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Prospect theory in experiments: behaviour in loss domain and framing effects. *

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Abstract

In the original specification of cumulative prospect theory, distinct sets of parameters control for the curvature of the value function and the shape of the probability weighting function. There is one for the gain domain and one for the loss domain. However, in most estimations, behaviour over losses is assumed to perfectly reflect behaviour over gains, through a unique set of parameters. We examine the consequences of relaxing this simplifying assumption in the context of Tanaka et al.'s (2010) risk-experiment procedure. On the one hand, we show that subjects' behaviour for gains is mostly reflected for losses at the aggregate and individual levels, and is consistent with the cumulative prospect theory fourfold pattern. However reflection is partial as the mean curvature of the value function is slightly less convex for losses than it is concave for gains. These results are robust to a high-stake context. Then, we demonstrate that assuming reflection when measuring loss aversion is innocuous neither at the aggregate nor at the individual level. On the other hand, we highlight the existence of a strong, negative and persistent framing effect on values elicited for loss aversion.

Keywords: risk preferences, Tanaka-Camerer-Nguyen method, probability weighting, loss aversion, reflected behaviour

JEL Codes: C91; D81

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1 Introduction

Kahneman and Tversky (1979) started developing Prospect Theory (PT) as an alternative to standard Expected Utility (EU) to describe individual choices in a stochastic environment, while taking into account important cognitive biases. Since then, the cumulative version of PT (CPT, Tversky and Kahneman (1992)) proved to be one of the most promising decision theories (Harrison and Rutström, 2009; Barberis, 2013) and has progressively disseminated into empirical applications, leading the way to a positive approach of behaviour under risk. Examples include for instance Babcock (2015) in the field of agricultural economics, Barberis et al. (2001) and Grinblatt and Han (2005) in finance, and Mercer (2005) in political science. Applying PT requires manipulating several parameters that code for several aspects of individual risk preferences. Some parameters control the curvature of the value function, others control the shape of the probability weighting function, and a last one captures loss aversion. Measuring these parameters in different contexts has been a major preoccupation, both to validate the relevancy of the theoretical model in describing real behaviour and to provide values for empirical applications. Due to the multidimensional nature of PT, experiments are the preferred approach, and values are now available for a variety of populations (see, e.g., Nguyen and Leung (2009) for Vietnamese fishermen, Booij et al. (2010) for Dutch households, Bocquého et al. (2014) for French farmers, Bocquého et al. (2018) for Middle East refugees, L'Haridon and Vieider (2019) for students from 30 countries, Zhao and Yue (2020) for U.S. farmers). Most of these studies rely on lottery choices organized in multiple price lists, using Tanaka et al.'s (2010) design (henceforth TCN), on choices between a lottery and a sure amount, using certainty equivalents (Tversky and Kahneman, 1992; Abdellaoui et al., 2008; L'Haridon and Vieider, 2019), or on choices made on lottery pairs (Harrison and Rutström, 2009).

Parametric methods for preference estimation are the most common approaches because they are easy to estimate and interpret, but are susceptible to a contamination effect. A misspecification of one of the value function or probability weighting function will bias the other one (Booij et al., 2010). [1] In Tversky and Kahneman's (1992) description of CPT, two different parameters control the curvature of the value function, one for the gain domain and one for the loss domain. However, in many

[1] Non-parametric methods include Wakker and Deneffe (1996), extended by Abdellaoui (2000) and Abdellaoui et al. (2007), but they are typically more difficult to administer and may suffer from error propagation because of their chained nature (L'Haridon and Vieider, 2019). They are also generally less efficient due to more questions needed (Abdellaoui et al., 2008). Last, they are not incentive compatible (Booij et al., 2010). See Bauermeister et al. (2018) for a comparison of TCN and Wakker and Deneffe's (1996) methods.

empirical applications they are merged. A similar simplifying assumption is often made about the CPT parameters controlling the shape of the probability weighting function, in line with Kahneman and Tversky's (1979) original PT. These two assumptions apply in particular to studies based on TCN risk-experiment design (e.g., Nguyen and Leung, 2009; Liu, 2013; Bocquého et al., 2014; Bauermeister et al., 2018; Bocquého et al., 2018; Zhao and Yue, 2020) [2], but not only. Nonetheless, the authors who rather account for distinct CPT parameters in the gain and loss domains find close values in most cases, whatever the estimation method (e.g., Tversky and Kahneman, 1992; Harrison and Rutström, 2009; Booij et al., 2010; L'Haridon and Vieider, 2019).

In this context, the main objective of this study is methodological. We investigate the impact of relaxing such simplifying assumptions in the context of the TCN experimental design. We test the robustness of our findings to the size of the lottery stakes. A secondary objective is to provide new insights on individual behaviour when subjects are faced with losses, at the aggregate and individual levels.

We carry out a series of risk experiments in the lab on a sample of students. We test the original TCN design, and two alternative frames, a reflected *loss* frame and a *high-stake* frame, using monetary incentives. The reflected frame allows us to elicit individual values for the curvature of the value function and the probability weighting function specifically on loss outcomes. In a second step, we assess the consequences for the loss aversion estimates, in particular whether loss aversion is consistent between the gain and the loss frames. We use the *high-stake* frame as a robustness check. We are not aware of any other attempt to formally test extensions or alternative framings of TCN risk experiment.

This paper proceeds as follow. In Section 2 we outline the relevant literature. In Section 3 we describe the sample and experimental protocol, and in Section 4 we present the estimation methods. In Section 5 we report non-parametric results on behaviour under the baseline treatment, *loss* frame and *high-stake* frame, as well as estimates of CPT parameters. We develop our analysis at the aggregate and individual levels. In Section 6 we fine-tune the estimates of elicited loss aversion, by isolating a pure framing effect and by allowing the curvature of the value function to differ between the gain and loss domains. Section 7 concludes.

[2]Bougherara et al. (2017) is an exception in this respect.

2 Literature review

2.1 Experiments in the loss domain

The idea that individuals behave differently towards gambles expressed as losses or gains is not new. It appears with Slovic and Lichtenstein (1968) who find that individuals give much less importance to probabilities of losses than to probabilities of gains. This idea is at the basis of the PT Kahneman and Tversky (1979) propose as an alternative to EU. Indeed, in EU, value is assigned to final assets, which integrate gains and losses in the same way. On the contrary, in PT, value is assigned to gains or losses which are defined with respect to a reference point, and probabilities are replaced by decision weights. Consequently, PT is able to account for the *reflection effect*: subjects who are risk averse in the domain of gains become risk seeking in the domain of losses, and *vice versa*. The reflection effect is a well-known empirical finding backed by numerous experimental studies (e.g., Kühberger et al., 1999; Laury and Holt, 2008; Bosch-Domènech and Silvestre, 2006), even if a few ones do not corroborate such a result (Hershey et al., 1982). The later CPT version reflects a more general *fourfold pattern* of risk attitudes: risk aversion (risk seeking) over gains (losses) occurring with large probabilities, and risk seeking (risk aversion) over gains (losses) occurring with small probabilities. This pattern has been largely investigated in experimental economics (Cohen et al., 1987; Wehrung, 1989; Harbaugh et al., 2010).

In terms of structural parameters, one may associate the reflection effect with the shape of the value function, and the fourfold pattern with the shape of the probability weighting function (Lau et al., 2019). Although in CPT distinct parameters control the shape of these two functions in gains and losses, many experimental studies *a priori* assume that unique parameters operate in both domains. This is largely the case for those based on TCN risk experiment (Nguyen and Leung, 2009; Tanaka et al., 2010; Liu, 2013; Bocquého et al., 2014, 2018; Zhao and Yue, 2020), but also for some of those using other experimental designs, like Harrison and Rutström (2008, pp.92-95), and Harrison and Rutström (2009) as far as the weighting parameters are concerned. These constraints on parameter values take for granted the reflected behavioural patterns described above, while there is little evidence on whether such constraints are innocuous (Lau et al., 2019). In particular, it may directly affect the loss aversion measure(Booij et al., 2010).

Reasons for such assumptions beyond mere simplicity hardly appear. In the case of the value function, Wakker (2010, pp. 267–271) suggests it avoids the analytical problems that a power value function brings for analyzing loss aversion. First, he demonstrates that, unless the powers for gains and losses agree, loss aversion cannot be defined clearly because it depends on the unit of money. Second, he explains that a power value function cannot accommodate all plausible empirical observations whenever the powers for gains and for losses differ.[3] In the case of the probability weighting function, it is noteworthy that Kahneman and Tversky's (1979) original description of PT does assume identical parameters for the gain and the loss domains.

2.2 Experiments assuming distinct functions for the gain and loss domains

The authors who assume distinct parameters in the gain and loss domains when eliciting PT parameters often report close values, whatever the estimation method. It means that phenomena for gains are in general reflected for losses, even if behaviour for losses deviates less from linearity, and thus from expected value maximization (Wakker, 2010). This is what Booij et al.'s (2010) summary table of PT empirical estimates illustrates. In the studies under review, losses are always evaluated equally or more linearly than gains through the power value function. In this last case, the function for losses is generally still convex (except in Fehr-Duda et al. (2006) and Abdellaoui et al. (2008)). In addition, the power parameters for both domains are always close (except in Fennema and van Assen (1998) and Abdellaoui et al. (2008)). This last observation also applies to the weighting function, even though, in the 2-parameter forms, elevation is often higher in the loss domain. The predominant shape for the weighting function is 'inverse S'.

In more detail, Tversky and Kahneman (1992) find that the median exponent of the value function is exactly the same for gains and losses, while the median values of the weighting function parameters in the gain and loss domains are very close, and imply a slightly more pronounced curvature for gains.

If Abdellaoui et al.'s (2007) aggregate findings also suggest that the curvature of the value function on the gain and loss domains are very close, at the individual level there is less support for reflection according to various correlation coefficients.

Using a structural PT model, Harrison and Rutström (2009) report similar power value functions for gains and losses as well. However, they are different from each other under a mixture model that

[3]Let assume the following value functions defined separately over the gain and loss domains: for $y > 0$, $v(y) = y^a$ and, for $y < 0$, $v(y) = -\lambda(-y)^b$, where $\lambda > 0$ is the coefficient of loss aversion. Wakker (2010) recalls that there is always a part of the domain where $v(y) > -v(-y)$ for some outcome $y > 0$, whereas it is empirically plausible that $v(y) \leq -v(-y)$ for all $y > 0$.

simultaneously estimates parameters for EU and PT, and indicate a much more pronounced curvature for losses this time. Note that Booij and van de Kuilen (2009) obtain analogous evidence that the value function is concave for gains but is even more convex for losses. They use a rank-sum test on raw sample data. For the population, though, they are not able to conclude about such a difference.

Booij et al. (2010) themselves collect data from a large representative panel of Dutch households. They report power parameters for gains and for losses that are not significantly different from one another. Using a two-parameter specification for the weighting function, they find that the elevation parameter for losses is significantly higher than that of gains, while, on the contrary, the point estimates for the degree of curvature in both domains are very similar. It advocates for the standard inverse-S shape in both the gain and the loss domains.

More recently, L'Haridon and Vieider (2019) find that the two parameters they use to describe the probability weighting function are significantly different between gains and losses, but reaffirm that the two functions can be seen as economically very similar.

Nevertheless, a number of studies highlight mixed evidence as to these mirror effects about the reference point. Wakker et al. (2007, pp. 224) build three lists of authors whose research supports a partial reflection of the value function. Most found a more concave value function for gains than convex value function for losses, like in many studies of Booij et al.'s (2010) review. In this category, we add Bougherara et al. (2017) who apply precisely the TCN design to a sample of French farmers. They find significantly more curvature of the value function for gains than for losses when they ignore loss aversion, and less probability distortion for losses than for gains. Some others find the opposite finding, with more convexity for losses than concavity for gains. We already cited Fehr-Duda et al. (2006) and Abdellaoui et al. (2008) in this respect, as well as Harrison and Rutström (2009, mixture model) and Booij and van de Kuilen (2009). A few last ones find unclear or balanced findings, like the above cited Abdellaoui et al. (2007).

Very uncommon combinations for power coefficients include concavity for gains and slight concavity for losses (Abdellaoui et al., 2008) and even slight concavity in both domains (Fehr-Duda et al., 2006). These results apply to both individual and pooled data in the case of Abdellaoui et al. (2008).

Last, Lau et al. (2019) revisit data from five experimental studies in order to examine specifically the reflection effect and the fourfold pattern of risk attitudes. They account for three different criteria at the aggregate (population means of relevant parameters) and individual levels (within-individual correlation in parameters between gain and loss domains, and population share of individuals who display the reflection effect or fourfold pattern). They find conclusive evidence of the reflection effect and the fourfold pattern for only two of the five datasets under scrutiny, i.e., the datasets for which at least two of the three properties hold.

3 Experimental design

3.1 Participants and incentives

The experiment was conducted at the Laboratory of Experimental Economics of Strasbourg (LEES) in October 2017 using computers (EconPlay platform). We recruited 191 students from different study programs of the University of Strasbourg (France). Each subject participated in one session only. Before running the experiment, we collected a few socio-demographic characteristics. Descriptive statistics for the corresponding variables are given in Table 1. Students are on average 22 years old, of whom half are female. About 25% are engaged in master studies and half study economics, management, mathematics, or political sciences.

We ran 8 sessions (with 21 to 27 subjects each) of a lottery choice experiment based on TCN, with lottery payoffs in a virtual currency called ECU (Experimental Currency Unit). Each session lasted approximately 1 hour. Before starting, we informed subjects that two lottery choices would be randomly selected for payment at the end of the experiment. We also informed subjects that the currency exchange rate was ECU 200 for € 1. Subjects received € 17 as an initial endowment and € 5 as a show-up fee to compensate for travel expenses. These amounts ensured final earnings would always be positive. Final payment ranged from ECU -190 + ECU 3400 (€ -0.95 + € 22.00)

Table 1: Descriptive statistics of socio-demographics

	Mean	Std. Dev.
age (in years)	21.77	3.44
dummy if female	0.50	0.50
dummy if education level is at least master	0.25	0.43
dummy if education background is Econ., Mgmt, Maths or Pol. Sc.	0.50	0.50
Nb. of obs.	191	

Econ: Economics, Mgmt: Management, Pol. Sc.: Political Sciences to ECU 595 + ECU 3400 (€ 2.98 + € 22.00), with an average of ECU 18 + ECU 3400 (€ 0.09 + € 22.00).

3.2 Treatments

We defined and used four treatments by manipulating two factors of two levels each, in a full factorial design: the main stake domain (G = *gain* and L = *loss*) and the stake level (Lo = *low* and Hi = *high*). Our baseline treatment, called GLo, is a replication of TCN experiment in which we substituted ECUs for thousands of Vietnamese dongs. In this treatment, subjects are confronted successively with three series of choices between two lotteries, as displayed in Table 2. The first series consists of fourteen choices, where lottery A gives a 30% chance of winning ECU 40 (other payoff is ECU 10), while lottery B gives a 10% chance of winning ECU 68 to ECU 1,700 (other payoff is ECU 5). In the fourteen choices of the second series, lottery A gives a 90% chance of winning ECU 40 (other payoff is ECU 30), while lottery B gives a 70% chance of winning ECU 54 to ECU 130 (other payoff is ECU 5). The third series exhibits only seven rows and mixes positive with negative payoffs: payoffs of lottery A range from ECU 25 to 1 in the winning case or from ECU -4 to ECU -8 in the opposite case. Payoffs of lottery B equal ECU 30 in the winning case or range from ECU -21 to ECU -11 in the opposite case. Probabilities of winning are always 50% in this series. An important distinction with usual multiple price lists like Holt and Laury's (2002) is the enforcement of monotonic switching by asking subjects about their switching point in each series, i.e., the row at which they start to prefer lottery B rather than lottery A. [4]

The GHi treatment is identical to the GLo treatment except that all stakes are multiplied by 2 in all three series. In the LLo treatment, all payoffs from the baseline are multiplied by -1 and the two columns in which lotteries are displayed for subjects to choose one are reversed (see Appendix A). The LHi treatment combines the *loss* frame with the *high-stake* frame.

In each session, subjects are confronted successively with all treatments (within-subject design). To counterbalance potential order effects, we vary the order of treatments across sessions using a balanced Latin square design. Participants are then randomly assigned to sessions. Table 3 provides details about the order of treatments and number of subjects in each session (from 23 to 27).

The two lottery choices used for the final payment are selected such as, in a first step, the *high* or

[4] In usual multiple price list procedures, subjects are allowed to switch back and forth and inconsistent subjects are often excluded from the analysis, which is not the case in the TCN experiment.

Table 2: Lottery options corresponding to the baseline GLo treatment

	Payoffs				(Expected value A-B)
	Option A		Option B		
Series 1					
Probabilities	0.30	0.70	0.10	0.90	
row 1	40	10	68	5	(7.7)
row 2	40	10	75	5	(7.0)
row 3	40	10	83	5	(6.2)
row 4	40	10	93	5	(5.2)
row 5	40	10	106	5	(3.9)
row 6	40	10	125	5	(2.0)
row 7	40	10	150	5	(-0.5)
row 8	40	10	185	5	(-4.0)
row 9	40	10	220	5	(-7.5)
row 10	40	10	300	5	(-15.5)
row 11	40	10	400	5	(-25.5)
row 12	40	10	600	5	(-45.5)
row 13	40	10	1,000	5	(-85.5)
row 14	40	10	1,700	5	(-155.5)
Series 2					
Probabilities	0.90	0.10	0.70	0.30	
row 1	40	30	54	5	(-0.3)
row 2	40	30	56	5	(-1.7)
row 3	40	30	58	5	(-3.1)
row 4	40	30	60	5	(-4.5)
row 5	40	30	62	5	(-5.9)
row 6	40	30	65	5	(-8.0)
row 7	40	30	68	5	(-10.1)
row 8	40	30	72	5	(-12.9)
row 9	40	30	77	5	(-16.4)
row 10	40	30	83	5	(-20.6)
row 11	40	30	90	5	(-25.5)
row 12	40	30	100	5	(-32.5)
row 13	40	30	110	5	(-39.5)
row 14	40	30	130	5	(-53.5)
Series 3					
Probabilities	0.50	0.50	0.50	0.50	
row 1	25	-4	30	-21	(6.0)
row 2	4	-4	30	-21	(-4.5)
row 3	1	-4	30	-21	(-6.0)
row 4	1	-4	30	-16	(-8.5)
row 5	1	-8	30	-16	(-10.5)
row 6	1	-8	30	-14	(-11.5)
row 7	1	-8	30	-11	(-13.0)

Design adapted from Tanaka et al. (2010). Lottery payoffs are in ECUs. Information on expected value is not displayed to respondents.

Table 3: Characteristics of the experimental sessions

Order of treatments in each session	Number of subjects
1:GLo-GHi-LHi-LLo	25
2:GHi-LLo-GLo-GHi	25
3:LLo-LHi-GHi-GLo	22
4:LHi-GLo-LLo-GHi	27
5:GLo-GHi-LHi-LLo	21
6:GHi-LLo-GLo-LHi	22
7:LLo-LHi-GHi-GLo	24
8:LHi-GLo-LLo-GHi	25
Total:	191

low frame is randomly selected. In a second step, one choice from the corresponding *gain* treatment and one from the corresponding *loss* treatment is randomly drawn and played for real. Instructions provided to subjects are translated into English in Appendix B.

4 Estimation methods

4.1 Specification of choice model

We estimate individual risk preference parameters using the CPT framework. It exhibits two key features that can explain EU anomalies, namely reference dependence and probability weighting. Whereas EU theory does not distinguish between gains and losses, in CPT outcomes are classified with respect to a reference point, and people are allowed to behave differently in each of the two gain and loss domains. Probability weighting refers to people's tendency to distort objective probabilities into decision weights. Following Tversky and Kahneman (1992) and most experimental studies, we assume that subjects' reference point corresponds to the *status quo*, or, equivalently, their asset position before making the choices of interest. In the context of our experiment, subjects' assets include their personal assets, the initial endowment and the show-up fee. It means the reference point which distinguishes gains from losses is zero, and subjects perceive positive lottery payoffs as gains and negative ones as losses.

Let first assume that subjects value lottery payoffs y through a two-part power value function of the form (Tversky and Kahneman, 1992):

$$v(y) = \begin{cases} y^{\sigma^+} & \text{if } y > 0 \\ 0 & \text{if } y = 0 \cdot \\ -\lambda(-y)^{\sigma^-} & \text{if } y < 0 \end{cases} \tag{1}$$

In this specification, parameter σ^+ ($\sigma^+ > 0$) determines the shape of the value function in the gain domain and acts as an *anti*-index of concavity. In the loss domain, parameter σ^- ($\sigma^- > 0$) controls curvature (as an index of concavity) while parameter λ ($\lambda > 0$) modifies the slope. Parameter λ is the decision maker's coefficient of loss aversion. The value function is convex (resp. concave) in the gain domain when $\sigma^+ > 1$ (resp. $\sigma^+ < 1$). In the loss domain, $\sigma^- > 1$ means that the value function is concave. The decision maker is more (resp. less) sensitive to losses than to gains when $\lambda > 1$ (resp. $\lambda < 1$). The usual empirical finding is $\lambda > 1$ (loss aversion), along with $\sigma^+ < 1$ and $\sigma^- < 1$ (concave value function for gains, but convex for losses).

We now define decision weights over cumulative probabilities. The value of any binary lottery $(y_1, p; y_2)$ is the following prospect value:

$$PV(y_1, p; y_2) = \begin{cases} \omega^d(p).v^d(y_1) + [1 - \omega^d(p)].v^d(y_2) & \text{if } y_1 \geq y_2 \geq 0 \text{ or } y_1 \leq y_2 \leq 0 \\ \omega^d(p).v^d(y_1) + \omega^d(1-p).v^d(y_2) & \text{if } y_1 < 0 < y_2 \end{cases} \tag{2}$$

where the probability weighting function $\omega^d(.)$ is continuous, strictly increasing from the unit interval into itself, and satisfies $\omega^d(0) = 0$ and $\omega^d(1) = 1$; and the superscript d indicates the payoff domain and can take the values $+$ for gains and $-$ for losses. In PT, risk behaviour results from the interplay of the curvature of the value function, loss aversion and probability weighting. The form of the weighting function has been widely discussed. In line with TCN, we adopt the one-parameter form of Prelec's (1998) specification:

$$\omega^d(p) = \exp\left[-(-\ln p)^{\gamma^d}\right] \tag{3}$$

where d again indicates gains and losses; and γ^d is the parameter controlling the curvature of the probability weighting function ($\gamma^d > 0$). This parameter can be interpreted as an index of likelihood sensitivity, with $\gamma^d = 1$ reflecting the absence of probability distortion ($\omega^d(p) = p$). In other words, as γ^d decreases, the distinction between different levels of probability gets more and more blurred.

Extreme behaviours are described by very high γ^d values where subjects perceive probabilities as either 0 or 1 (extreme likelihood sensitivity), or by values close to nullity where subjects tend to perceive probabilities as all being equal (extreme likelihood insensitivity). The typical case, backed by a substantial amount of empirical evidence is $\gamma^d < 1$, and gives to the weighting function an inverse S-shape. In the case of a binary prospect such as a lottery, it characterises an overweighting of the low-probability outcome and an underweighting of the high-probability outcome. If $\gamma^d > 1$, the function takes the less conventional 'S-shape'.

4.2 Parameter elicitation

For each subject and each treatment, we calculate the three individual CPT parameters using the TCN analytical interval approach. In their experiment, the choices are carefully designed so bounds for σ^+ and γ^+ can be jointly inferred by crossing responses to Series 1 and Series 2. In a second step, conditionally to the σ^+ value previously elicited, bounds for λ are inferred from the switching point in Series 3. Parameter values are approximated by taking the midpoint of intervals. When there is no switch, the value at the boundary is used.

For the choices expressed in the *gain* frame (GLo and GHi treatments), we use the correspondence TCN give between the combination of switching points in the three series and the parameter values. In the *loss* frame (reflected treatments LLo and LHi), the correspondence between the couple of switching points in Series 1 and Series 2 and the couple of (σ^d, γ^d) values is the same. However, we need to recalculate λ values from Series 3 choices. [5]

We define the λ value for each treatment (conditional to σ^+ or σ^-) as depending on the choices subjects make for the three series of the same treatment. We also define two alternative values for loss aversion. We calculate a λ_{oppos} for each treatment from the choices in Series 3 of the same treatment, but conditional to the value function parameter from the corresponding opposite *gain* or *loss* treatment (respectively σ^+ and σ^-). The opposite couples are treatments GLo and LLo on the one hand, and GHi and LHi on the other hand. We also calculate a λ_{gen} for each treatment from the choices in Series 3 of the same treatment, but conditional to both σ^+ and σ^- from respectively the corresponding *gain* and *loss* treatments. In other words, the two value function parameters are applied to Series 3 payoffs depending whether they are a gain or a loss. More precisely, we calculate λ_{gen} in

[5] We provide the calculation details in Appendix C.

treatments GLo and LLo using the individual σ^+ from GLo and σ^- from LLo, and λ_{gen} in treatments GHi and LHi using the σ^+ from GHi and σ^- from LHi. It means, for λ_{gen}, we implicitly relax the initial assumption that a single parameter controls the curvature of the value function in the gain and loss domains.

5 Results about frame effects

We start by presenting the general pattern of behaviour each treatment reveals using the total number of risky or safe choices and estimates of parameter values. We also look at the shape of the value function at the individual level. We investigate the effect of the *loss* and *high-stake* frames on the number of risky or safe choices in a second stage, and on parameter values in a last stage.

5.1 Pattern of behaviour

Table 4 collates the number of left-hand side (LHS) choices by series in the four treatments.[6] In the *gain* treatments GLo and GHi, the LHS lottery is the *safe* lottery, while the right-hand side (RHS) lottery is the *risky* one.[7] It is the contrary in the reflected *loss* treatments LLo and LHi. In Series 1 of the *gain* treatments, those who still choose the LHS lottery (i.e., option A) as of row 7 can be qualified as risk averse as the expected value of the RHS lottery (i.e., option B in Table 2) starts exceeding the expected value of the LHS lottery. On the contrary, those choosing the RHS lottery at earlier rows can be qualified as risk lovers. In Series 2 it is as soon as row 1, and in Series 3 it is as of row 2.

In Series 1 of the baseline GLo treatment (gain domain, low stakes), 46% of the subjects choose the LHS lottery at row 7 while 40% choose the RHS lottery at row 6. It means that at least 46% of the subjects are risk averse and at least 40% are risk lovers. The behaviour of the remaining 14% is close to neutrality. The low proportion of risk-averse subjects compared to usual observations under EU can be explained by subjects being risk seeking over low-probability gains, typically the best outcomes of the RHS lotteries (see lotteries B of Series 1 in Table 2). This is consistent with the distinctive

[6]Appendix D gives the distribution of subjects' switching points in the baseline GLo treatment. Similarly to other studies based on TCN risk experiment and reporting raw experimental results from rural areas (e.g., Tanaka et al., 2010; Bocquého et al., 2014), we find that students choose massively extreme switching points in all three series. The *never* switch option in Series 1 is an exception as very few of the students we had enrolled opted for it.

[7]As put by Bosch-Domènech and Silvestre (2013), "'*the terms* safe *and* risky*, used by Holt and Laury (2002), must be understood in a loose sense and relative to each other: in a given pair, [the risky] lottery (...) gives a larger good payoff, but a lower bad payoff, than [the safe lottery].*"

Table 4: Proportion of left-hand side choices by row and treatment

	Treatment GLo	Treatment GHi	Treatment LLo	Treatment LHi
Series 1				
row 1	0.83	0.80	0.77	0.67
row 2	0.83	0.80	0.75	0.64
row 3	0.81	0.77	0.70	0.60
row 4	0.77	0.71	0.63	0.55
row 5	0.69	0.64	0.54	0.49
row 6	0.60	0.60	0.48	0.43
row 7	***0.46***	***0.46***	***0.36***	***0.29***
row 8	***0.38***	***0.34***	***0.28***	***0.20***
row 9	***0.27***	***0.28***	***0.21***	***0.16***
row 10	***0.18***	***0.19***	***0.16***	***0.10***
row 11	***0.12***	***0.13***	***0.12***	***0.07***
row 12	***0.07***	***0.05***	***0.08***	***0.06***
row 13	***0.04***	***0.03***	***0.07***	***0.05***
row 14	***0.02***	***0.02***	***0.06***	***0.05***
Series 2				
row 1	***0.79***	***0.75***	***0.81***	***0.75***
row 2	***0.77***	***0.73***	***0.79***	***0.74***
row 3	***0.76***	***0.70***	***0.73***	***0.69***
row 4	***0.74***	***0.68***	***0.68***	***0.62***
row 5	***0.69***	***0.62***	***0.58***	***0.53***
row 6	***0.68***	***0.59***	***0.50***	***0.48***
row 7	***0.61***	***0.53***	***0.41***	***0.38***
row 8	***0.52***	***0.49***	***0.33***	***0.31***
row 9	***0.48***	***0.45***	***0.27***	***0.23***
row 10	***0.39***	***0.39***	***0.20***	***0.17***
row 11	***0.30***	***0.31***	***0.17***	***0.14***
row 12	***0.19***	***0.21***	***0.12***	***0.10***
row 13	***0.17***	***0.17***	***0.10***	***0.09***
row 14	***0.13***	***0.15***	***0.10***	***0.09***
Series 3				
row 1	0.92	0.94	0.94	0.96
row 2	***0.68***	***0.73***	***0.64***	***0.69***
row 3	***0.46***	***0.58***	***0.43***	***0.56***
row 4	***0.31***	***0.42***	***0.21***	***0.32***
row 5	***0.15***	***0.15***	***0.12***	***0.12***
row 6	***0.08***	***0.11***	***0.08***	***0.09***
row 7	***0.07***	***0.07***	***0.07***	***0.09***
Number of observations	191	191	191	191

For treatments GLo and GHi, bold italic rows are those where left-hand side choices denote risk aversion. For the other two treatments, bold italic rows are those where left-hand side choices denote risk seeking.

fourfold pattern of behaviour that Tversky and Kahneman (1992) describe about CPT. [8] This pattern depends on outcome sign and probability level:

- risk aversion over medium to high-probability gains
- risk seeking over medium to high-probability losses (avoiding a sure loss)
- risk seeking over low-probability gains
- risk aversion over low-probability losses.

In Series 2 of the baseline treatment, 79% of the subjects choose the LHS lottery (i.e., lottery A) at row 1, meaning at least 79% of the subjects are risk averse. This time, there is no best outcome with a low probability, and subjects are predominantly risk averse. It is also consistent with the CPT fourfold pattern of behaviour. Series 3 uses 50-50 lotteries which mix gains and losses. In the baseline treatment, 68% of the subjects choose the LHS lottery (i.e., lottery A) at row 2, meaning at least 68% of the subjects are risk averse. We cannot directly comment this result with respect to the fourfold pattern as lotteries are mixed. Nevertheless, we can note that it is consistent with the usual empirical finding of loss aversion as the RHS lottery features high losses.

We now turn to the alternative treatments. If choosing the LHS lottery in the bold rows of Table 4 is an indicator of risk aversion in the *gain* treatments, it is on the contrary an indicator of risk seeking in the *loss* treatments. In Series 1 of the *loss* treatment LLo, 36% of the subjects choose the LHS lottery at row 7 while 52% choose the RHS lottery at row 6. It means that at least 36% of the subjects are risk lovers and at least 52% are risk averse. The behaviour of the remaining 12% is close to risk neutrality. The low proportion of risk-seeking subjects can be explained by subjects being very risk averse over low-probability losses, typically the worst outcomes of the LHS lottery. This is again in accordance with the fourfold pattern as far as the loss behaviour is concerned. In Series 2 of LLo, 81% of the subjects choose the LHS lottery at row 1, meaning at least 81% of the subjects are risk seeking. In the absence of a worst outcome with a low probability, subjects are predominantly risk seeking as predicted by the fourfold pattern. Finally, in Series 3 of LLo, 64% of the subjects choose the LHS lottery at row 2, meaning at least 64% of the subjects are risk lovers. This time this result cannot be fully explained by loss aversion as it is the LHS lottery which features the worst losses.

In the *high-stake* treatments (GHi and LHi), the number of LHS choices is close to that in the corresponding *low-stake* treatments. It leads to the same conclusions, that is subjects mostly follow the CPT fourfold pattern of behaviour.

[8] Tversky and Kahneman (1992) observe the entire fourfold pattern for 88% of the 25 subjects they tested.

Table 5: Aggregate CPT parameter values by treatment (interval approach)

	Treatment GLo	Treatment GHi	Treatment LLo	Treatment LHi
	Mean/(Std. Err.)	Mean/(Std. Err.)	Mean/(Std. Err.)	Mean/(Std. Err.)
σ^d	0.65	0.69	0.76	0.84
	(0.032)	(0.033)	(0.029)	(0.028)
γ^d	0.64	0.64	0.66	0.64
	(0.012)	(0.026)	(0.018)	(0.023)
λ	2.46	2.76	1.21	1.11
	(0.165)	(0.197)	(0.092)	(0.124)
Nb. of obs.	191	191	191	191
Wald test σ^d =1	0.000	0.000	0.000	0.001
Wald test γ^d =1	0.000	0.000	0.000	0.000
Wald test λ =1	0.000	0.000	0.060	0.423

For Wald tests, the number displayed is the p-value.

The mean parameter estimates we calculate assuming the functional forms of Section 4 confirm the non-parametric analysis. The first column of Table 5 displays mean estimates of σ^d, γ^d and λ, and corresponding standard errors for the underlying population in the baseline GLo treatment. We find respective values of about 0.65, 0.64 and 2.46, with orders of magnitude similar to other studies using the TCN design, parametric specifications and estimation method.[9] It means that, on average, subjects have a concave value function in the gain domain (and convex in the loss domain), tend to overweight low-probability extreme events in both domains, and value losses more than twice as much as gains. This is also consistent with the fourfold pattern of behaviour. The other three columns of Table 5 show that parameter estimates in the alternative treatments vary, in particular in the case of loss aversion. However, they determine roughly the same pattern of behaviour at the aggregate level, i.e., $\sigma^d < 1$, $\gamma^d < 1$ and $\lambda > 1$.

At the individual level, the picture is less clear-cut. Table 6 classifies subjects according to the power estimates directing the shape of their individual value function in the gain and loss domains. It leads to four categories, depending on the respective values of σ^+ and σ^-. The majority of our sample displays a standard S-shape value function, concave in gains and convex in losses (i.e., $\sigma^+ < 1$ and $\sigma^- < 1$). It amounts to 72% of the subjects in the low-stake conditions and 67% in the high-stake conditions. This is also the most common shape in Abdellaoui et al.'s (2007), who also estimate

[9]See Bocquého et al. (2018, p.35) for a graphical comparison of mean parameter values from our study and TCN; Liu (2013); Campos-Vazquez and Cuilty (2014); Bocquého et al. (2014); Bauermeister et al. (2018); Bocquého et al. (2018).

Table 6: Proportion of subjects according to the curvature of the value function in the gain and loss domains

	low stakes	high stakes
standard S-shape	0.72	0.67
everywhere concave	0.16	0.18
everywhere convex	0.08	0.10
anti-standard	0.04	0.05
Number of observations	191	191

individual power coefficients for the value function. However, with a similar power specification, but focusing on losses and allowing a linear category, Etchart-Vincent (2004) finds that roughly only half of her sample exhibited convexity when facing small (54%) or large (46%) losses. Booij and van de Kuilen's (2009) classification of subjects based on a large sample of Dutch people and non-parametric individual value functions reveals that concavity in gains applied to 42% of their sample and convexity in losses to 47% of their sample. However, only 25% of the subjects combine both into the S-shape.

Another category is quite well represented in our sample: 16 to 18% of the subjects exhibit a concave value function in the two gain and loss domains ($\sigma^+ < 1$ and $\sigma^- > 1$). Concave and linear value functions for losses are not uncommon at the individual level under PT. Abdellaoui et al. (2008) report the everywhere concave category was the most common in their study, but highlight it does not correspond to a significantly different proportion of subjects than the category with a standard S-shape value function. Etchart-Vincent (2004) counts 34 and 45% of subjects with a concave value function for small and large losses respectively. In Booij and van de Kuilen (2009), the linear-concave shape (almost 25%) is as prevalent as the standard concave-convex S-shape. In total, 22% of the subjects under study exhibit a concave value function and 30% a linear one. The everywhere concave category is about 9%.

The two other categories of Table 6, corresponding to a convex value function for gains, are anecdotal. Subjects with an everywhere convex value function represent 8 to 10% of the sample, and subjects who behave oppositely to the standard represent only 4 to 5%.

5.2 Frame effects on the number of LHS choices

We implement the *loss* treatments to test whether behaviour for gains is reflected for losses. Should reflection be perfect at the sample level, the proportion of LHS choices at each row should be very close between the *gain* and *loss* frames. Indeed, under this hypothesis, subjects should follow a symmetrical risk behaviour in the two frames, while the LHS and the RHS are reversed when lottery stakes are multiplied by -1. Thus, we expect those subjects to collectively repeat within each row the choice of the RHS or the LHS lottery between the two frames, at least in Series 1 and 2. Indeed, loss aversion is not at play when comparing all-loss lotteries between them. For instance, a similar proportion of subjects should switch at row 12 in Series 1 both in the *gain* frame (very risk averse) and in the *loss* frame (very risk seeking).

This is not what we observe in Table 4 as the LHS choices are lower, in treatment LLo compared to baseline GLo in all three series, although to a lesser extent in Series 3. The same applies to the *high-stake* treatments. In Table 7, we regress the total number of LHS choices over all rows on frame characteristics, by series, and control for the interacted frame effects and individual socio-demographics. We observe consistent results: a highly significant negative effect of the *loss* frame in Series 1 and 2, but small (about -0.9 and -1.5 choices respectively out of 764) and similar between the high- and low-stake conditions. It means that, when faced with losses, on average, subjects switch comparatively earlier, i.e., they find the LHS lottery less attractive compared to the RHS lottery.

Table 7: Regression (OLS) of total number of left-hand side choices on frame characteristics and socio-demographics by series

	Series 1		Series 2		Series 3	
Covariate	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	7.271***	(650)	6.074***	(606)	531***	(0.572)
Frames:						
Loss	-0.853**	(0.360)	-450***	(0.403)	-0.162	(0.174)
High	-0.267	(0.290)	-0.461	(0.365)	0.330**	(0.149)
Loss×High	-0.586	(0.407)	-0.010	(0.502)	0.000	(0.208)
Individual characteristics:						
Age	-0.064	(0.076)	0.052	(0.067)	0.042	(0.026)
Female	0.221	(0.396)	0.736	(0.467)	0.527***	(0.154)
Master	-0.244	(0.552)	-701***	(0.620)	-0.194	(0.209)
Economics	0.302	(0.411)	0.134	(0.467)	0.007	(0.154)
Model R-squared	0.035		0.049		0.034	
Nb. of obs. /clusters	764/191		764/191		764/191	

*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
OLS stands for Ordinary Least Squares.
All monetary terms are in euros.

As determined in Section 5.1, our sample is mostly risk averse in the gain domain and risk seeking in the loss domain, and thus over-values the LHS lottery in both domains. Thus, switching earlier when facing losses means that the gap between the CPT values of the two LHS and RHS lotteries is thinner in the loss domain than in the gain domain. It advocates for a more linear value function in the loss domain.

Probability weighting may provide another explanation for the LHS lottery becoming less attractive compared to the RHS lottery in the *loss* frame, as regards Series 1 and 2. Indeed, in the *loss* treatments the LHS lotteries feature low-probability losses. Yet, our sample mostly overweights low-probability extreme events (see Section 5.1), and thus under-values the LHS lottery in the *loss* treatments. Thus, switching earlier when facing losses may mean that probability weighting is stronger in the loss domain than in the gain domain. This time it would be consistent with a more curved probability weighting function in the loss domain. As for Series 3, loss aversion can also contribute to explain why behaviour is only partially reflected for losses at several rows, although the loss-frame effect is overall unsignificant in this series. Indeed, while in the *gain* treatments the loss outcomes of the LHS lottery are small (in absolute terms) and those of the RHS lottery are high, in the *loss* treatments the high loss outcomes are those of the LHS lottery, and are more extreme than in the *gain* treatments. In other words, in the *loss* treatments, the LHS may become less attractive compared to the RHS because the difference in the penalties applied to lotteries for featuring losses get mechanically larger, even if loss aversion is stable between the gain and loss domains.

Although in this paper the focus is on the *loss* frame, the effect on behaviour of the *high-stake* frame in itself deserves a few comments. We already mentioned in Section 5.1 that the number of LHS choices in the *high-stake* treatments (GHi and LHi) is close to that in the corresponding *low-stake* treatments. It is in accordance with Table 7 which shows that the *high-stake* frame has no significant effect on the total number of LHS choices in Series 1 and 2. Thus, at the aggregate level, the non-parametric analysis reveals no evidence of the '*forgotten*' fourfold pattern described by Scholten and Read (2014), which depends on outcome sign and outcome level:

- risk aversion over medium to high gains
- risk seeking over medium to high losses
- risk seeking over small gains
- risk aversion over small losses.

One exception is Series 3, for which we find that the high-stake frame has a significant effect on the total number of LHS choices, at the 5% level. The effect is positive but very small (+0.3), suggesting that when faced with high stakes, on average, subject switch comparatively later, i.e., find the LHS lottery more attractive than the RHS lottery. Following the same reasoning than for the *loss-frame* effect, and accounting again for the fact that subjects are collectively risk averse in the gain domain and risk seeking in the loss domain, we conclude that this result supports the idea of a more curved value function when stakes are higher.

Manipulating payoff ranges in multiple price lists has been common, and, in line with our work, mostly delivered evidence in favour of risk aversion increasing with payoff level. For instance, Holt and Laury (2002, 2005) show that the proportion of safe choices increases sharply when positive real payoffs are scaled up by factors of 20, 50 and 90. Using different probability levels and a multiplying factor of 6 to 10, Bouchouicha and Vieider (2017) show that the mean risk premia move up across gain stakes for every probability. However, using a sample of nearly 2,000 students and scaling up lottery gain and loss outcomes by a factor 10, Booij et al. (2010) find no difference between the high and low treatments in the non-parametric estimates. Stake effects for losses are especially inconclusive in the literature. For instance, Etchart-Vincent (2004) mentions that behaviour towards risk in general appears not to be sensitive to the magnitude of negative payoffs. In the same vein, Bouchouicha and Vieider (2017) cannot replicate for losses the pattern they describe for gains, whatever the probability level.

The curvature of the value function is not the only possible interpretation for stake effects. Probability weighting does not interfere in Series 3 choices due to homogeneous probabilities, but loss aversion does. In the case of the *gain* frame, loss aversion can indeed provide a sufficient explanation. In the *gain* treatment GHi, the RHS (or risky) lottery features the highest losses. Since higher stakes mean a higher penalty for the highest losses compared to other outcomes, loss-averse subjects tend to reduce the CPT value of the RHS lottery proportionally more than the LHS lottery. It results in a higher proportion of LHS choices and of risk-averse subjects (73% for high stakes vs. 68% for low stakes). But this reasoning does not hold in the *loss* treatment LHi as, this time, the highest losses belong to the LHS (or risky) lottery. Thus, we should observe a decrease in the proportion of LHS choices and of risk-seeking subjects. On the contrary, at least 69% of the subjects are risk seeking in treatment LHi, but only 64% in treatment LLo.

5.3 Frame effects on parameter estimates

In order to assess the effect of the *loss* and *high-stake* frames on the CPT parameters previously elicited at the aggregate level (Table 5), we regress the latter on frame characteristics and individual socio-demographics. Results are displayed in Tables 8, 9 and 10 for σ^d, γ^d and λ respectively. In each table, model (1) only includes frame characteristics as covariates, while model (2) also includes socio-demographics.

Table 8: Regression (OLS) of σ^d on several sets of covariates including frame

Covariate	(1) Coef.	Std. Err.	(2) Coef.	Std. Err.
Constant	0.647***	(0.026)	0.620***	(0.137)
Frames:				
Loss	0.118***	(0.032)	0.118***	(0.032)
High	0.040	(0.026)	0.040	(0.026)
Loss×High	0.036	(0.037)	0.036	(0.037)
Socio-demographics:				
Age			0.002	(0.006)
Female			-0.050	(0.035)
Master			0.107**	(0.047)
Economics			-0.023	(0.035)
Model R-squared	0.041		0.065	
Adjusted R-squared	0.038		0.056	
Nb. of obs. /clusters	764/191		764/191	
AIC	609.045		598.302	
BIC	627.599		635.410	

Standard errors are clustered at the individual level.
*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
OLS stands for Ordinary Least Squares.
AIC and BIC stand for Akaike and Schwarz's Bayesian information criteria respectively.
All monetary terms are in euros.

Table 9: Regression (OLS) of γ^d on several sets of covariates including frame

Covariate	(1) Coef.	Std. Err.	(2) Coef.	Std. Err.
Constant	0.636***	(0.020)	0.767***	(0.108)
Frames:				
Loss	0.029	(0.025)	0.029	(0.025)
High	0.009	(0.022)	0.009	(0.023)
Loss×High	-0.034	(0.031)	-0.034	(0.031)
Socio-demographics:				
Age			-0.006	(0.005)
Female			-0.026	(0.029)
Master			0.068*	(0.041)
Economics			0.008	(0.030)
Model R-squared	0.002		0.011	
Adjusted R-squared	-0.002		0.002	
Nb. of obs. /clusters	764/191		764/191	
AIC	258.555		259.300	
BIC	277.109		296.409	

Standard errors are clustered at the individual level.
*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
OLS stands for Ordinary Least Squares.
AIC and BIC stand for Akaike and Schwarz's Bayesian information criteria respectively.
All monetary terms are in euros.

Table 10: Regression (OLS) of λ on several sets of covariates including frame

Covariate	(1) Coef.	Std. Err.	(2) Coef.	Std. Err.
Constant	2.456***	(0.179)	2.175***	(0.665)
Frames:				
Loss	-249***	(0.201)	-249***	(0.202)
High	0.303	(0.215)	0.303	(0.216)
Loss×High	-0.404*	(0.239)	-0.404*	(0.240)
Socio-demographics:				
Age			0.004	(0.029)
Female			0.262*	(0.147)
Master			0.306	(0.249)
Economics			-0.049	(0.151)
Model R-squared	0.128		0.138	
Adjusted R-squared	0.124		0.130	
Nb. of obs. /clusters	764/191		764/191	
AIC	3173.122		3172.127	
BIC	319676		3209.236	

Standard errors are clustered at the individual level.
*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
OLS stands for Ordinary Least Squares.
AIC and BIC stand for Akaike and Schwarz's Bayesian information criteria respectively.
All monetary terms are in euros.

The *loss* frame has a significant positive impact on curvature σ^d (+0.12, significant at the 1% level), meaning respondents exhibit a value function which is less convex for losses than it is concave for gains. As expected, they thus tend towards being less risk seeking for losses than they are risk averse for gains, but the difference is very low. We thus conclude in favour of a partial reflection of the value function at the aggregate level towards more linearity in the loss domain, for low stakes and high stakes, as found in many experimental studies (e.g., Kahneman and Tversky, 1979; Fennema and van Assen, 1998; Abdellaoui, 2000; Laury and Holt, 2008). However, our results do not support any significant *loss*-frame effect on the weighting parameter γ^d. Thus, the parametric analysis reveals that the decrease in the number of LHS choices of the *loss* frame we have identified in Section 5.2 is due to a more linear value function rather than a more curved probability weighting function. The only study documenting distinct loss and gain parameters using the TCN design is Bougherara et al. (2017). The authors rely on a structural estimation procedure, but they report like us close and significantly different power parameters for the curvature of the value function (0.60 for gains vs. 0.66 for losses) when loss aversion is set to 1. However, they are able to detect a small significant difference as well in the probability weighting function (parameter is 0.79 for gains vs. 0.84 for losses, even when loss aversion is not constrained), in line with Tversky and Kahneman's (1992) and Abdellaoui (2000) who use the same one-parameter form.

About loss aversion λ, recall that the estimation derives from Series 3 answers, conditionally to the σ^+ or σ^- values elicited from Series 1 and 2. It implicitly assumes that the curvature of the value function is similar in the gain and loss domains as we apply the same value indifferently to the gain and loss outcomes. In the *gain* treatments, we apply only the value elicited over gains, even for losses, whereas in the *loss* treatments we apply the one elicited over losses, even for gains. We find a strong and significant negative impact of the *loss* frame on elicited λ (-1.25, significant at the 1% level), with an additional small negative impact in the high-stake conditions (-0.40, significant at the 10%level). This result seems to reveal that, surprisingly, subjects are less loss averse when gain outcomes are converted into losses (and conversely), and even less when outcomes are high. It leads to λ mean values cut by more than half and ending up close to the neutrality threshold (1.21 under the low-stake conditions, and 1.11 under the high-stake conditions, Table 5). The Wald tests at the bottom of Table 5 demonstrate that mean λ is still statistically different from 1 in the low-stake case, but at the 10% level only. In the high-stake case, loss aversion is not significant anymore, meaning subjects are on average neutral with respect to losses. This unexpected result is too strong to be explained only by response error. We bring forward two possible explanations. We suspect a pure loss-frame effect. As highlighted by many authors, loss aversion elicitation is indeed very sensitive to framing (Abdellaoui et al., 2007; Wakker, 2010). Another possible explanation is the sequential structure of the TCN procedure, and the fact that λ is calculated in a second step conditionally to a unique σ^d value from the first step.

As regards the *high-stake* frame, it has no significant impact on any of the three CPT parameters. Thus, we are not able to confirm the hypotheses we made in Section 5.2 about why the number of LHS choices decreases in Series 3 when stakes are higher. Other authors having studied the effect of stake size on the curvature of the value function are not able to report either a significant difference when outcomes get larger (Booij and van de Kuilen, 2009; Booij et al., 2010). [10] Evidence regarding the probability weighting parameter is mixed. Tversky and Kahneman (1992) already suspect that decision weights might be sensitive to framing, including the level of outcomes. Booij et al. (2010) cannot find any significant effect of stake size while Etchart-Vincent (2004) reports the opposite result

[10] On the contrary, in the EU context, Reynaud and Couture (2012) replicate Holt and Laury's (2002) as well as Eckel and Grossman's (2008) baseline lotteries, and also multiply stakes by 20. They find that, for both methods, the mean constant relative risk aversion coefficients are statistically different, subjects being more risk averse for high payoffs than for low payoffs. However, in the case of Holt and Laury's (2002) experiment, they report that distribution of the coefficients is not modified by the payoff level.

based on loss lotteries, but only when using a 2-parameter specification. Fehr-Duda et al. (2010) and Bouchouicha and Vieider (2017) find a significant effect of stake size in the gain domain but not in the loss domain. As regards loss aversion, Schmidt and Traub (2002), Booij and van de Kuilen (2009) and Booij et al. (2010) detect no effect of stake size on the controlling parameter, similarly to us. However, in Abdellaoui et al. (2007), the mean value of the loss aversion coefficient decreases with the size of the gains and losses involved. Bleichrodt and Pinto (2002) observe a similar phenomenon in the health domain.

About the choice of the econometric model, one may argue that ordinary least squares is not suitable although it is widely used in the experimental literature after eliciting risk parameters analytically from multiple price lists. Indeed, the most common technique is to calculate intervals for parameter values, advocating for the use of interval regression as in Appendix E, Tables 20 to 22. Note that regressing each parameter independently is another simplification as the TCN procedure elicits σ^d and γ^d intervals jointly from Series 1 and 2. [11] Furthermore, the distribution of λ is far from normal (see Appendix F), and thus a log-normal interval regression may even seem more adequate for this parameter, as the Akaike and Schwarz's Bayesian information criteria reveal (Appendix E, Table 23). These alternative specifications show that the results from the ordinary least square regresssions are robust. The only difference is in Table 23 where the interaction term between the *loss* and *high-stake* frames becomes significant at the 5% level (instead of 1%), and a weekly significant positive effect of stake size appears.

So far, we have shown that subjects' behaviour is consistent with the CPT fourfold pattern and loss aversion at the aggregate level, whatever the treatment. The parameter estimates confirm the non-parametric analysis. At the individual level the picture for the value function is less clear-cut, but a large majority of our sample follows the standard S-shape. We have then revealed that the total number of LHS choices significantly increases when gain lotteries are reversed into loss lotteries whatever the stake size, due to a slightly more linear value function. It brings proof of partial reflection of the value function at the aggregate level. Last, we have unvealed that mirroring into the opposite domain the mixed lotteries of TCN Series 3 has an unexpected strong negative effect on elicited loss aversion, that may be due either to mere framing or to the sequential structure of the TCN design. In the following section, we fine-tune the estimates of the loss aversion parameter by accounting for

[11] In Tables 20 and 21 the intervals for σ^d and γ^d are artificially rebuilt based on the matrix of point estimates in TCN and the information the authors give about the 0.5 approximation.

these last two phenomena.

6 Consequences on elicited loss aversion

In this section, we provide new estimates of the loss aversion parameter. We first investigate further the negative effect of the *loss* frame on loss aversion in Series 3. Second, we explore the consequences of relaxing the hypothesis of identical value functions in the gain and loss domains. We analyse the results at the aggregate and individual levels.

6.1 When a pure framing effect is isolated

In Section 5.3 we have measured a strong negative effect of the *loss* frame on λ. We aim at disentangling its two components by identifying which part is due to subjects being less loss averse when gains and losses of Series 3 are exactly mirrored in the opposite domain (pure framing effect), and which part is due to loss aversion in the *loss* treatments being calculated conditionally to the curvature of the value function over losses (sequential calculation procedure).

To this end, we use the alternative λ_{oppos} parameter described in Section 4. In the *gain* treatments, λ_{oppos} values are conditional to σ^- elicited over losses, and in the *loss* treatments, they are conditional to σ^+ elicited over gains. The mean value and distribution percentiles of λ_{oppos} by treatment are displayed in Table 11. Comparing λ of baseline GLo to λ_{oppos} of treatment LLo (i.e, using σ^+) allows to assess the pure framing effect in the low-stake conditions. The mean and median values drop by half: from 2.46 to 1.34 and from 1.60 to 0.65 respectively. In the high-stake conditions, the effect is even larger. On average, neutrality towards loss cannot be excluded anymore as the Wald test reported in the bottom panel shows (p-value is 0.145). The first two lines of Table 12 give the corresponding proportion of respondents. A subject is classified as loss averse when the parameter under scrutiny is higher than 1. [12] We find that the pure framing effect decreases the proportion of loss-averse subjects from 69% to 36% in the low-stake conditions, and from 76% to 31% in the high-stake conditions.

[12]Corresponding distributions are represented in Appendix G, Figures 5 and 6.

Table 11: Aggregate λ, λ_{oppos} and λ_{gen} values by treatment (interval approach)

	Treatment GLo		Treatment GHi		Treatment LLo		Treatment LHi	
	Mean (S.E.)	25^{th} 50^{th} 75^{th}	Mean (S.E.)	25^{th} 50^{th} 75^{th}	Mean (S.E.)	25^{th} 50^{th} 75^{th}	Mean (S.E.)	25^{th} 50^{th} 75^{th}
λ	2.46	0.91	2.76	1.11	1.21	0.48	1.11	0.35
	(0.16)	1.60	(0.20)	2.01	(0.09)	0.62	(0.12)	0.51
		3.01		3.10		2.03		1.81
λ_{oppos}	2.47	0.91	2.76	1.11	1.34	0.49	1.21	0.35
	(0.16)	1.65	(0.21)	2.02	(0.07)	0.65	(0.13)	0.51
		3.01		3.04		2.19		2.03
λ_{gen}	8.43	0.36	7.47	0.31	3.37	0.15	7.66	0.09
	(2.18)	1.08	(1.98)	1.03	(0.92)	0.41	(4.84)	0.43
		2.95		3.46		2.03		1.59
Nb. of obs.	191		191		191		191	
Wald test λ =1	0.000		0.000		0.060		0.423	
Wald test λ_{oppos} =1	0.000		0.000		0.002		0.145	
Wald test λ_{gen} =1	0.011		0.014		0.036		0.211	

S.E. stands for standard error.
Labels 25^{th}, 50^{th} and 75^{th} stand for the corresponding percentiles.
For Wald tests, the number displayed is the p-value.

Table 12: Proportion of subjects exhibiting loss aversion (parameter value $\geq$)

	Low stakes	High stakes
λ in gain frame	0.69	0.76
λ_{oppos} in loss frame	0.36	0.31
λ_{oppos} in gain frame	0.68	0.76
λ_{gen} in gain frame	0.52	0.50
λ_{gen} in loss frame	0.33	0.31
Number of observations	191	191

Now, comparing λ of baseline GLo to λ_{oppos} of the same treatment (i.e, using σ^-) allows to assess the sequentiality effect in the low-stake conditions. Sequentiality slightly increases mean (from 2.46 to 2.47) and median loss aversion (from 1.60 to 1.65, Table 11). In the high-stake conditions (GHi treatment), there is no salient difference. This is in accordance with our previous finding that the curvature of the value function has significantly different but close values in the gains and loss domains, whatever the size of stakes. The first and third lines of Table 12 confirm that the sequentiality effect is neither prominent at the individual level. Proportions of loss-averse subjects are unchanged: 68% vs. 69% when low stakes, and 76% vs. 76% when high stakes.

As a consequence, decreasing loss aversion in the *loss* versions of Series 3 is rather due to a pure framing effect rather than to a sequentiality effect, and it holds for both the low-stake and high-stake conditions. Our finding gives credit to the volatility of loss aversion and its sensitivity to small details of framing as put by Wakker (2010). Wakker (2010) explains violations of asset integration entailed by reference dependence are highly irrational, and can explain part of this volatility. Andersen et al. (2006) and Harrison and Rutström (2008) also discuss the crucial role of the reference point as a source of volatility, in particular in dynamic tasks and in the field. As a remedy, based on several studies, Wakker (2010) recommends proper learning and incentives.[13] More largely, Tversky and Kahneman (1992) highlight heuristics of choices, and thus PT parameters, might be sensitive to the formulation of the problem, the method of elicitation and the context of choice.

6.2 When behaviour is free to jointly differ between gains and losses

We have seen in Section 5.3 that the *loss* frame has a significant impact on the estimated curvature of value function and loss aversion, especially on the latter. In this section, we fully relax the assumption about equal curvature in the gain and loss domains and assess the consequences for elicited loss aversion at the aggregate and individual levels. In particular, we expect that accounting jointly for σ^+ and σ^- when measuring loss aversion allows a more accurate elicitation and might also moderate the pure framing effect we have isolated in the previous section.

We use the more general λ_{gen} value defined in Section 4, which is calculated conditionally to

[13]Loss aversion also varies widely between studies. Abdellaoui et al. (2007) mention as reasons for it different parametric assumptions about the other PT components, reports of either mean or median values for loss aversion indices and different definition of loss aversion. In this paper loss aversion is defined as $-v^d(-1)/v^f(1)$ where d and f can take the value $+$ when the value function is estimated on all-gain lotteries or the value $-$ when is is estimated on all-loss lotteries. This is also the definition that Tversky and Kahneman (1992) implicitly use. See Abdellaoui et al. (2007) for an assessment of the extent to which the degree of loss aversion varies with the definition used.

both σ^+ and σ^-. We compare on the one hand λ with λ_{gen} in the *gain* treatments, and on the other hand λ_{oppos} with λ_{gen} in the *loss* treatments. It allows us to assess the effect of applying σ^- to Series 3 negative payoffs instead of σ^+ when measuring loss aversion. Table 11 shows it dramatically increases mean loss aversion in the *gain* treatments: from 2.46 to 8.43 in the low-stake conditions, and from 2.76 to 7.47 in the high-stake conditions.[14] This is partly due to extreme outliers with very high loss aversion values, including 2- and 3-digit numbers. Extreme values in the vicinity of 0 do also appear. It leads to high standard errors, and despite a high mean value, λ_{gen} becomes significantly different from 1 at the 5% level only (p-value is 0.011 in the low-stake context and 0.014 in the high-stake context). These extreme λ_{gen} values belong to subjects whose σ^+ and σ^- are on either side of the 1 threshold, meaning an everywhere-concave or everywhere-convex value function. Summing the second and third lines of Table 6 shows they represent 24% and 28% of our sample, respectively in the low-stake and high-stake conditions. Looking at corresponding medians and individual values gives indeed opposite results to mean values. Median loss aversion decreases from 1.60 to 1.08 in the low-stake conditions, and from 2.01 to 1.03 in the high-stake conditions (Table 11). The first and fourth lines of Table 12 reveal that the proportion of loss-averse subjects falls from 69% to 52% for low stakes, and even more from 76% down to 50% for high stakes.

In the *loss* treatments, applying σ^- to loss outcomes entails similar effects although less pronounced. In the low-stake conditions, mean loss aversion jumps from 1.34 to 3.37 (and from 1.21 to 7.66 in the high-stake conditions), but median loss aversion decreases from 0.65 to 0.41 (and from 0.51 to 0.43 in the high-stake conditions). The proportion of loss-averse subjects decreases only slightly in the low-stake conditions, from 36% to 33%, while it remains unchanged in the high-stake conditions.

These results suggest that assuming a unique curvature for the value function leads to strongly underestimating mean loss aversion in the TCN method. On the contrary, it overestimates median loss aversion. It also skews distribution to the right and minors heterogeneity. Furthermore, the proportion of loss-averse subjects is artificially inflated. As a result, loss aversion may not be the dominant behaviour in all circumstances. Loss-neutral and loss-seeking subjects seem to be much more common than usually assumed, whether at the aggregate or individual level. Abdellaoui et al. (2007) also evaluate how bad it is to measure loss aversion assuming reflection by imposing for each

[14] Other examples of high loss aversion estimates include Harrison and Rutström (2009, mixture model) and Abdellaoui et al. (2007, Köbberling and Wakker definition) with respective mean values of 5.80 and 8.27.

subject the power coefficient for gains on the function for losses. At the aggregate level they do not find any major distortion in the median values of the loss aversion coefficients, but considerable distortions arise at the individual level. The interquartile ranges are much wider and 33% of the subjects are misclassified with respect to their attitude towards losses.

There are several experimental studies that, at the same time, relax some of the reflection constraints and report low levels of loss aversion, if compared to the reference value of 2.25 obtained by Tversky and Kahneman (1992). For instance, Bougherara et al. (2017) estimate through the TCN design but under structural estimation based on pooled observations a mean value of 1.37 or French farmers. The authors assume reflection for the value function only. [15] Also using structural preference models, Andersen et al. (2006), Abdellaoui et al. (2008), Harrison and Rutström (2009), and Booij et al. (2010) find mean values of 1.07, 1.38, 1.58, and 1.60 respectively. The first two studies rely on a student sample and assume reflection for the weighting function only, while the last one assumes reflection for the power value function only. The third one applies to Dutch citizens and is free from any reflection constraint. With a model variant featuring an endogenous reference point, Andersen et al. (2006) estimate mean loss aversion to be as low as 0.5. At the individual level, when they allow for demographic heterogeneity with respect to preference parameters, the results show a clear first mode indicating loss neutrality or slight loss aversion. The two other modes reflect loss aversion but also loss seeking.

Assuming a piecewise linear value function but no constraint on probability weighting, Schmidt and Traub (2002) estimate an average index of loss aversion of 1.43. At the individual level, they find mixed evidence for loss aversion. Their tests indeed classify about 30% of their student sample as strictly loss averse, but also 25% as loss seeking, while about 45% cannot be classified. Andersen et al. (2006) also assume a piecewise linear value function in one of their models, which leads to a mean loss version value as high as 2.66. Similar to Schmidt and Traub (2002), at the individual level, when they allow for demographic heterogeneity with respect to preference parameters, the range of individual values is strikingly large. The first mode reflects extreme loss aversion, but the second mode lies in the loss-seeking domain. Abdellaoui et al. (2008) report considerable variation in loss aversion at the individual level as well. However, loss aversion is clearly the dominant pattern in their study. The same applies to Abdellaoui et al. (2007) who test five definitions of loss aversion. They

[15] Liebenhem and Waibel (2014) report with the same methods a mean loss aversion of 1.35 for African farmers, although they enforce reflection both for the value function and the probability weighting function.

find that 54 to 81% of the subjects are loss averse when response error is not taken into account as in our paper, and 2 to 25% are loss seeking, with a lot of subjects left unclassified.

To assess whether using two different power parameters in the value function modifies the pure framing effect we identified in the previous section on loss aversion, we compare λ_{gen} in the *gain* treatments to λ_{gen} in the *loss* treatments. We find in the low-stake conditions that the mean and median loss aversion values now drop by more than half: from 8.43 to 3.37 and from 1.08 to 0.41 respectively (Table 11). The proportion of loss-averse subjects also strongly decreases from 52% to 33% (Table 12). In the high-stake conditions, results are similar, except for the mean loss aversion which stays pretty stable. It implies that, despite less stringent parametric constraints, a pure loss-framing effect towards less loss aversion is still substantial both at the aggregate and individual levels.

7 Conclusion

In this paper, we examine the consequences of relaxing the simplifying assumption of similar CPT parameter values over gains and losses, in the context of the TCN risk experiment procedure. We implement in the lab the original experiment and additional treatments involving a *loss* frame and a *high-stake* frame. On the one hand, we show that subjects' behaviour for gains is mostly reflected for losses at the aggregate and individual levels, and is consistent with the CPT fourfold pattern. However reflection is partial as the mean curvature of the value function is slightly less convex for losses than it is concave for gains. These results are robust to a high-stake context. Then, we demonstrate that assuming reflection when measuring loss aversion is innocuous neither at the aggregate nor at the individual level. It leads to underestimating mean loss aversion while overestimating median loss aversion. It also skews distribution to the right, minors heterogeneity and inflates the proportion of loss-averse subjects. On the other hand, we highlight the existence of a strong, negative and persistent framing effect on the loss aversion elicited from mixed lotteries, regardless of whether reflection about the other parameters is assumed.

Loss aversion may not be the dominant behaviour in all circumstances. Our results indeed confirm previous evidence that loss-neutral and loss-seeking behaviours are much more common than usually presumed. However, because we chose to fully follow the TCN elicitation procedure based on intervals, in our study we account neither for individual response error, nor for the joint influence of the PT parameters on lottery choices. Introducing a probabilistic choice function and pooling observations in a structural econometric model would refine our quantitative analysis, and probably lessen the preference heterogeneity we report. Alternative functional specifications like a 2-parameter weighting function and varying reference points may also yield additional fruitful conclusions.

The TCN methodology is becoming increasingly popular to elicit risk preferences in the field because it combines the simplicity of the multiple price list format with the sophistication of PT. However, in the field, control on framing effects is typically more difficult to achieve than in the lab. We thus recommend that future practitioners be particularly cautious about the instability of the loss aversion estimates they obtain. Examples of good practice are tests for sensitivity in responses with respect to parametric constraints such as reflection, and to framing in relation to reference dependence. For the whole set of CPT parameters, we also call for a more systematic recourse to percentile aggregate estimates, as well as individual-level analyses.

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Appendices

A Lotteries of the LLo treatment

Table 13: Lottery options corresponding to the loss LLo treatment

	Payoffs				(Expected value C-D)
	Option C		Option D		
Series 1					
Probabilities	0.10	0.90	0.30	0.70	
row 1	-68	-5	-40	-10	(7.7)
row 2	-75	-5	-40	-10	(7.0)
row 3	-83	-5	-40	-10	(6.2)
row 4	-93	-5	-40	-10	(5.2)
row 5	-106	-5	-40	-10	(3.9)
row 6	-125	-5	-40	-10	(2.0)
row 7	-150	-5	-40	-10	(-0.5)
row 8	-185	-5	-40	-10	(-4.0)
row 9	-220	-5	-40	-10	(-7.5)
row 10	-300	-5	-40	-10	(-15.5)
row 11	-400	-5	-40	-10	(-25.5)
row 12	-600	-5	-40	-10	(-45.5)
row 13	-1,000	-5	-40	-10	(-85.5)
row 14	-1,700	-5	-40	-10	(-155.5)
Series 2					
Probabilities	0.70	0.30	0.90	0.10	
row 1	-54	-5	-40	-30	(-0.3)
row 2	-56	-5	-40	-30	(-1.7)
row 3	-58	-5	-40	-30	(-3.1)
row 4	-60	-5	-40	-30	(-4.5)
row 5	-62	-5	-40	-30	(-5.9)
row 6	-65	-5	-40	-30	(-8.0)
row 7	-68	-5	-40	-30	(-10.1)
row 8	-72	-5	-40	-30	(-12.9)
row 9	-77	-5	-40	-30	(-16.4)
row 10	-83	-5	-40	-30	(-20.6)
row 11	-90	-5	-40	-30	(-25.5)
row 12	-100	-5	-40	-30	(-32.5)
row 13	-110	-5	-40	-30	(-39.5)
row 14	-130	-5	-40	-30	(-53.5)
Series 3					
Probabilities	0.50	0.50	0.50	0.50	
row 1	-30	21	-25	4	(6.0)
row 2	-30	21	-4	4	(-4.5)
row 3	-30	21	-1	4	(-6.0)
row 4	-30	16	-1	4	(-8.5)
row 5	-30	16	-1	8	(-10.5)
row 6	-30	14	-1	8	(-11.5)
row 7	-30	11	-1	8	(-13.0)

Lottery payoffs are in ECUs. Information on expected value is not displayed to respondents.

B Experimental instructions

The experiment you are going to participate studies individual decision-making in risky situations. You will be confronted with 12 series of choices between two options A and B. The gains/losses associated with these options will be expressed in a virtual currency called ECU (Experimental Currency Unit).

At the end of the experiment you will be asked questions about your personal characteristics (age, gender, education, etc.).

Let's take an example to become familiar with the choices to be made. Here are two series, presented in tables 14 and 15, that look like the ones you will be facing.

Table 14: Series 1

	Option A		Option B	
Row	Prob 30%	Prob 70%	Prob 10%	Prob 90%
1	20	5	34	2.5
2	20	5	37.5	2.5
3	20	5	41.5	2.5
4	20	5	46.5	2.5
5	20	5	53	2.5
6	20	5	62.5	2.5
7	20	5	75	2.5
8	20	5	92.5	2.5
9	20	5	110	2.5
10	20	5	150	2.5
11	20	5	200	2.5
12	20	5	300	2.5
13	20	5	500	2.5
14	20	5	850	2.5

This Series 1 contains 14 choices or rows to be made between two options, option A and option B.

Details of Row 1:

Option A: Consider an urn composed of 10 balls of which 3 are yellow and 7 are blue. If a yellow ball was drawn (Prob 30%) then you would get ECU 20 and if the drawn ball was blue (Prob 70%) then you would get ECU 5.

Option B: Consider an urn composed of 10 balls of which 1 is yellow and 9 are blue. If a yellow ball was drawn (Prob 10%) then you would get ECU 34 and if the drawn ball was blue (Prob 90%) then you would get ECU 2.5.

The question that will be asked about this series is:

- I choose option A for choices 1 to __

- I choose option B for choices __ at 14.

You must choose between option A and option B for each of the 14 rows. Suppose you choose option A for rows 1 to 3, and option B for rows 4 to 14, should then appear respectively in the spaces above the numbers 3 and 4. It is also possible to choose option A for all rows. In this case, the first number will be 14 and write the letter X in the second space. It is also possible to choose option B for all rows. In this case, write the letter X in the first space and the number 1 in the second one.

Table 15: Series 2

	Option A		Option B	
Row	Prob 50%	Prob 50%	Prob 50%	Prob 50%
1	12.5	-2	15	-10.5
2	2	-2	15	-10.5
3	0.5	-2	15	-10.5
4	0.5	-2	15	-8
5	0.5	-4	15	-8
6	0.5	-4	15	-7
7	0.5	-4	15	-5.5

This Series 2 contains 7 choices to be made between two options, option A and option B. Details of Row 1:

Option A: Consider an urn composed of 10 balls of which 5 are yellow and 5 are blue. If a yellow ball was drawn (Prob 50%) then you would get ECU 12.5 and if the drawn ball was blue (Prob 50%) then you would lose ECU 2.

Option B: Consider an urn composed of 10 balls of which 5 are yellow and 5 are blue. If a yellow ball was drawn (Prob 50%) then you would get ECU 15 and if the drawn ball was blue (Prob 50%) then you would lose ECU 10.5.

The question that will be asked about this series is:

- I choose option A for choices 1 to __

- I choose option B for choices __ at 7.

You must choose between option A and option B for each row. Suppose you choose option A for rows 1 to 3, and option B for rows 4 to 7, should then appear respectively in the spaces above the numbers 3 and 4. It is also possible to choose option A for all rows. In this case, the first number will be 7 and write the letter X in the second space. It is also possible to choose option B for all rows. In this case, write the letter X in the first space and the number 1 in the second one.

Two series of choices have just been presented as examples. In total, you will be confronted with 12 different series.

You need to take the time to choose the answers that really fit your preferences. There is no right or wrong answer, just different behaviors to observe. You also have no time constraint, you have all the time you need. At the end of the experiment, two of your choices will be randomly drawn by the computer to determine your payment for the participation to the experiment. This remuneration will correspond to a sum of money. The ECU (Experimental Currency Unit) will be converted at the rate of ECU 200 = €1. As some choices may result in losses, we are now giving you an initial endowment of €17. To this sum will be added: i) the gain or loss that you will realize during the experiment; ii) a show-up fee of €5 to compensate for travel expenses. We will ask you to sign a receipt for the final amount obtained. The payment protocol has been built in such a way that you get a positive final amount regardless of your choice.

For the purposes of the experiment, you must answer all the questions. Your answers will be recorded by the computer network and processed anonymously. The confidentiality of the information contained in this questionnaire is ensured by the anonymity of the respondent. Your answers will therefore remain completely confidential. The results will be presented in synthetic form in scientific publications with scrupulous respect for the anonymity of the answers. The absence of communication between participants is a guarantee of success. We ask you not to discuss with other participants.

During the experience do not hesitate to ask questions to the organizers. They are at your disposal.

C Calculation of the individual CPT parameters according to frame

We distinguish parameters and functions between the *gain* and *loss* frames through index d (d is $+$ in the *gain* frame, d is $-$ in the *loss* frame).

C.1 Calculation of σ^d and γ^d

The following calculations are valid for Series 1 and 2.

C.1.1 Gain frame

Let $A(x_A, p_A; y_A)$ be the LHS lottery and $B^l(x_{B_l}, p_B; y_B)$ the RHS lottery of row l (x_A, y_A, x_{B_l} and y_B are strictly positive $\forall l$, and $0 < p_A < 1$ and $0 < p_B < 1$). The lottery structure is such that only x_{B_l} varies over rows l, while the other lottery attributes remain similar. For a given subject, switching at row s means the following inequalities in terms of prospect value:

$$\begin{cases} PV(A) > PV(B_{s-1}) \\ PV(A) < PV(B_s). \end{cases} \tag{4}$$

From Equation (2) we know that the prospect value of any lottery $(x, p; y)$ is $v^d(y) + \omega^d(p) \cdot (v^d(x) - v^d(y))$ when $xy \geq 0$ and $|x| > |y|$. Equations (1) and (3) give the functional forms for the value and probability weighting functions respectively. Thus, we obtain:

$$(4) \Leftrightarrow \begin{cases} y_A^{\sigma^+} + \exp\left[-(-\ln p_A)^{\gamma^+}\right](x_A^{\sigma^+} - y_A^{\sigma^+}) & > & y_B^{\sigma^+} + \exp\left[-(-\ln p_B)^{\gamma^+}\right](x_{B_{s-1}}^{\sigma^+} - y_B^{\sigma^+}) \\ y_A^{\sigma^+} + \exp\left[-(-\ln p_A)^{\gamma^+}\right](x_A^{\sigma^+} - y_A^{\sigma^+}) & < & y_B^{\sigma^+} + \exp\left[-(-\ln p_B)^{\gamma^+}\right](x_{B_s}^{\sigma^+} - y_B^{\sigma^+}) \end{cases}$$

$$\begin{aligned} \Leftrightarrow y_B^{\sigma^+} + \exp\left[-(-\ln p_B)^{\gamma^+}\right](x_{B_{s-1}}^{\sigma^+} - y_B^{\sigma^+}) < y_A^{\sigma^+} + \exp\left[-(-\ln p_A)^{\gamma^+}\right](x_A^{\sigma^+} - y_A^{\sigma^+}) \\ < y_B^{\sigma^+} + \exp\left[-(-\ln p_B)^{\gamma^+}\right](x_{B_s}^{\sigma^+} - y_B^{\sigma^+}). \end{aligned} \tag{5}$$

C.1.2 Loss frame

Let $C^l(x_{C_l}, p_C; y_C)$ be the LHS lottery of row l and $D(x_D, p_D; y_D)$ the RHS lottery (x_{C_l}, y_C, x_D, and y_D are strictly negative $\forall l$, and $0 < p_C < 1$ and $0 < p_D < 1$). The lottery structure is such that only x_{C_l} varies over rows l. This time, switching at row s means:

$$\begin{cases} PV(C) > PV(D_{s-1}) \\ PV(C) < PV(D_s). \end{cases} \tag{6}$$

As $xy \geq 0$ still, any lottery $(x, p; y)$ has the same prospect value than in the previous section, i.e., $v^d(y) + \omega^d(p) \cdot (v^d(x) - v^d(y))$ when $|x| > |y|$. Equation (1) gives the specific value function for the loss domain $v^d(x) = -\lambda(-x)^{\sigma^d}$ $\forall x < 0$. Thus,

$$(6) \Leftrightarrow \begin{cases} -\lambda(-y_C)^{\sigma^-} + \exp\left[-(-\ln p_C)^{\gamma^-}\right](-\lambda)((-x_{C_{s-1}})^{\sigma^-} - (-y_C)^{\sigma^-}) \\ > -\lambda(-y_D)^{\sigma^-} + \exp\left[-(-\ln p_D)^{\gamma^-}\right](-\lambda)((-x_D)^{\sigma^-} - (-y_D)^{\sigma^-}) \\ -\lambda(-y_C)^{\sigma^-} + \exp\left[-(-\ln p_C)^{\gamma^-}\right](-\lambda)((-x_{C_s})^{\sigma^-}(-y_C)^{\sigma^-}) \\ < -\lambda(-y_D)^{\sigma^-} + \exp\left[-(-\ln p_D)^{\gamma^-}\right](-\lambda)((-x_D)^{\sigma^-} - (-y_D)^{\sigma^-}). \end{cases}$$

Simplifying by $-\lambda$, we obtain:

$$(6) \Leftrightarrow \begin{cases} (-y_C)^{\sigma^-} + \exp\left[-(-\ln p_C)^{\gamma^-}\right]((-x_{C_{s-1}})^{\sigma^-} - (-y_C)^{\sigma^-}) \\ < (-y_D)^{\sigma^-} + \exp\left[-(-\ln p_D)^{\gamma^-}\right]((-x_D)^{\sigma^-} - (-y_D)^{\sigma^-}) \\ (-y_C)^{\sigma^-} + \exp\left[-(-\ln p_C)^{\gamma^-}\right]((-x_{C_s})^{\sigma^-}(-y_C)^{\sigma^-}) \\ > (-y_D)^{\sigma^-} + \exp\left[-(-\ln p_D)^{\gamma^-}\right]((-x_D)^{\sigma^-} - (-y_D)^{\sigma^-}). \end{cases}$$

As $x_{C_l} = -x_{B_l}$, $y_C = -y_B$, $x_D = -x_A$, $y_D = -y_A$, and $p_D = p_A$, $p_C = p_B$, we further obtain:

$$(6) \Leftrightarrow \begin{cases} y_B^{\sigma^-} + \exp\left[-(-\ln p_B)^{\gamma^-}\right](x_{B_{s-1}}^{\sigma^-} - y_B^{\sigma^-}) & < & y_A^{\sigma^-} + \exp\left[-(-\ln p_A)^{\gamma^-}\right](x_A^{\sigma^-} - y_A^{\sigma^-}) \\ y_B^{\sigma^-} + \exp\left[-(-\ln p_B)^{\gamma^-}\right](x_{B_s}^{\sigma^-} - y_B^{\sigma^-}) & > & y_A^{\sigma^-} + \exp\left[-(-\ln p_A)^{\gamma^-}\right](x_A^{\sigma^-} - y_A^{\sigma^-}) \end{cases}$$

$$\begin{aligned} y_B^{\sigma^-} + \exp\left[-(-\ln p_B)^{\gamma^-}\right](x_{B_{s-1}}^{\sigma^-} - y_B^{\sigma^-}) &< y_A^{\sigma^-} + \exp\left[-(-\ln p_A)^{\gamma^-}\right](x_A^{\sigma^-} - y_A^{\sigma^-}) \\ &< y_B^{\sigma^-} + \exp\left[-(-\ln p_B)^{\gamma^-}\right](x_{B_s}^{\sigma^-} - y_B^{\sigma^-}). \end{aligned} \tag{7}$$

We see that (7) is equivalent to (5), meaning that a similar couple of switching points in Series 1 and 2 (s_1, s_2) in the gain domain and in the loss domain leads to a similar couple of parameters(σ^d, γ^d).

C.2 Calculation of λ, λ_{oppos}, and λ_{gen} conditionally to σ^d

The following calculations are valid for Series 3 only, where lotteries mix positive and negative payoffs. We distinguish σ^{d1} and σ^{d2}, depending on which type of payoff the parameter applies to: σ^{d1} applies to gains while σ^{d2} applies to losses.

C.2.1 Gain frame

Let $A^l(x_{A_l}, p; y_{A_l})$ be the LHS lottery and $B^l(x_B, p; y_{B_l})$ the RHS lottery of row l (x_{A_l} and x_B are strictly positive $\forall l$, while y_{A_l} and y_{B_l} are strictly negative $\forall l$, and $p = \frac{1}{2}$). The lottery structure is such that only x_B does *not* vary over rows. A subject switching at row s means:

$$\begin{cases} PV(A_{s-1}) > PV(B_{s-1}) \\ PV(A_s) < PV(B_s). \end{cases} \tag{8}$$

From Equation (2), we know that the prospect value of any binary lottery $(x, p; y)$ is $\omega^d(p) \cdot v^d(x) + \omega^d(p)(1-p) \cdot v^d(y)$ when $xy \leq 0$. As $p = \frac{1}{2}$ it simplifies to $\omega^d(\frac{1}{2}) \cdot (v^d(x) + v^d(y))$. We designate as λ_{12} the loss aversion parameter, which is equivalent to λ, λ_{oppos} or λ_{gen} depending on the hypotheses relative to σ^{d1} and σ^{d2}. We obtain:

$$(8) \Leftrightarrow \begin{cases} \exp[-(-\ln\frac{1}{2})^{\gamma^d}][(x_{A_{s-1}})^{\sigma^{d1}} + (-\lambda_{12})(-y_{A_{s-1}})^{\sigma^{d2}}] \\ > \exp[-(-\ln\frac{1}{2})^{\gamma^d}][(x_{B_{s-1}})^{\sigma^{d1}} + (-\lambda_{12})(-y_{B_{s-1}})^{\sigma^{d}}] \\ \exp[-(-\ln\frac{1}{2})^{\gamma^d}][(x_{A_s})^{\sigma^{d1}} + (-\lambda_{12})(-y_{A_s})^{\sigma^{d2}}] \\ < \exp[-(-\ln\frac{1}{2})^{\gamma^d}][(x_{B_s})^{\sigma^{d1}} + (-\lambda_{12})(-y_{B_s})^{\sigma^{d2}}] \end{cases}$$

$$\Leftrightarrow \begin{cases} (x_{A_{s-1}})^{\sigma^{d1}} - \lambda_{12}(-y_{A_{s-1}})^{\sigma^{d2}} & > & (x_{B_{s-1}})^{\sigma^{d1}} - \lambda_{12}(-y_{B_{s-1}})^{\sigma^{d2}} \\ (x_{A_s})^{\sigma^{d1}} - \lambda_{12}(-y_{A_s})^{\sigma^{d2}} & < & (x_{B_s})^{\sigma^{d1}} - \lambda_{12}(-y_{B_s})^{\sigma^{d2}} \end{cases}$$

$$\Leftrightarrow \begin{cases} \lambda_{12}[(-y_{B_{s-1}})^{\sigma^{d2}} - (-y_{A_{s-1}})^{\sigma^{d2}}] & > & (x_{B_{s-1}})^{\sigma^{d1}} - (x_{A_{s-1}})^{\sigma^{d1}}) \\ \lambda_{12}[(-y_{B_s})^{\sigma^{d2}} - (-y_{A_s})^{\sigma^{d2}}] & < & (x_{B_s})^{\sigma^{d1}} - (x_{A_s})^{\sigma^{d1}}). \end{cases}$$

Last, as y_{A_l} and y_{B_l} are negative payoffs such as $|y_{A_l}| < |y_{B_l}|$, $\sigma^{d1} > 0$, and $\sigma^{d2} > 0$, we can write:

$$(8) \Leftrightarrow \begin{cases} \lambda_{12} & > & \frac{(x_{B_{s-1}})^{\sigma^{d1}} - (x_{A_{s-1}})^{\sigma^{d1}}}{(-y_{B_{s-1}})^{\sigma^{d2}} - (-y_{A_{s-1}})^{\sigma^{d2}}} \\ \lambda_{12} & < & \frac{(x_{B_s})^{\sigma^{d1}} - (x_{A_s})^{\sigma^{d1}}}{(-y_{B_s})^{\sigma^{d2}} - (-y_{A_s})^{\sigma^{d2}}}. \end{cases} \tag{9}$$

Inequations (9) define the bound values of λ when $\sigma^{d1} = \sigma^{d2} = \sigma^+$, λ_{oppos} when $\sigma^{d1} = \sigma^{d2} = \sigma^-$, and λ_{gen} when $\sigma^{d1} = \sigma^+$ and $\sigma^{d2} = \sigma^-$.

C.2.2 Loss frame

Let $C^l(x_C, p; y_{C_l})$ be the LHS lottery and $D^l(x_{D_l}, p; y_{D_l})$ the RHS lottery of row l (x_C and x_{D_l} are strictly negative $\forall l$, while y_{C_l} and y_{D_l} are strictly positive $\forall l$, and $p = \frac{1}{2}$). The lottery structure is such that only x_C does *not* vary over rows. A subject switching at row s means:

$$\begin{cases} PV(C_{s-1}) > PV(D_{s-1}) \\ PV(C_s) < PV(D_s). \end{cases} \tag{10}$$

As $xy \leq 0$ still, any lottery $(x, p; y)$ has the same prospect value than in the previous section, i.e., $\omega^d(\frac{1}{2}) \cdot (v^d(x) + v^d(y))$. Equation (1) gives the specific value function for the loss domain $v^d(x) = -\lambda_{12}(-x)^{\sigma^d}\ \forall x < 0$. We obtain:

$$(10) \Leftrightarrow \begin{cases} \exp[-(-\ln\frac{1}{2})^{\gamma}][(-\lambda)(-x_{C_{s-1}})^{\sigma^{d2}} + (y_{C_{s-1}})^{\sigma^{d1}}] \\ > \exp[-(-\ln\frac{1}{2})^{\gamma}][(-\lambda_{12})(-x_{D_{s-1}})^{\sigma^{d2}} + (y_{D_{s-1}})^{\sigma^{d1}}] \\ \exp[-(-\ln\frac{1}{2})^{\gamma}][(-\lambda)(-x_{C_s})^{\sigma^{d2}} + (y_{C_s})^{\sigma^{d1}}] \\ < \exp[-(-\ln\frac{1}{2})^{\gamma}][(-\lambda_{12})(-x_{D_s})^{\sigma^{d2}} + (y_{D_s})^{\sigma^{d1}}] \end{cases}$$

$$\Leftrightarrow \begin{cases} (y_{C_{s-1}})^{\sigma^{d1}} - \lambda_{12}(-x_{C_{s-1}})^{\sigma^{d2}} & > & (y_{D_{s-1}})^{\sigma^{d1}} - \lambda_{12}(-x_{D_{s-1}})^{\sigma^{d2}} \\ (y_{C_s})^{\sigma^{d1}} - \lambda_{12}(-x_{C_s})^{\sigma^{d2}} & < & (y_{D_s})^{\sigma^{d1}} - \lambda_{12}(-x_{D_s})^{\sigma^{d2}} \end{cases}$$

$$\Leftrightarrow \begin{cases} \lambda[(-x_{D_{s-1}})^{\sigma^{d2}} - (-x_{C_{s-1}})^{\sigma^{d2}}] & > & (y_{D_{s-1}})^{\sigma^{d1}} - (y_{C_{s-1}})^{\sigma^{d1}} \\ \lambda[(-x_{D_s})^{\sigma^{d2}} - (-x_{C_s})^{\sigma^{d2}}] & < & (y_{D_s})^{\sigma^{d1}} - (y_{C_s})^{\sigma^{d1}}. \end{cases}$$

Last, as x_C and x_{D_l} are negative payoffs such as $|x_C| > |x_{D_l}|$, $\sigma^{d1} > 0$, and $\sigma^{d2} > 0$, we can write:

$$(10) \Leftrightarrow \begin{cases} \lambda_{12} & < \frac{(y_{D_{s-1}})^{\sigma^{d1}} - (y_{C_{s-1}})^{\sigma^{d1}}}{(-x_{D_{s-1}})^{\sigma^{d2}} - (-x_{C_{s-1}})^{\sigma^{d2}}} \\ \lambda_{12} & > \frac{(y_{D_s})^{\sigma^{d1}} - (y_{C_s})^{\sigma^{d1}}}{(-x_{D_s})^{\sigma^{d2}} - (-x_{C_s})^{\sigma^{d2}}}. \end{cases} \tag{11}$$

As $x_C = -x_B$, $y_C = -y_B$, $x_D = -x_A$ and $y_D = -y_A$, then Equation (11) can be written as:

$$\left\{ \begin{array}{lll} \lambda_{12} & < & \frac{(-y_{A_{s-1}})^{\sigma^{d1}} - (-y_{B_{s-1}})^{\sigma^{d1}}}{(x_{A_{s-1}})^{\sigma^{d2}} - (x_{B_{s-1}})^{\sigma^{d2}}} \\ \lambda_{12} & > & \frac{(-y_{A_s})^{\sigma^{d1}} - (-y_{B_s})^{\sigma^{d1}}}{(x_{A_s})^{\sigma^{d2}} - (x_{B_s})^{\sigma^{d2}}} \end{array} \right\}$$

$$\Leftrightarrow \left\{ \begin{array}{lll} \lambda_{12} & < & \frac{(-y_{B_{s-1}})^{\sigma^{d1}} - (-y_{A_{s-1}})^{\sigma^{d1}}}{(x_{B_{s-1}})^{\sigma^{d2}} - (x_{A_{s-1}})^{\sigma^{d2}}} \\ \lambda_{12} & > & \frac{(-y_{B_s})^{\sigma^{d1}} - (-y_{A_s})^{\sigma^{d1}}}{(x_{B_s})^{\sigma^{d2}} - (x_{A_s})^{\sigma^{d2}}}. \end{array} \right\} \tag{12}$$

Inequations (12) define the bound values of λ when $\sigma^{d1} = \sigma^{d2} = \sigma^-$, λ_{oppos} when $\sigma^{d1} = \sigma^{d2} = \sigma^+$, and λ_{gen} when $\sigma^{d1} = \sigma^+$ and $\sigma^{d2} = \sigma^-$.

As a last remark, in the special case when $\sigma^{d1} = \sigma^{d2}$, note that the bound values of the loss aversion parameter in the *gain* and in the *loss* frames are linked. Recall that, in the *gain* frame, the bounds of the loss aversion parameter are (Equation (9)):

$$\left\{ \begin{array}{lll} \lambda^G_{12,min} & = & \frac{(x_{B_{s-1}})^{\sigma^{d1}} - (x_{A_{s-1}})^{\sigma^{d1}}}{(-y_{B_{s-1}})^{\sigma^{d2}} - (-y_{A_{s-1}})^{\sigma^{d2}}} \\ \lambda^G_{12,max} & = & \frac{(x_{B_s})^{\sigma^{d1}} - (x_{A_s})^{\sigma^{d1}}}{(-y_{B_s})^{\sigma^{d2}} - (-y_{A_s})^{\sigma^{d2}}}. \end{array} \right\}$$

Comparing with Equation (12) provides the following equivalencies for λ bounds, which also apply to λ_{oppos}:

$$\left\{ \begin{array}{lll} \lambda^L_{max} & = & 1/\lambda^G_{min} \\ \lambda^L_{min} & = & 1/\lambda^G_{max}. \end{array} \right\}$$

D Raw results

Table 16: Distribution of switching points for treatment GLo

Row	Percentage of respondents Series 1	Series 2	Series 3
1	16.8	20.9	8.4
2	0.0	1.6	23.6
3	2.6	1.6	22.0
4	3.1	1.6	15.2
5	8.9	5.2	16.2
6	8.4	1.6	6.8
7	14.1	6.3	0.5
8	8.4	9.4	
9	10.5	3.7	
10	8.9	8.9	
11	6.8	9.4	
12	4.2	10.5	
13	3.1	2.1	
14	2.6	4.7	
never	1.6	12.6	7.3
Total	100.0	100.0	100.0
Number of observations	191	191	191

Table 17: Distribution of switching points for treatment GHi

	Percentage of respondents		
Row	Series 1	Series 2	Series 3
1	20.4	25.1	6.3
2	0.0	2.1	20.9
3	2.6	2.6	14.7
4	5.8	2.6	16.2
5	6.8	5.2	26.7
6	4.7	3.7	4.2
7	14.1	5.2	4.2
8	11.5	4.2	
9	5.8	4.2	
10	9.4	6.3	
11	5.8	7.9	
12	7.9	9.9	
13	2.6	3.7	
14	1.0	2.1	
never	1.6	15.2	6.8
Total	100.0	100.0	100.0
Number of observations	191	191	191

Table 18: Distribution of switching points for treatment LLo

	Percentage of respondents		
Row	Series 1	Series 2	Series 3
1	23.0	18.8	5.8
2	1.6	2.1	29.8
3	5.2	6.3	21.5
4	7.3	5.2	21.5
5	8.9	9.9	9.9
6	5.8	7.3	3.1
7	12.0	9.4	1.0
8	8.4	7.9	
9	6.8	5.8	
10	4.7	7.3	
11	4.2	3.1	
12	3.7	5.2	
13	1.0	1.0	
14	1.6	0.5	
never	5.8	9.9	7.3
Total	100.0	100.0	100.0
Number of observations	191	191	191

Table 19: Distribution of switching points for treatment LHi

	Percentage of respondents		
Row	Series 1	Series 2	Series 3
1	33.0	25.1	4.2
2	2.6	1.0	26.7
3	4.7	4.7	13.1
4	4.7	7.3	24.1
5	6.3	8.4	19.9
6	5.2	5.2	2.6
7	14.7	10.5	0.5
8	8.4	6.3	
9	4.2	8.9	
10	6.3	5.8	
11	2.6	3.1	
12	1.6	3.7	
13	0.5	1.0	
14	0.5	0.0	
never	4.7	8.9	8.9
Total	100.0	100.0	100.0
Number of observations	191	191	191

E Alternative regressions

Table 20: Interval regression of σ^d on several sets of covariates including frame

Covariate	(1) Coef.	Std. Err.	(2) Coef.	Std. Err.
Constant	0.649***	(0.027)	0.626***	(0.146)
Frames:				
Loss	0.120***	(0.034)	0.120***	(0.034)
High	0.041	(0.027)	0.041	(0.027)
Loss×High	0.040	(0.039)	0.040	(0.039)
Socio-demographics:				
Age			0.002	(0.006)
Female			-0.054	(0.037)
Master			0.110**	(0.049)
Economics			-0.027	(0.037)
Constant	-0.973***	(0.038)	-0.986***	(0.039)
Nb. of obs. /clusters	764/191		764/191	
Estimated standard error of the model	0.378		0.373	
AIC	4035.529		4025.424	
BIC	4058.722		4067.171	

Standard errors are clustered at the individual level.
*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
All monetary terms are in euros.
The estimated standard error of the model is comparable to the root mean squared error that would be obtained in an OLS regression.
AIC and BIC stand for Akaike and Schwarz's Bayesian information criteria respectively.

Table 21: Interval regression of γ^d on several sets of covariates including frame

Covariate	(1) Coef.	Std. Err.	(2) Coef.	Std. Err.
Constant	0.634***	(0.021)	0.763***	(0.110)
Frames:				
Loss	0.030	(0.025)	0.030	(0.025)
High	0.008	(0.023)	0.008	(0.023)
Loss×High	-0.033	(0.032)	-0.033	(0.032)
Socio-demographics:				
Age			-0.006	(0.005)
Female			-0.026	(0.029)
Master			0.068*	(0.041)
Economics			0.010	(0.030)
Constant	-241***	(0.032)	-246***	(0.031)
Nb. of obs. /clusters	764/191		764/191	
Estimated standard error of the model	0.289		0.288	
AIC	3752.779		3753.742	
BIC	3775.971		3795.489	

Standard errors are clustered at the individual level.
*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
All monetary terms are in euros.
The estimated standard error of the model is comparable to the root mean squared error that would be obtained in an OLS regression.
AIC and BIC stand for Akaike and Schwarz's Bayesian information criteria respectively.

Table 22: Interval regression of λ on several sets of covariates including frame

Covariate	(1) Coef.	Std. Err.	(2) Coef.	Std. Err.
Constant	2.396***	(0.197)	2.249***	(0.760)
Frames:				
Loss	-323***	(0.228)	-324***	(0.228)
High	0.289	(0.241)	0.289	(0.241)
Loss×High	-0.445	(0.280)	-0.444	(0.280)
Socio-demographics:				
Age			-0.003	(0.032)
Female			0.292*	(0.164)
Master			0.398	(0.283)
Economics			-0.049	(0.168)
Constant	0.757***	(0.077)	0.749***	(0.076)
Nb. of obs. /clusters	764/191		764/191	
Estimated standard error of the model	2.132		2.116	
AIC	3969.289		3968.305	
BIC	3992.481		4010.052	

Standard errors are clustered at the individual level.
*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
All monetary terms are in euros.
The estimated standard error of the model is comparable to the root mean squared error that would be obtained in an OLS regression.
AIC and BIC stand for Akaike and Schwarz's Bayesian information criteria respectively.

Table 23: Log-interval regression of λ on several sets of covariates including frame

Covariate	(1) Coef.	Std. Err.	(2) Coef.	Std. Err.
Constant	0.459***	(0.084)	0.580	(0.383)
Frames:				
Loss	-0.900***	(0.122)	-0.900***	(0.122)
High	0.170*	(0.095)	0.169*	(0.095)
Loss×High	-0.329**	(0.141)	-0.329**	(0.141)
Socio-demographics:				
Age			-0.011	(0.017)
Female			0.092	(0.081)
Master			0.191	(0.127)
Economics			0.069	(0.085)
Constant	0.039	(0.062)	0.036	(0.061)
Nb. of obs. /clusters	764/191		764/191	
Estimated standard error of the model	040		036	
AIC	3204.499		3207.211	
BIC	3227.692		3248.958	

Standard errors are clustered at the individual level.
*, ** and *** stand for significance at the 10, 5 and 1% level respectively.
All monetary terms are in euros.
The estimated standard error of the model is comparable to the root mean squared error that would be obtained in an OLS regression.
AIC and BIC stand for Akaike and Schwarz's Bayesian information criteria respectively.

F Distribution of individual CPT parameter values

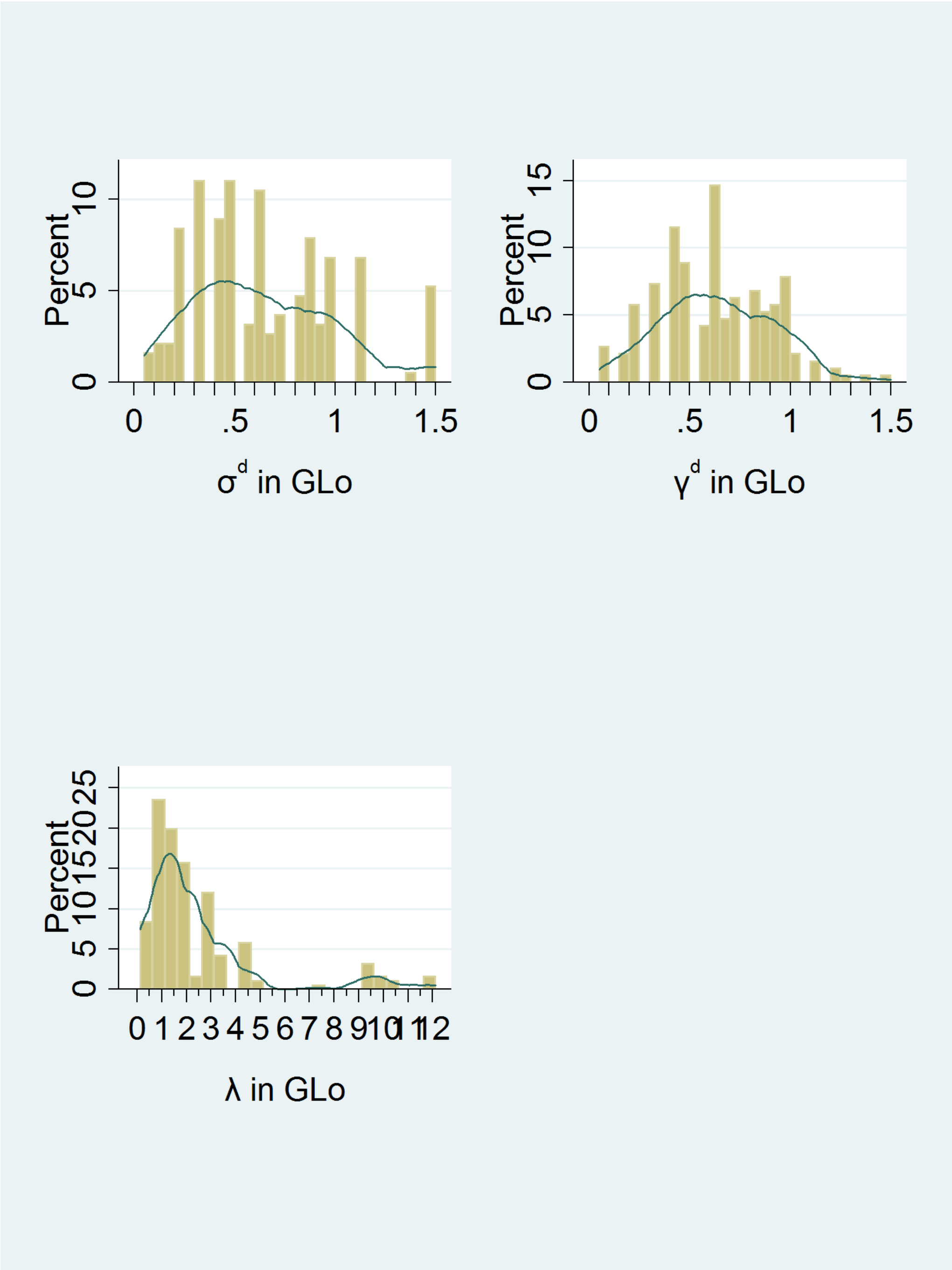

Figure 1: Distribution of individual CPT parameters for baseline treatment GLo.

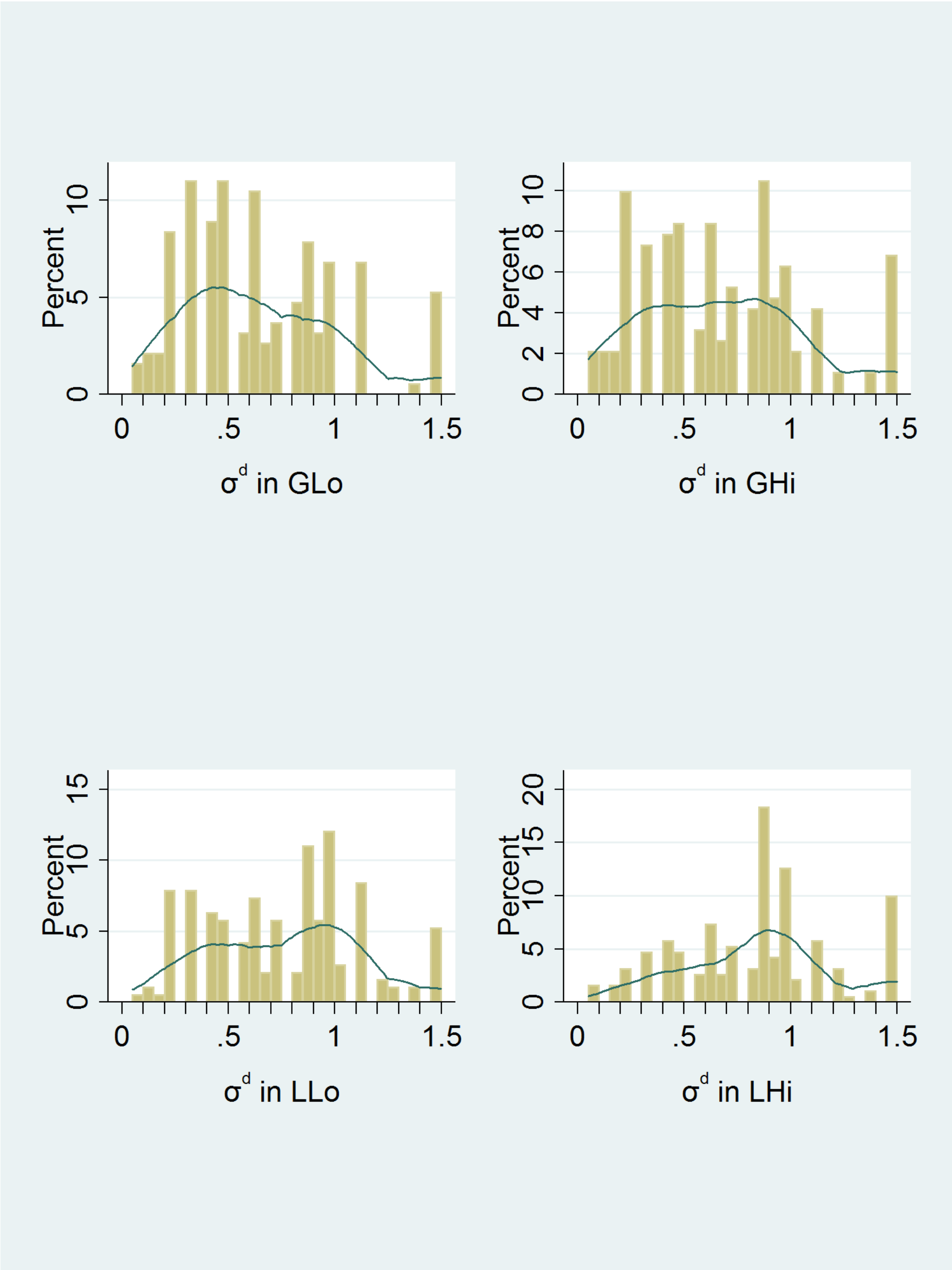

Figure 2: Distribution of individual σ^d parameters over treatments.

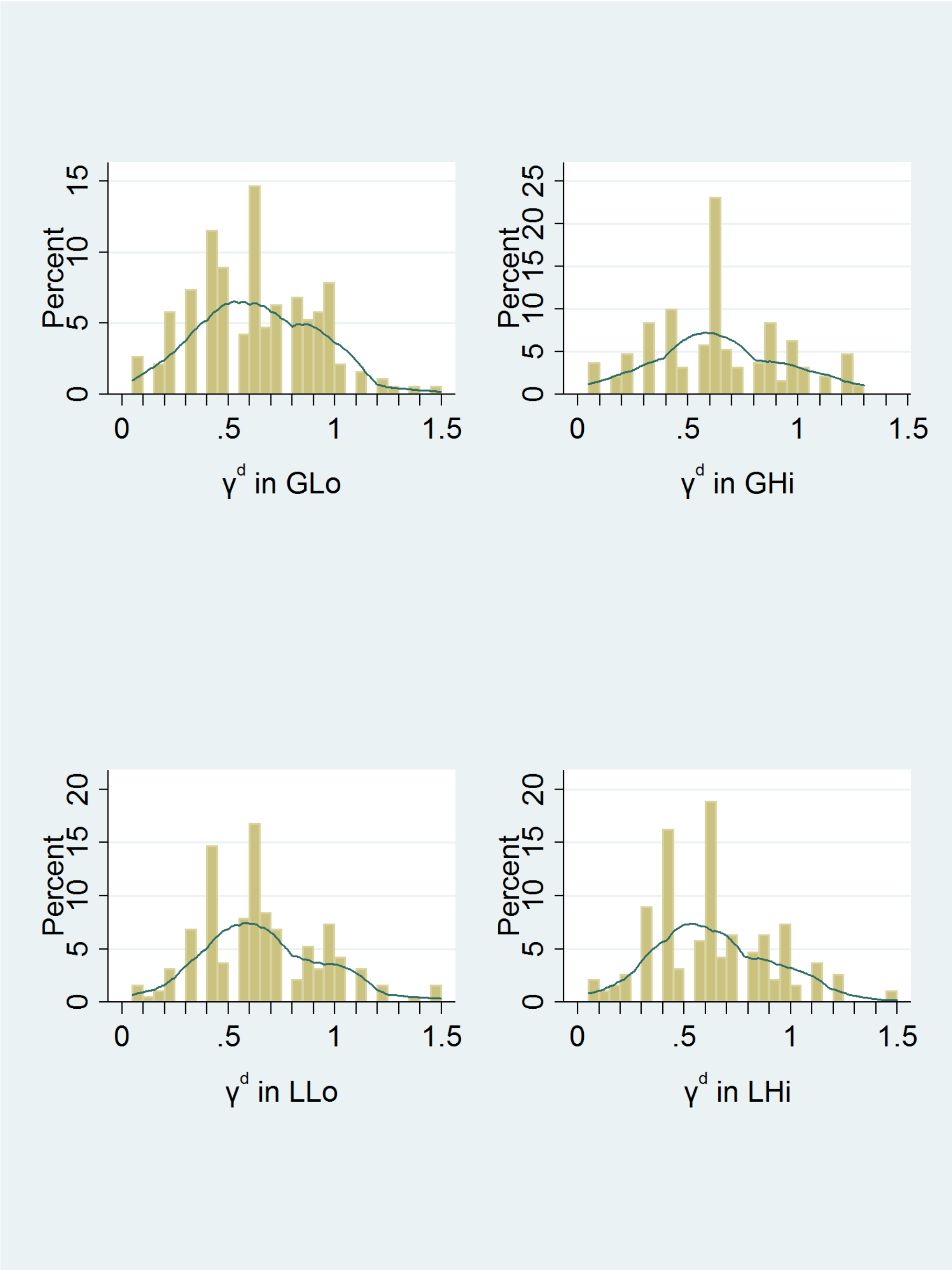

Figure 3: Distribution of individual γ^d parameters over treatments.

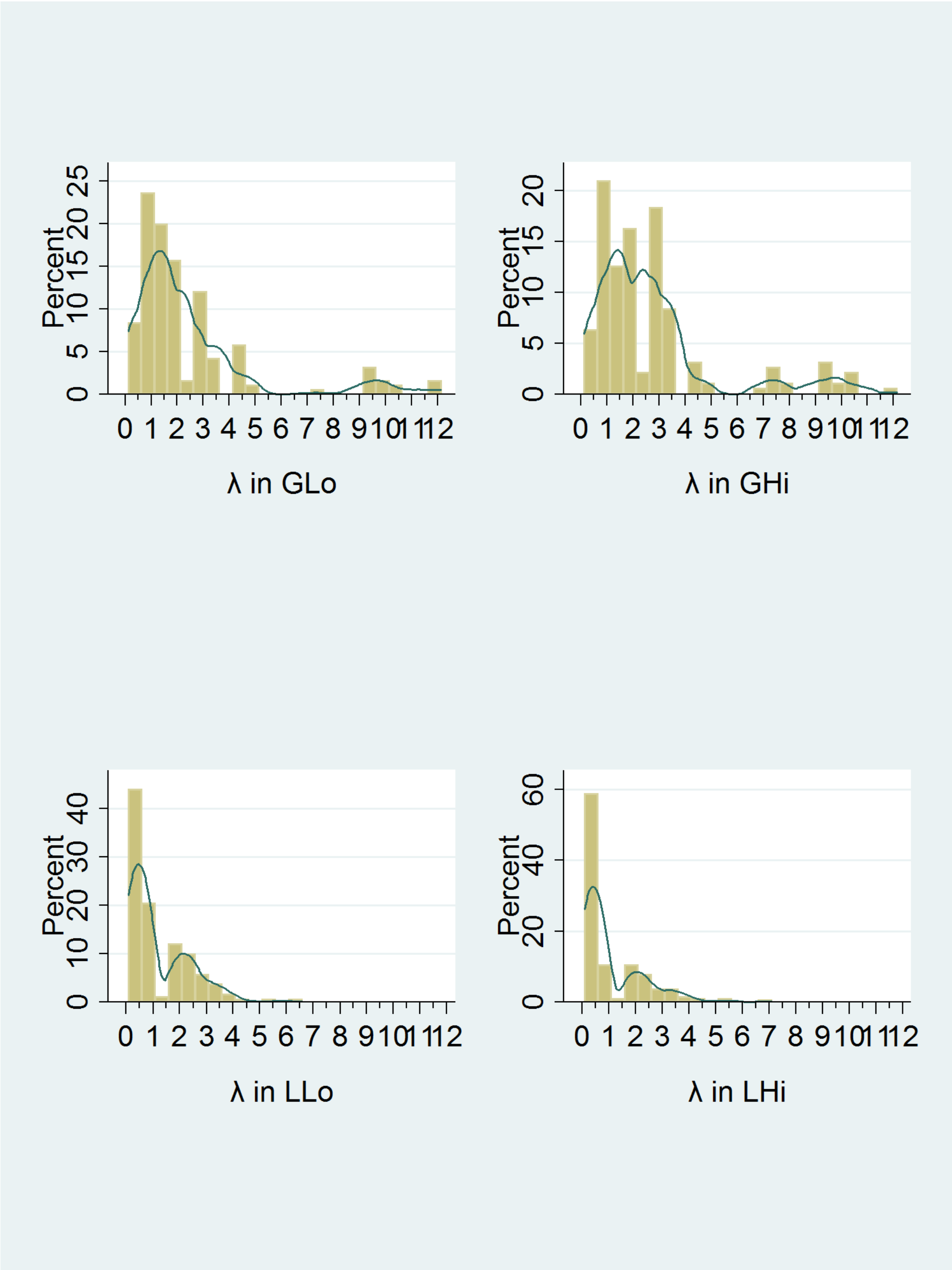

Figure 4: Distribution of individual λ parameters over treatments.

G Distribution of selected individual loss-aversion values

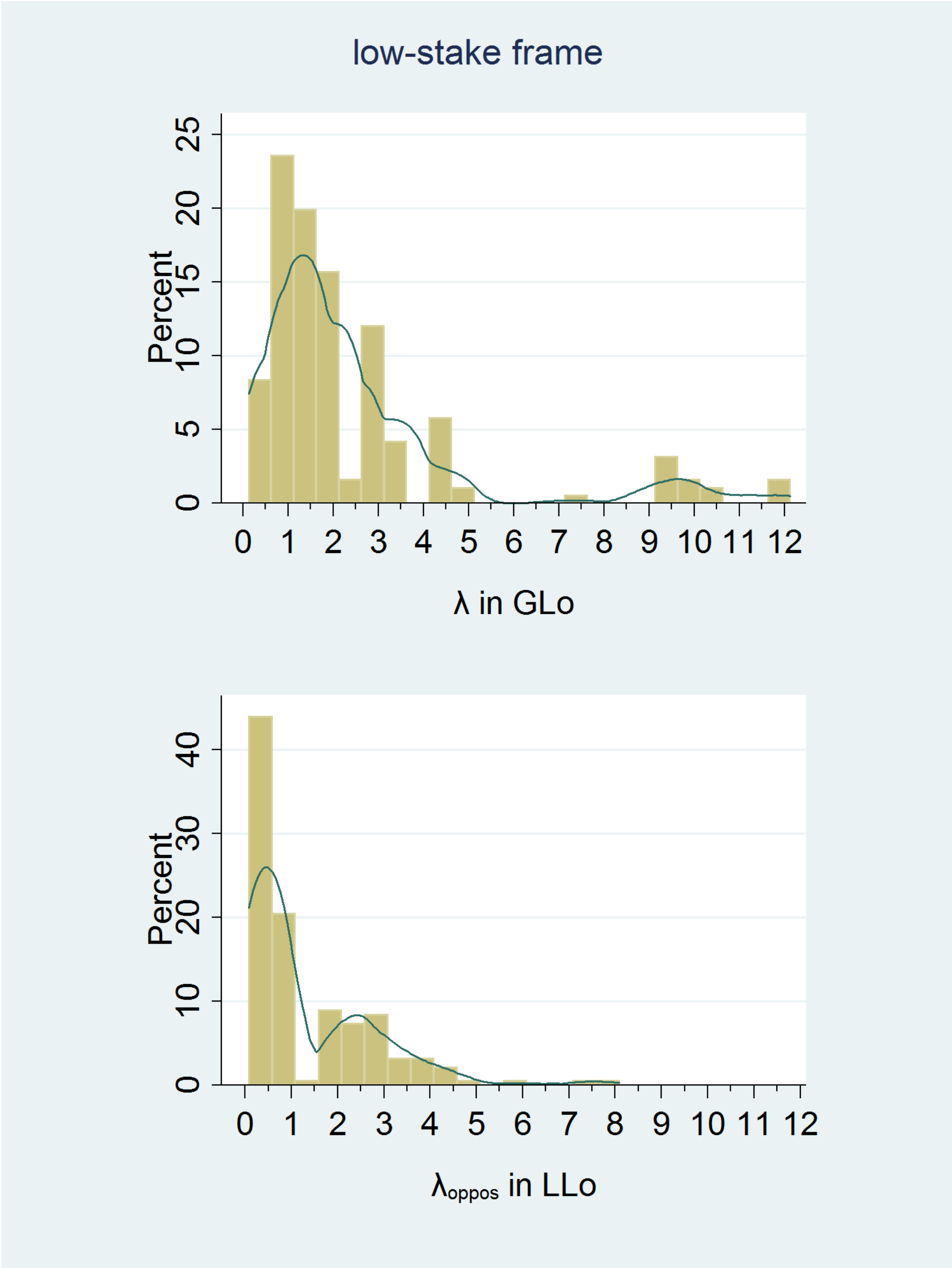

Figure 5: Distribution of individual λ values in baseline GLo and λ_{oppos} values in treatment LLo.

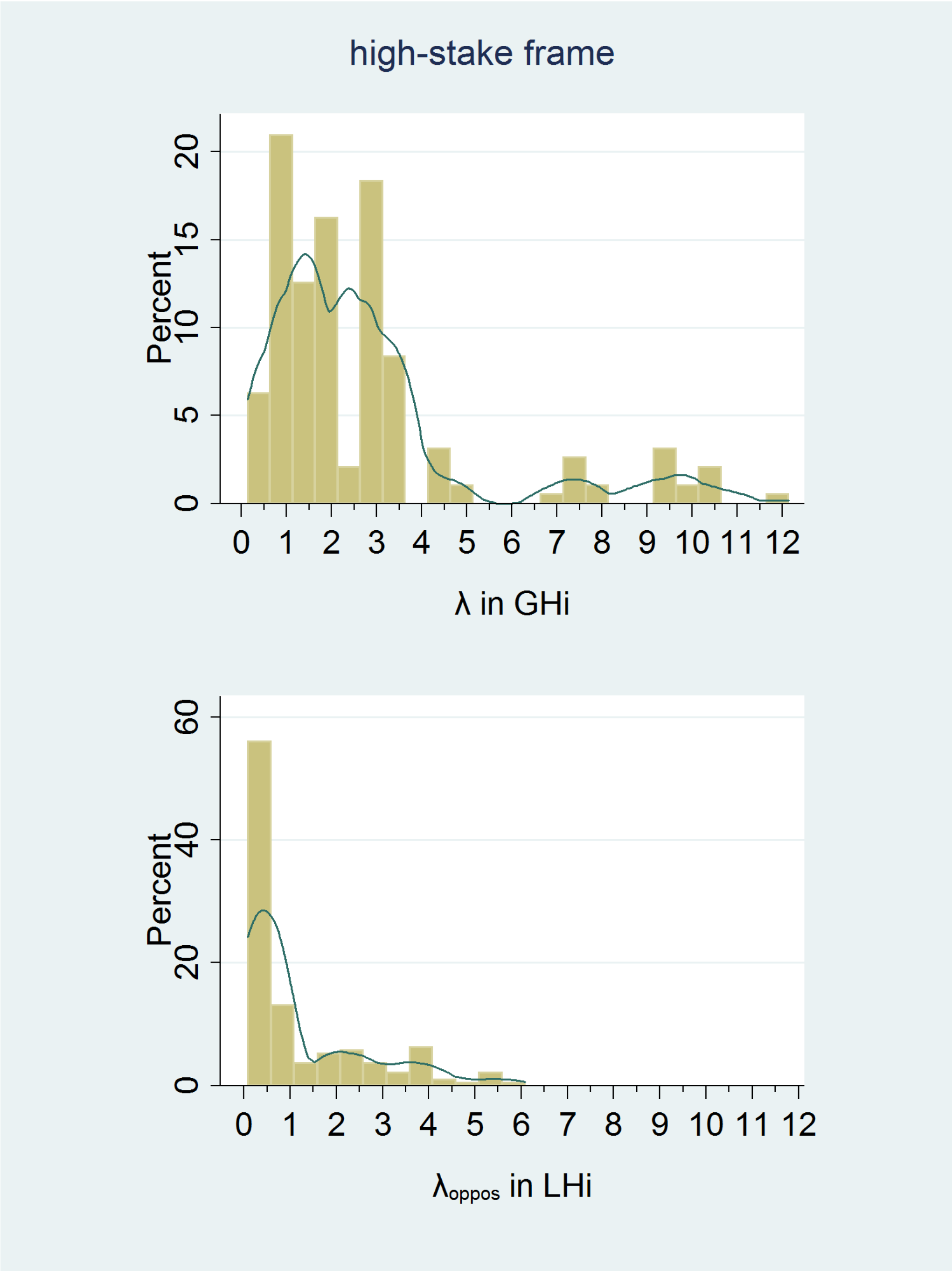

Figure 6: Distribution of individual λ values in treatment GHi and λ_{oppos} values in treatment LHi.