450	450	450		
1000	A5	B5	300	300	500	500	500	500	500	500		
1000	A6	B6	350	350	550	550	550	550	550	550		
1000	A7	B7	400	400	600	600	600	600	600	600		
1000	A8	B8	450	450	650	650	650	650	650	650		
1000	A9	B9	500	500	700	700	700	700	700	700		
1000	A10	B10	550	550	750	750	750	750	750	750		
1000	A11	B11	600	600	800	800	800	800	800	800		
1000	A12	B12	650	650	850	850	850	850	850	850		
1000	A13	B13	700	700	900	900	900	900	900	900		
1000	A14	B14	750	750	950	950	950	950	950	950		
1000	A15	B15	800	800	1000	1000	1000	1000	1000	1000		
1000	A16	B16	850	850	1050	1050	1050	1050	1050	1050		
1000	A17	B17	900	900	1100	1100	1100	1100	1100	1100		
1000	A18	B18	950	950	1150	1150	1150	1150	1150	1150		
1000	A19	B19	1000	1000	1200	1200	1200	1200	1200	1200		
1000	A20	B20	1050	1050	1250	1250	1250	1250	1250	1250		
1000	A21	B21	1100	1100	1300	1300	1300	1300	1300	1300		

Select an option for TABLEAU #23

**TABLEAU #24**

Option A		Option B										
1000	A1	B1	0	0	120	120	120	120	120	120		
1000	A2	B2	50	50	170	170	170	170	170	170		
1000	A3	B3	100	100	220	220	220	220	220	220		
1000	A4	B4	150	150	270	270	270	270	270	270		
1000	A5	B5	200	200	320	320	320	320	320	320		
1000	A6	B6	250	250	370	370	370	370	370	370		
1000	A7	B7	300	300	420	420	420	420	420	420		
1000	A8	B8	350	350	470	470	470	470	470	470		
1000	A9	B9	400	400	520	520	520	520	520	520		
1000	A10	B10	450	450	570	570	570	570	570	570		
1000	A11	B11	500	500	620	620	620	620	620	620		
1000	A12	B12	550	550	670	670	670	670	670	670		
1000	A13	B13	600	600	720	720	720	720	720	720		
1000	A14	B14	650	650	770	770	770	770	770	770		
1000	A15	B15	700	700	820	820	820	820	820	820		
1000	A16	B16	750	750	870	870	870	870	870	870		
1000	A17	B17	800	800	920	920	920	920	920	920		
1000	A18	B18	850	850	970	970	970	970	970	970		
1000	A19	B19	900	900	1020	1020	1020	1020	1020	1020		
1000	A20	B20	950	950	1070	1070	1070	1070	1070	1070		
1000	A21	B21	1000	1000	1120	1120	1120	1120	1120	1120		

Select an option for TABLEAU #24

**TABLEAU #25**

Option A		Option B										
1000	A1	B1	-30	-30	-30	-30	-30	210	210	210	210	210
1000	A2	B2	20	20	20	20	20	260	260	260	260	260
1000	A3	B3	70	70	70	70	70	310	310	310	310	310
1000	A4	B4	120	120	120	120	120	360	360	360	360	360
1000	A5	B5	170	170	170	170	170	410	410	410	410	410
1000	A6	B6	220	220	220	220	220	460	460	460	460	460
1000	A7	B7	270	270	270	270	270	510	510	510	510	510
1000	A8	B8	320	320	320	320	320	560	560	560	560	560
1000	A9	B9	370	370	370	370	370	610	610	610	610	610
1000	A10	B10	420	420	420	420	420	660	660	660	660	660
1000	A11	B11	470	470	470	470	470	710	710	710	710	710
1000	A12	B12	520	520	520	520	520	760	760	760	760	760
1000	A13	B13	570	570	570	570	570	810	810	810	810	810
1000	A14	B14	620	620	620	620	620	860	860	860	860	860
1000	A15	B15	670	670	670	670	670	910	910	910	910	910
1000	A16	B16	720	720	720	720	720	960	960	960	960	960
1000	A17	B17	770	770	770	770	770	1010	1010	1010	1010	1010
1000	A18	B18	820	820	820	820	820	1060	1060	1060	1060	1060
1000	A19	B19	870	870	870	870	870	1110	1110	1110	1110	1110
1000	A20	B20	920	920	920	920	920	1160	1160	1160	1160	1160
1000	A21	B21	970	970	970	970	970	1210	1210	1210	1210	1210

Select an option for TABLEAU #25



**TABLEAU #26**

Option A		Option B											
1000	A1	B1	50	50	50	50	50	50	50	650	650	650	
1000	A2	B2	100	100	100	100	100	100	100	700	700	700	
1000	A3	B3	150	150	150	150	150	150	150	750	750	750	
1000	A4	B4	200	200	200	200	200	200	200	800	800	800	
1000	A5	B5	250	250	250	250	250	250	250	850	850	850	
1000	A6	B6	300	300	300	300	300	300	300	900	900	900	
1000	A7	B7	350	350	350	350	350	350	350	950	950	950	
1000	A8	B8	400	400	400	400	400	400	400	1000	1000	1000	
1000	A9	B9	450	450	450	450	450	450	450	1050	1050	1050	
1000	A10	B10	500	500	500	500	500	500	500	1100	1100	1100	
1000	A11	B11	550	550	550	550	550	550	550	1150	1150	1150	
1000	A12	B12	600	600	600	600	600	600	600	1200	1200	1200	
1000	A13	B13	650	650	650	650	650	650	650	1250	1250	1250	
1000	A14	B14	700	700	700	700	700	700	700	1300	1300	1300	
1000	A15	B15	750	750	750	750	750	750	750	1350	1350	1350	
1000	A16	B16	800	800	800	800	800	800	800	1400	1400	1400	
1000	A17	B17	850	850	850	850	850	850	850	1450	1450	1450	
1000	A18	B18	900	900	900	900	900	900	900	1500	1500	1500	
1000	A19	B19	950	950	950	950	950	950	950	1550	1550	1550	
1000	A20	B20	1000	1000	1000	1000	1000	1000	1000	1600	1600	1600	
1000	A21	B21	1050	1050	1050	1050	1050	1050	1050	1650	1650	1650	

Select an option for TABLEAU #26

**TABLEAU #27**

Option A		Option B										
1000	A1	B1	-30	-30	-30	-30	-30	-30	330	330	330	
1000	A2	B2	20	20	20	20	20	20	380	380	380	
1000	A3	B3	70	70	70	70	70	70	430	430	430	
1000	A4	B4	120	120	120	120	120	120	480	480	480	
1000	A5	B5	170	170	170	170	170	170	530	530	530	
1000	A6	B6	220	220	220	220	220	220	580	580	580	
1000	A7	B7	270	270	270	270	270	270	630	630	630	
1000	A8	B8	320	320	320	320	320	320	680	680	680	
1000	A9	B9	370	370	370	370	370	370	730	730	730	
1000	A10	B10	420	420	420	420	420	420	780	780	780	
1000	A11	B11	470	470	470	470	470	470	830	830	830	
1000	A12	B12	520	520	520	520	520	520	880	880	880	
1000	A13	B13	570	570	570	570	570	570	930	930	930	
1000	A14	B14	620	620	620	620	620	620	980	980	980	
1000	A15	B15	670	670	670	670	670	670	1030	1030	1030	
1000	A16	B16	720	720	720	720	720	720	1080	1080	1080	
1000	A17	B17	770	770	770	770	770	770	1130	1130	1130	
1000	A18	B18	820	820	820	820	820	820	1180	1180	1180	
1000	A19	B19	870	870	870	870	870	870	1230	1230	1230	
1000	A20	B20	920	920	920	920	920	920	1280	1280	1280	
1000	A21	B21	970	970	970	970	970	970	1330	1330	1330	

Select an option for TABLEAU #27

**TABLEAU #28**

Option A		Option B										
1000	A1	B1	-30	-30	-30	-30	-30	-30	-30	-30	-30	1170
1000	A2	B2	20	20	20	20	20	20	20	20	20	1220
1000	A3	B3	70	70	70	70	70	70	70	70	70	1270
1000	A4	B4	120	120	120	120	120	120	120	120	120	1320
1000	A5	B5	170	170	170	170	170	170	170	170	170	1370
1000	A6	B6	220	220	220	220	220	220	220	220	220	1420
1000	A7	B7	270	270	270	270	270	270	270	270	270	1470
1000	A8	B8	320	320	320	320	320	320	320	320	320	1520
1000	A9	B9	370	370	370	370	370	370	370	370	370	1570
1000	A10	B10	420	420	420	420	420	420	420	420	420	1620
1000	A11	B11	470	470	470	470	470	470	470	470	470	1670
1000	A12	B12	520	520	520	520	520	520	520	520	520	1720
1000	A13	B13	570	570	570	570	570	570	570	570	570	1770
1000	A14	B14	620	620	620	620	620	620	620	620	620	1820
1000	A15	B15	670	670	670	670	670	670	670	670	670	1870
1000	A16	B16	720	720	720	720	720	720	720	720	720	1920
1000	A17	B17	770	770	770	770	770	770	770	770	770	1970
1000	A18	B18	820	820	820	820	820	820	820	820	820	2020
1000	A19	B19	870	870	870	870	870	870	870	870	870	2070
1000	A20	B20	920	920	920	920	920	920	920	920	920	2120
1000	A21	B21	970	970	970	970	970	970	970	970	970	2170

Select an option for TABLEAU #28

**TABLEAU #29**

Option A		Option B										
1000	A1	B1	210	210	210	210	210	770	770	770	770	770
1000	A2	B2	260	260	260	260	260	820	820	820	820	820
1000	A3	B3	310	310	310	310	310	870	870	870	870	870
1000	A4	B4	360	360	360	360	360	920	920	920	920	920
1000	A5	B5	410	410	410	410	410	970	970	970	970	970
1000	A6	B6	460	460	460	460	460	1020	1020	1020	1020	1020
1000	A7	B7	510	510	510	510	510	1070	1070	1070	1070	1070
1000	A8	B8	560	560	560	560	560	1120	1120	1120	1120	1120
1000	A9	B9	610	610	610	610	610	1170	1170	1170	1170	1170
1000	A10	B10	660	660	660	660	660	1220	1220	1220	1220	1220
1000	A11	B11	710	710	710	710	710	1270	1270	1270	1270	1270
1000	A12	B12	760	760	760	760	760	1320	1320	1320	1320	1320
1000	A13	B13	810	810	810	810	810	1370	1370	1370	1370	1370
1000	A14	B14	860	860	860	860	860	1420	1420	1420	1420	1420
1000	A15	B15	910	910	910	910	910	1470	1470	1470	1470	1470
1000	A16	B16	960	960	960	960	960	1520	1520	1520	1520	1520
1000	A17	B17	1010	1010	1010	1010	1010	1570	1570	1570	1570	1570
1000	A18	B18	1060	1060	1060	1060	1060	1620	1620	1620	1620	1620
1000	A19	B19	1110	1110	1110	1110	1110	1670	1670	1670	1670	1670
1000	A20	B20	1160	1160	1160	1160	1160	1720	1720	1720	1720	1720
1000	A21	B21	1210	1210	1210	1210	1210	1770	1770	1770	1770	1770

Select an option for TABLEAU #29

**TABLEAU #30**

Option A		Option B										
1000	A1	B1	50	50	317	317	317	317	317	317		
1000	A2	B2	100	100	367	367	367	367	367	367		
1000	A3	B3	150	150	417	417	417	417	417	417		
1000	A4	B4	200	200	467	467	467	467	467	467		
1000	A5	B5	250	250	517	517	517	517	517	517		
1000	A6	B6	300	300	567	567	567	567	567	567		
1000	A7	B7	350	350	617	617	617	617	617	617		
1000	A8	B8	400	400	667	667	667	667	667	667		
1000	A9	B9	450	450	717	717	717	717	717	717		
1000	A10	B10	500	500	767	767	767	767	767	767		
1000	A11	B11	550	550	817	817	817	817	817	817		
1000	A12	B12	600	600	867	867	867	867	867	867		
1000	A13	B13	650	650	917	917	917	917	917	917		
1000	A14	B14	700	700	967	967	967	967	967	967		
1000	A15	B15	750	750	1017	1017	1017	1017	1017	1017		
1000	A16	B16	800	800	1067	1067	1067	1067	1067	1067		
1000	A17	B17	850	850	1117	1117	1117	1117	1117	1117		
1000	A18	B18	900	900	1167	1167	1167	1167	1167	1167		
1000	A19	B19	950	950	1217	1217	1217	1217	1217	1217		
1000	A20	B20	1000	1000	1267	1267	1267	1267	1267	1267		
1000	A21	B21	1050	1050	1317	1317	1317	1317	1317	1317		

Select an option for TABLEAU #30

Thank you for your participation. Your response has been recorded.

Payments will be made early next week to allow all participants to complete the session and calculate your winnings.



# General conclusion

This thesis contributes to the behavioral and experimental economics literature on risk, beliefs, ambiguity, and incentives. In particular, this thesis (*i*) proposes new methods to measure utility function, weighting function, loss aversion, and beliefs and (*ii*) derives new theoretical insights in the realm of incentive setting along with the development of a new experimental paradigm.

Chapter 1 establishes a comprehensive semi-parametric method that satisfies the four desirable properties of parametric methods: tractable, data-efficient, error-robust, and easy. Chapter 2 provides a nonparametric version of the semi-parametric method in Chapter 1 with a smoothing spline approximation of the utility function. Applications of both chapters 1 and 2 on existing data involving risk confirm deviations from expected utility theory through evidence of probability weighting function and loss aversion.

Chapter 3 extends the semi-parametric method in Chapter 1 to measure beliefs and ambiguity attitudes towards discrete sources of uncertainty. Subjects make decisions under these types of uncertain situations in a daily life basis. In various applications, the method successfully passes validity tests and provides insightful results in the case of trust and coordination games. This chapter finds deviations from subjective expected utility theory through evidence of ambiguity attitudes. The chapter highlights that people are more insensitive to likelihood in the presence of asymmetric events than symmetric events, suggesting that

belief formation is cognitively demanding. For equal sources of uncertainty, people exhibit *payoff dependence aversion* and *variety of payoffs seeking*. *Payoff dependence aversion* means that people dislike that their own payoffs depend on the preferences of others. This behavior is captured by a more concave utility function. *Variety of payoffs seeking* means that subjects prefer a greater number of possible payoffs when such possible payoffs depend on the preferences of others. This behavior is captured by more optimism.

Chapter 4 studies the existence of the Risk-incentives tradeoff (RIT) under Rank Dependent Utility (RDU) and Mean-Variance-Skewness (MVS). Theoretical analyses show that RIT is remarkably robust under RDU but not under MVS. With data based on a novel experimental design that eliminates confounding factors, Chapter 4 provides evidence for RIT even in the case of risk-seeking agents, which is a distinct prediction of RDU. The results provide support for the RIT and suggest that it applies to a broad range of situations, including cases in which agents are risk-seeking (e.g., executive compensation).

Naturally, the thesis has both limitations and potential extensions for future research. The following are some of the limitations and possible extensions.

The methods in Chapters 1 and 2 can be extended in several directions. Even though these methods do not readily apply to the context envisioned by [Kőszegi and Rabin \(2007\)](#), one can speculate on a possible procedure combining Kőszegi and Rabin's approach and these methods. This procedure could start by introducing probability weighting functions in [Kőszegi and Rabin \(2007\)](#) following the work of [Baillon et al. \(2020\)](#). Also, these methods can be used to extend the popular elicitation technique of [Holt and Laury \(2002\)](#) to the case in which probabilities are distorted, following the approach of [Abdellaoui et al. \(2011\)](#).



Following [Li et al. \(2020\)](#), Chapter 3 conducted two-stage experiments. In the first stage, people played trust games. In the second stage, the first movers in the first stage made decisions in which the sources of uncertainty were the unknown decisions of the second movers in the first stage. Two important identification assumptions are behind the experimental results of [Li et al. \(2020\)](#) as well as the ones in Chapter 3. The first is that social preferences collapse in the second stage. This is quite reasonable because in the second stage, the decisions of the first movers will have no impact on the first-stage payoffs of the first movers. The second assumption is that betrayal attitudes continue to play a role in the second stage. But, this second assumption is less trivial. Indeed, it is possible that betrayal attitudes collapse in the second stage as it is the case of social preferences. This could explain why these two papers do not find evidence in favor of betrayal aversion. A future avenue of research is to quantify the role of betrayal aversion in trust decisions under the more reasonable assumption that betrayal aversion collapses in the second stage of the experimental design.

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# CUMULATIVE PROSPECT THEORY FOR RISK AND UNCERTAINTY: NEW MEASUREMENT METHODS AND APPLICATIONS

Yao Thibaut Kpegli

## Abstract

The thesis is at the intersection of behavioral economics, experimental economics, and decision theory. Chapters 1, 2, and 3 develop methods to estimate different components of decision models under risk and uncertainty: utility function, weighting function, loss aversion, and beliefs. Applications confirm deviations from standard theories (Expected Utility and Subjective Expected Utility) through evidence of weighting function, loss aversion, and ambiguity attitudes. People are more insensitive to likelihood in the presence of asymmetric events than symmetric events, suggesting that belief formation is cognitively demanding. For equal sources of uncertainty, people exhibit *payoff dependence aversion* and *variety of payoffs seeking*. *Payoff dependence aversion* means that people dislike that their own payoffs depend on the preferences of others. This behavior is captured by a more concave utility function. *Variety of payoffs seeking* means that subjects prefer a greater number of possible payoffs when such possible payoffs depend on the preferences of others. This behavior is captured by more optimism. Chapter 4 studies the existence of the Risk-incentives tradeoff (RIT) under Rank Dependent Utility (RDU) and Mean-Variance-Skewness (MVS). Theoretical analyses show that RIT is remarkably robust under RDU but not under MVS. With data based on a novel experimental design that eliminates confounding factors, chapter 4 provides evidence for RIT even in the case of risk-seeking agents, which is a distinct prediction of RDU. The results provide support for the RIT and suggest that it applies to a broad range of situations, including cases in which agents are risk-seeking (e.g., executive compensation).

**Keywords:** Risk, uncertainty, beliefs, ambiguity attitudes, experiment.

## Résumé

La thèse se situe à l'intersection de l'économie comportementale, de l'économie expérimentale et de la théorie de la décision. Les chapitres 1, 2 et 3 développent des méthodes pour estimer les différentes composantes des modèles de décision en situation de risque et d'incertitude : fonction d'utilité, fonction de pondération, aversion aux pertes et croyances. Les applications confirment des déviations par rapport aux théories standard (utilité espérée et utilité espérée subjective) à travers la fonction de pondération, l'aversion aux pertes et les attitudes d'ambiguïté. Les gens sont plus insensibles à la probabilité en présence d'événements asymétriques qu'en présence d'événements symétriques, ce qui suggère que la formation des croyances demande des efforts cognitifs. Pour une même source d'incertitude, les individus font preuve d'*aversion à la dépendance des gains* et de *préférence pour la variété des gains*. L'*aversion à la dépendance des gains* signifie que les individus n'aiment pas que leurs gains dépendent des préférences des autres. Ce comportement se traduit par une fonction d'utilité concave. La *préférence pour la variété des gains* signifie que les individus préfèrent un plus grand nombre de possibilité de gains lorsque les gains dépendent des préférences des autres. Ce comportement se traduit par l'optimisme. Le chapitre 4 étudie l'existence de l'arbitrage entre risque et incitations (RIT) dans le cadre de l'utilité dépendante du rang (RDU) et de la moyenne-variance-skewness (MVS). Les analyses théoriques montrent que le RIT est remarquablement robuste sous RDU mais pas sous MVS. Avec des données basées sur un nouveau modèle expérimental qui élimine les facteurs de confusion, le chapitre 4 fournit des preuves de l'existence du RIT même dans le cas où les individus ont des préférences pour le risque, ce qui est une prédiction distincte du RDU. Les résultats confirment l'existence du RIT et suggèrent qu'il s'applique à un large éventail de situations, y compris les cas où les individus ont des préférences pour le risque (par exemple, la rémunération des dirigeants).

**Mots Clés :** Risque, incertitude, croyances, attitudes face à l'ambiguïté, expérience.