Abstract We let experimental subjects play a social dilemma game and vary whether payoffs are framed as losses or as gains. Subjects cooperate substantially more in the loss domain. We account for this finding with a theory that features noisy equilibrium behavior and reference-dependent risk preferences. We estimate a structural econometric model that incorporates risk preferences into an augmented cognitive hierarchy model. The estimated risk preference parameters are in line with evidence from individual decision-making tasks. Our model fits the experimental data well and is consistent with other puzzling results in the experimental literature on games played over losses. These findings have several important applications, including price competition between firms during recessions or concessions in climate change negotiations.

Keywords: traveller’s dilemma, cognitive hierarchy, prospect theory, diminishing sensitivity, cooperation.

JEL classification: C90, C81, D01, D03, D81.
1 Introduction

We seek to understand whether people cooperate more to avoid losses than they do in the pursuit of gains. A large literature investigates cooperation in social dilemmas in the gain domain and studies of individual decision making reveal some key differences in the choices people make when losses rather than gains are at stake. Yet little is known about cooperative behavior in social dilemmas played over losses.

We provide a theory of cooperation in the loss domain that is based on risk preferences and noisy decision making that predicts that individuals are likely to cooperate more when losses rather than gains are at stake. Noisy behavior implies uncertainty over outcomes and risk preferences mediate how this uncertainty is felt by an individual. We argue that, in a social dilemma with noisy behavior, moving away from the least cooperative outcome entails accepting a downside risk, which is realized when another player happens to undercut or defect. The more risk averse an individual, the less willing she is to take on the downside risk that cooperation entails. Since we know from experiments on individual decision making tasks, starting with (Kahneman and Tversky, 1979), that individuals are risk averse in the gain domain, but risk loving in the loss domain, we expect more cooperation in the latter.

To test our hypothesis we let subjects in a computerized experiment play the traveller’s dilemma (henceforth, TD), a game in which private interests are at odds with public interests. We compare subjects’ strategic behavior when the game is played in the gain domain to subject behavior in an otherwise identical experimental game in which payoffs are framed as losses and find that, as we predict, subjects cooperate substantially more in the loss domain.

Our theory and evidence are a first step in understanding social dilemmas in the loss domain. This is an important endeavor, because examples of strategic interactions in which losses are at stake and that share many of the features of social dilemmas abound: firms compete in prices and need to cover sunk costs before they achieve profitability; a community contributes time or money to a neighborhood watch that is tasked with deterring burglaries; governments decide whether or not to cut carbon emissions in order to avoid losses due to climate change; and two prisoners decide whether or not to defect on one another in order to avoid imprisonment. If we accept that an agent’s reference point is determined by her expectation (as in Koszegi and Rabin 2006 and Ericson and Fuster 2011), even more settings may be captured by a social dilemma in the loss domain, such as competition between firms in a worse than expected economic climate.

Perhaps the most interesting applications of our experimental game are settings in which features of the environment (e.g., consumer demand) put economic actors (e.g., firms) in either the gain domain (e.g., economic boom) or the loss domain (e.g., recession). Then, our treatment provides a comparative static in changes to the economic environment. For example, our finding that agents cooperate more in the loss domain may help explain the survival of inefficient small firms: they are not driven to bankruptcy during recessions because of less fierce competition.

In the TD, two players simultaneously submit claims that may take any value between a

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1 The game’s name derives from the parable with which Basu (1994) originally introduced it: two travellers purchase identical items on a vacation and these items are then damaged by the airline on their flight home. The airline’s reimbursement policy resembles the structure of the game we study.

2 Important experimental studies of strategic interactions in which losses are possible, but that feature different games, include Cachon and Camerer (1996), Camerer and Lovallo (1999) and Delgado, Schotter, Ozbay, and Phelps (2008).
lower bound $l$ and an upper bound $u$. Both players then receive the lower of the two submitted claims. In addition, if the two claims differ, a reward of size $R$ is paid to the player making the lower claim and a penalty of size $R$ is deducted from the payoff of the player making the larger claim. If the claims are the same, both players receive the correspondent amount with neither a reward or a penalty. Thus, if player 1 and 2 choose $x_1$ and $x_2$, respectively, player 1’s payoff is:

$$\pi_1 = \begin{cases} 
x_1 + R & \text{if } x_1 < x_2; \\
x_2 - R & \text{if } x_1 > x_2; \\
x_1 & \text{if } x_1 = x_2.
\end{cases}$$

(1)

For any claim $x_2$, player 1 has an incentive to minimally undercut. Iterated elimination of dominated strategies thus leads to the strategy pair $(x_1 = l, x_2 = l)$, in which both players claim the lower bound of the action space. This is the unique Nash equilibrium, regardless of the size of the reward/penalty parameter $R$.

As a social dilemma and a stylized model of competition, the TD speaks to all of the real world examples of competition in the loss domain we have alluded to. Given our theory, it is furthermore useful to study a game that has a unique Nash equilibrium in pure strategies, as this precludes mixed strategies or failures to coordinate on one of many equilibria from being confounds of noisy behavior. The TD is a close relative of the prisoner’s dilemma and the former can be transformed into the latter by eliminating all actions other than the two highest claims. But despite its simplicity, the TD enables us to observe a richer distribution of actions than a game with a binary action set would. This will prove instrumental in our efforts to disentangling the effect of noise and risk preferences on equilibrium behavior. Finally, insights from previous experiments that use the TD can guide us in the parametrization of our treatments. Appendix A features further discussion of the TD and the literature that has featured it.

We implement two main treatments. In the *gain treatment* subjects are playing for gains and admissible claims lie between $l = 3$ euros and $u = 8$ euros. In the *loss treatment* subjects are given 11 euros for their participation and then stand to lose money with admissible claims ranging from $l = -8$ euros to $u = -3$ euros. In both treatments subjects are allowed to claim any multiple of 0.1 euros between $l$ and $u$ and the penalty reward parameter $R$ takes a value of 3 euros. The two treatments are identical except for the fact that subjects are paid before the experiment in the loss treatment and payoffs could thus be framed as losses. Suppose, for example, player 1 chooses the fully cooperative action, which is 8 in the gain treatment and -3 in the loss treatment, and player 2 undercuts her by 0.1. Then in both the loss and the gain treatment, player 1 leaves the experiment with 4.9 euros and player 2 with 10.9 euros.

Our treatment effect in the loss treatment relies on subjects feeling that leaving the experiment with less than 11 euros counts as a loss and, by design, such framing being absent in the minds of subjects in the gain treatment. If subjects were expected utility maximizers and attached the same value to gains and losses, or if our framing did not have an impact on subjects’ perception of payoffs, then our two treatments would be equivalent and we would not expect to observe a treatment effect.

For the sake of comparability and to highlight that our treatments only differ in the way payoffs are framed and ultimately perceived, we will henceforth think in *net claims*, which we
obtain by adding a treatment’s participation fee to its claim space. That is, we translate claims in the loss treatment to claims in the gain treatment by adding the 11 euros up front participation fee.

We find a large difference in behavior between our two treatments, with average net claims in the loss treatment being significantly higher than in the gain treatment. In particular, net claims in the loss treatment converge to 4.96 euros, which is 41 percent larger than the average claim of 3.51 euros in the gain treatment. Our results thus indicate that framing payoffs as losses leads to a sizable increase in cooperation and a drastic departure from the TD’s Nash equilibrium.

Our explanation for this finding takes off from the assertion that uncertainty pervades human interactions. First, uncertainty may stem from an agent’s inability to always implement her preferred action given her beliefs about the behavior of others. When making a choice, a person may be susceptible to small mistakes, unpredictable surges of emotions, unforeseen cues from the environment or limitations in her cognitive abilities. The assumption of noisy behavior by experimental subjects in a social dilemma certainly possesses some realism: Oppenheimer, Wendel, and Frohlich (2011) find that from round to round, individual behavior in social dilemmas appears to be almost random. Furthermore, models premised on noisy decision making do well at explaining the effect of changing the reward/penalty parameter on subject behavior in the TD (Capra, Goeree, Gomez, and Holt, 1999). Second, uncertainty may arise from the difficulty that heterogeneity in motives and cognitive abilities imposes on perfectly predicting others’ behavior.

We propose a model of our subjects’ behavior that acknowledges both sources of uncertainty. Following Camerer, Ho, and Chong (2004), we assume that players differ in their level of sophistication and that a player of a given level optimizes assuming that her opponent is drawn from a distribution of less sophisticated players. The model solves recursively after specifying the behavior of the least sophisticated players, subjective beliefs of players at each level about the distribution of less sophisticated players and an objective frequency distribution of types, whose mean measures the overall level of sophistication of subjects. At the same time, we also allow for noisy optimizing behavior (Rosenthal, 1989; Stahl and Wilson, 1995; McKelvey and Palfrey, 1995; Rogers, Palfrey, and Camerer, 2009): given her beliefs about the opponent’s behavior, a player has a tendency to best respond, but may sometimes choose suboptimal actions. More specifically, a player’s probability of choosing an action is proportional to its associated expected payoffs and a noise parameter measures how sensitive probabilities are to differences in expected payoffs. Finally we also allow for curvature in a player’s utility function so that we may capture different risk preferences.

We then use maximum likelihood techniques to estimate risk preference, sophistication and noise parameters from the experimental data of our gain and loss treatment separately. We confirm that differences in our parameter estimates correspond to evidence from individual decision making that individuals are 1) risk loving in the loss domain and risk averse in the gain domain and 2) make more mistakes when they make decisions in the loss domain. We therefore establish that risk lovingness and noisy decision making are consistent with the finding that there is more cooperation when our experimental game is played in the loss domain.

It is worth considering whether our results could in fact be driven by other-regarding pref-
erlei (2008), for example, argues that heterogeneous social preferences can account for cooperation in a TD in the gain domain when the reward/punishment parameter is small. Brañas-Garza, Espinosa, and Rey-Biel (2011), instead, document that pro-social considerations are absent from a subject’s ex-post explanation of her own claim choice. Indisputably, explaining our experimental results by force of other-regarding considerations requires a social preference which is asymmetric in the loss and gain domain. More precisely, people would need to be more prosocial in the loss domain. None of the widely studied social preferences, such as inequity aversion or pure altruism, can account for such an asymmetry. Even if we allow for altruism and an appreciation of another player’s loss aversion, for example, any increase in the other-regarding part of one’s utility function due to loss aversion as one moves from the gain into the loss domain would be offset by the loss aversion felt with respect to one’s own payoffs. Furthermore, when experimental subjects play a dictator game in which they are in a position to take from rather than give to another experimental subject and thus inflict a loss on the other subject, their behavior is no more prosocial than in the standard game (List, 2007). It is therefore unlikely that asymmetric prosocial behavior is behind our treatment effect.

In section 7, we describe the experimental results of a treatment in which the reward/punishment parameter is very small. As we shall see, the role of risk preferences diminishes as $R$ gets small, while the effect of noisy behavior becomes more important. This implies that for a small $R$ we may expect slightly less cooperation in the loss domain than in the gain domain, which is what we observe in the experiment. Since there is no reason to expect the effect or social preferences on behavior to diminish with $R$, this evidence favors a theory based on risk preferences. It is important to emphasize, however, that we do not claim that social preferences do not matter in shaping the behavior in our experimental game. Instead, we argue that they are unlikely to directly drive our treatment effect. Heterogeneous social preferences may in fact be present in both of our main treatments and may introduce further uncertainty into the game by making a subject unsure about the other player’s utility function and preferred action. Our treatment effect, however, would still rely on risk preferences.

After introducing two hypotheses based on evidence from individual decision making in section 2, section 3 provides a simple non-strategic demonstration of the mechanism underlying our explanation. We then describe our experimental design and results in sections 4 and 5, respectively. Section 6 introduces a formal model and our estimation procedure. Sections 7 and 8 flesh out further implications of our theory and test its robustness. Section 9 describes some further treatments tailored to assess the role of concurrent explanations for our main treatment effect. Section 10 concludes.

2 Evidence from individual decision making and hypotheses

One of the central tenets of prospect theory (Kahneman and Tversky, 1979) holds that individuals are risk loving over losses and risk averse over gains. Such diminishing sensitivity to changes in payoffs as one moves further away from one’s reference point in either direction may be modeled by a utility function that is concave in the gain domain and convex in loss domain. Diminishing sensitivity implies that an individual is likely to reject a lottery in which she may either win 10 euros or zero with equal probability in favor of a sure gain of 5 euros, but that
she is unlikely to reject a gamble in which she may either lose 10 euros or nothing with equal probability in favor of losing 5 euros for sure. Using such simple lotteries, diminishing sensitivity has been documented in individual decision making of experimental subjects, most notably in Kahneman and Tversky (1979), and the general population (Boom, Van Praag, and Van de Kuilen, 2010; Tymula, Glimcher, Levy, and Belmaker, 2012). Camerer (2003) provides some examples from the field. For instance, consider the end-of-the-day effect in racetrack betting (McGlothlin, 1956; Ali, 1977), whereby bettors shift their bets towards longshots towards the end of the day. Since the majority of bettors are in the minus after a day of betting, risk lovingness in the loss domain provides a compelling explanation for the phenomenon.

In section 6 we propose a model to identify the risk preferences of our experimental subjects from the experimental data. We may then test the hypothesis that our findings are consistent with diminishing sensitivity by deriving the estimated risk preference parameters that for each treatment yield the closest fit between our theoretical distribution of claims and the one observed in the experiment. In particular, we use the following functional form for the utility function:

\[ U(z) = z^\alpha, \]  

where \( z \) is the material payoff of an individual. Then, \( \alpha \) is a measure of risk-lovingness. The hypothesis lays out what diminishing sensitivity implies for our parameter estimates:

**Hypothesis 1a:** \( \alpha_G < 1 \) and \( \alpha_L > 1 \), i.e. subjects are risk averse in the gain treatment (denoted by subscript \( G \)) and risk loving in the loss treatment (denoted by subscript \( L \)).

In a review of studies that estimate the curvature of individual’s utility functions in the gain and loss domain, Boom, Van Praag, and Van de Kuilen (2010) note that 9 out of 11 studies find risk loving preferences in the loss domain and risk aversion in the gain domain. Our explanation, however, merely relies on subjects being less risk averse or more risk loving in the loss compared to the gain domain. We thus also test the following, weaker hypothesis:

**Hypothesis 1b:** \( \alpha_G < \alpha_L \).

Note that a confirmation of hypothesis 1a implies that hypothesis 1b holds. We do not know how risk preferences elicited in individual decision making translate into strategic situations. One may, for example imagine a competition effect, whereby subjects in strategic interactions are more risk loving than in individual decision making tasks simply because they are playing a game. While such a mechanism could upset the validity of hypothesis 1a, the risk aversion differential of hypothesis 1b could persist.

Our model also allows us to estimate a noise parameter \( \mu \), which captures the accuracy with which agents are able to implement their preferences. A higher \( \mu \) is synonymous with more noisy decision making or with individual’s making larger or more mistakes in their choices. Looking at a sample of over 8000 individual choices, Tymula, Glimcher, Levy, and Belmaker (2012) find that stochastic dominance violations in choices between simple lotteries and certain payoffs are substantially more likely in the loss domain. In their paper, a subject is said to make a mistake or violate stochastic dominance, if in the gain domain she chooses a lottery of the form "you may win \( x \) with probability \( p < 1 \) and zero otherwise" over a certain payoff of \( x \), or if in the loss domain she chooses a certain loss of \( x \) over a lottery of the form "you may lose \( x \) with probability
In the gain domain, 8.9 percent of choices reflect such violations of stochastic dominance. In the loss domain, this percentage rises to 14.5 percent. Thus, we expect the following relationship between our estimated noise parameters, with subscripts once again denoting the treatment:

**Hypothesis 2**: $\mu_G < \mu_L$, i.e. people are more likely to make mistakes in the loss domain.

In our discussion of prospect theory’s diminishing sensitivity, we have thus far ignored its more prominent cousin, loss aversion. Loss aversion refers to the disutility from a loss being larger than the utility from an equivalent gain. Since our loss treatment is firmly embedded in the loss domain, with no possibility of payoffs in the gain domain, loss aversion that primarily governs how losses and gains are compared, should not have a direct effect. The idea that losses loom larger than gains, may, however, impact on the prevalence of mistakes by raising the psychological stakes of our game. Hypothesis 2 is consistent with experimental evidence by Ariely, Gneezy, Loewenstein, and Mazar (2009) that suggests that individual’s performance in tasks that draw on a diversity of skills including motor skills, memory and creativity may deteriorate in the face of increasing monetary incentives.\(^3\)

### 3 An intuitive example

Since the cognitive hierarchies model we adopt cannot be solved for analytically, it is difficult to extract an intuition for the precise mechanism that drives our results from it. To gain some understanding of how the structure of the TD implies an unambiguous effect of risk preferences on behavior, it is useful to translate the strategic interaction we study into a non-strategic decision problem.

Suppose player 1, a fully rational and self-interested agent whose utility is given by (2), is playing the TD outlined in the introduction with player 2, a non-strategic agent who plays the TD Nash equilibrium strategy $x_2 = 3$ with probability $(1 - p) \in [0, 1]$ and $x_2 = m + 0.1$ with complementary probability, with $m > 3$. We might interpret $p$ as the probability of a mistake, or as a measure of player 2’s sophistication. Faced with such a player, player 1 only has two sensible choices: she may either play her Nash strategy $x_1 = 3$, or she may try to capitalize from player 2’s mistake by minimally undercutting, i.e. by playing $x_1 = m$. Given the TD’s payoffs, player 1 finds it optimal to play $x_1 = m$ if and only if

\[
(1 - p)(3 - R) + p(m + R) \geq (1 - p)3 + p(3 + R). 
\]

The left-hand side of (3) is equal to player 1’s expected payoff from playing $x_1 = m$, while the right-hand side is equal to her payoff from playing $x_1 = 3$. When she plays $x_1 = m$, player 1 will find herself undercut by player 2 with probability $1 - p$, in which case she receives the lower of the two claims, which is equal to 3, and she has to pay a punishment equal to $R$. If player 2 makes a mistake, on the other hand, which happens with probability $p$, player 1 has the lower of the two claims and will thus not only receive $m$, but also a reward of $R$. When player 1 plays

\(^3\)Ariely, Gneezy, Loewenstein, and Mazar (2009) also provide a review of other studies that are in line with their findings
$x_1 = 3$, she receives a payoff of 3 if player 2 plays $x_1 = 3$ as well, since in the case of similar
claims no punishment is payable and no reward received. With probability $1 - p$, however, player
2 makes a mistake and a payoff of $3 + R$ is left to player 1, who has the lower claim in this case.

As a preliminary remark, note that the strategic player willingness to cooperate is decreasing
in the level of sophistication of her opponent.

**Claim 1.** There exists a unique $p^* \in (0,1)$ such that player 1 finds it optimal to deviate from
$x_1 = 3$ if and only if $p \geq p^*$.

**Proof.** The difference between the lhs and rhs of equation (3) is increasing in $p$, positive in $p = 1$
and negative in $p = 0$. The result follows. The exact value of $p^*$ is given by

$$p^* = \frac{3^\alpha - (3 - R)^\alpha}{3^\alpha - (3 - R)^\alpha + (m + R)^\alpha - (3 + R)^\alpha} \quad (4)$$

Besides, when player 1 deviates from $x_1 = 3$ to $x_1 = m$, she risks being undercut in situations
in which player 2 does not make a mistake. This downside risk associated with moving away
from the Nash allocation is a key feature of social dilemmas in uncertain environments and,
for instance, it would also be present if player 1 was choosing to defect or cooperate in a
prisoner’s dilemma. Crucially, we can see that the spread of payoffs is higher on the left-hand
side of equation (3) than on the right-hand side. Put differently, the minimum and maximum
payoff from playing $x_1 = m$ are respectively lower and higher than the minimum and maximum
payoff from playing $x_1 = 3$. Player 1 therefore has to decide between two gambles with equal
probabilities but different variances. A risk loving player 1 is more comfortable with a higher
variance in payoffs and thus more comfortable with playing $x_1 = m$ than a risk averse individual.
Since an individual is more risk loving in the loss domain, framing payoffs as losses, should result
in more cooperation, if players make mistakes like player 2 in our example.

To illustrate this point more formally, we are interested in how $p^*$ is affected by player 1’s risk
preferences. A parameter shift that decreases $p^*$ is said to weakly increase cooperation, because
it increases the set of $p$s for which player 1 will play $m$. We establish the following result in the
case of our main treatment with $R = 3$.

**Claim 2.** When $R = 3$, cooperation weakly increases with risk-lovingness, i.e.:

$$\frac{dp^*|_{R=3}}{d\alpha} < 0$$

**Proof.** Taking the first derivative of $p^*|_{R=3}$ w.r.t $\alpha$ yields

$$\frac{dp^*|_{R=3}}{d\alpha} = \frac{\frac{d}{d\alpha}((m + R)^\alpha - (3 + R)^\alpha) - \frac{d((m + R)^\alpha - (3 + R)^\alpha)}{d\alpha} 3^\alpha}{(3^\alpha + (m + R)^\alpha - (3 + R)^\alpha)^2}$$

Since the denominator of the above expression is always positive, the numerator tells us that
$\frac{dp^*}{d\alpha} < 0$ if and only if

$$-3^\alpha(m + R)^\alpha(ln(m + R) - ln(3)) + 3^\alpha(3 + R)^\alpha(ln(3 + R) - ln(3)) < 0,$$
which is clearly satisfied for all parameter values.

The likelihood that we observe apparent cooperation in the current scenario is therefore increasing in player 1’s risk aversion. We now establish what happens to the effect of risk preferences on cooperation when the reward/punishment parameter becomes small.

**Claim 3.** As \( R \) becomes small, the impact of risk preferences on cooperation disappears, i.e.:

\[
\lim_{R \to 0} \left( \frac{dp^*}{d\alpha} \right) = 0
\]

**Proof.** Differentiating (4) w.r.t. \( \alpha \) yields

\[
\frac{dp^*}{d\alpha} = \frac{d((3-R)^\alpha - (3+R)^\alpha)}{d\alpha} \frac{d((m+R)^\alpha - (3+R)^\alpha)}{d\alpha} \frac{d(\ln(m+R) - \ln(3-R))}{d\alpha}
\]

As \( R \) approaches zero, the denominator of \( \frac{dp^*}{d\alpha} \) converges to a positive constant, since \( m > 3 \) by assumption. The numerator of (5) may be rewritten as

\[
A = (m+R)^\alpha \left[ (3-R)^\alpha (\ln(m+R) - \ln(3-R)) - 3^\alpha (\ln(m+R) - \ln(3)) \right]
\]

\[
B = (3+R)^\alpha \left[ (3-R)^\alpha (\ln(3+R) - \ln(3-R)) - 3^\alpha (\ln(3+R) - \ln(3)) \right]
\]

Now it is easy to see that both \( A \) and \( B \) converge to zero as \( R \) approaches zero.

We therefore expect the differences between behavior in the loss domain and the gain domain that stem from the risk preference mechanism we emphasize to arise primarily in high stakes situations, i.e. situations in which raising one’s claim carries a sizable downside risk because potential punishment and forgone reward are high. For very low \( R \) we expect the size and frequency of mistakes to play a larger role than risk preferences, an assertion we shall test in section 7, which provides a robustness check for our proposed explanation.

4 Design

Subjects participated in one of two main treatments: a gain treatment or a loss treatment. Subjects in the gain treatment were given no participation fee and played the TD described in the introduction with a claims range between 3 and 8. In the loss treatment, subjects were given a participation fee of 11 euros and admissible claims lay between -3 and -8. Letting subjects play the experimental game in units of real currency rather than experimental currency enabled us to pay the 11 euros fee in cash upon subjects’ arrival, while instructing them that some of it may be lost during the experiment, in which case they would have to pay us back the money lost. Letting subjects hold on to their participation fee during the experiment might help in making them feel that any amount they paid back to the experimenter was a loss.

We set the reward/penalty parameter at 3 euros in both treatments and allowed any multiple of 0.1 euros between the lower and upper bound as admissible claim. We introduced the TD abstractly, i.e. without a parable. Subjects in both treatments played 15 rounds of the one-shot
game with a new partner each time. The first 5 rounds correspond to the main treatments above, while the last 10 rounds of each session were robustness checks that we discuss in section 7. At the end of the experiment we paid subjects for one randomly selected period. Random payment of one period avoids wealth effects.

We conducted six sessions of our computerized experiment at the Toulouse School of Economics Experimental Laboratory between March and September 2012, and no pilot sessions. We had 34 subjects participating in the two sessions that constitute the gain treatment and 32 subjects participating in the two session that constitute the loss treatment. The two remaining sessions were a further robustness check that we will also describe in section 7. Sessions lasted an average of 30 minutes, including all instructions and payment. On average, a subject earned 6.30 euros. All of our subjects were students at the Toulouse School of Economics. The majority had not previously participated in experiments. Most of them were undergraduate students and a few were enrolled in a Masters program. The experiment was run in French and programmed in z-Tree (Fischbacher, 2007).

5 Results

Figure 1 depicts the (smoothed) empirical distribution of net claims in the gain and loss treatment pooling all observations from the first 5 periods. Recall that for the sake of comparability we derive net claims by adding the participation fee of 11 euros to claims in the loss treatment, and from now on we will omit the word "net" whenever doing so generates no confusion.

![Fig. 1 Distribution of net claims](image)

The distribution of claims in the gain treatment has most of its mass concentrated around the Nash equilibrium, while the distribution in the loss treatment is more dispersed, with a single peak around the center of the action set and a higher mean. Note also that the mass around the most cooperative action (i.e. 8) is fairly similar. Applying the Wilcoxon rank sum test, we find that the difference in means of the two distributions is significant at the 1 percent level.

Figure 2 breaks down this difference by round, illustrating the mean claim in each period.

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4 The robustness checks were introduced to subjects after period 5 and hence, would not have affected subjects’ expectations or choices in the initial 5 periods.

5 Instructions for the loss treatment can be found in appendix C.
Average claims are consistently higher in the loss treatment than in the gain treatment. Again, a Wilcoxon rank sum test indicates that the difference in means is significant at the 1 percent level in each period. In period 5, the average claim in the loss treatment is roughly 4.96 euros, while the average net claim in the gain treatment is 3.51 euros. By framing payoffs as losses we have therefore increased average claims and hence, cooperation, by as much as 41 percent. Average claims in both treatments are highest in the initial round and decrease thereafter. Capra, Goeree, Gomez, and Holt (1999) explain this decreasing pattern of claims by alluding to a process of learning and place the most emphasis on the interpretation of actions in later periods. Alternatively, one may argue that looking at the first period is more instructive because a subject’s actions have not yet been contaminated by the reinforcement inherent in the disappointment of having been undercut or the joy of undercutting someone. In light of these two perspectives, it is important to note once more that average claims in the loss treatment lie above those in the gain treatment in all periods and that the distance between claims is fairly constant as rounds progress.

6 Diminishing sensitivity in a cognitive hierarchy model

We adopt a modified version of the cognitive hierarchy model by Camerer, Ho, and Chong (2004), to whom we refer for a detailed description of its properties. Subjects belong to different steps of sophistication, indexed by an integer $k$. Steps in the population follow a Poisson distribution parametrized by $t$, both the distribution’s mean and variance. Each step $k > 0$ player myopically believes to be the most sophisticated player and, in particular, that the distribution of other players follows a Poisson distribution parametrized by $t$ but truncated at $k - 1$. Thus, if we denote by $g_k(h)$ a step $k > 0$ player’s belief about the frequency of step $h < k$ players, we have:

$$g_k(h) = \frac{e^{-t}t^h}{h!} \sum_{l=0}^{k-1} \frac{e^{-t}t^l}{l!}.$$

While Camerer, Ho, and Chong (2004) assume that each step $k > 0$ player maximizes her

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6Our decision to let subjects play our main treatment for 5 periods has been informed by their finding that the average claim stabilizes at around 5 periods.
expected utility given her beliefs, we allow for noisy optimizing behavior\(^7\) (Rosenthal, 1989; Stahl and Wilson, 1995; McKelvey and Palfrey, 1995; Rogers, Palfrey, and Camerer, 2009). In particular, a logistic decision rule specifies that a player chooses each action \(x\) in her action set \(X\) with probability:

\[
P(x) = \frac{\exp \left( \frac{U(x)}{\mu} \right)}{\sum_{q \in X} \exp \left( \frac{U(q)}{\mu} \right)}.
\]

\(U(x)\) represents the player’s expected utility from action \(x\) and \(\mu\) is a parameter that measures the sensitivity of choice probabilities to payoffs. As \(\mu\) gets large, a player puts equal probability on all actions and hence plays randomly. As \(\mu\) converges to zero, instead, a player behaves as an expected utility maximizer. \(\mu\) is constant across types and common knowledge.\(^8\) Each step \(k > 0\) player computes \(U(x)\) in (7) from her beliefs specified in (6) anticipating that each step \(h < k\) behaves in a similar fashion. Thus, the model solves recursively after specifying the behavior of step 0 players. Camerer, Ho, and Chong (2004) impose that step 0 players randomize uniformly over the action set. Instead, we adopt the more flexible specification that a fraction \(1 - w\) does so, while the remaining fraction \(w\) play the highest action.\(^9\)

With the exception of Goeree, Holt, and Palfrey (2002) and Goeree, Holt, and Palfrey (2003), experimental papers that make use of models of noisy strategic interactions assume that players are risk neutral and simply replace \(U(x)\) with the expected material payoff associated with action \(x\). Since our explanation builds on the idea that risk attitudes over gains and losses might differ, we adopt the more general functional form \(U(z) = n(\alpha)z^\alpha\), where \(z\) represents the material payoff and \(n(\alpha)\) is a normalization factor that sets the minimal and maximal utility to 0 and 1 respectively. This normalization was introduced by Goeree, Holt, and Palfrey (2002) as a way to separately identify risk and noise parameters.\(^10\) Given the payoffs structure of the TD, and that we perform all of our estimations using net claims,\(^11\) the normalization takes the form \(n(\alpha) \equiv 1/(10.9^\alpha)\).

For any values of \(t, \alpha, \mu\) and \(w\), the model solves numerically. In particular, it nests the model of Camerer, Ho, and Chong (2004), which obtains for \(\alpha = 1, \mu = 0\) and \(w = 0\). We solve the model for a large set of combinations of parameters and, by maximum likelihood techniques, check which combination best replicates the observed distribution of our subjects’ actions. The downward trends in figure 2 might be interpreted as evidence of learning by subjects. We expect learning to have an impact on the per period estimates of \(t, \mu\) and \(w\) and, in particular, that \(w\) and \(\mu\) should decrease and \(t\) increase. Conversely, there is no reason to expect \(\alpha\) to change across periods. Thus, we estimate the model both separately in each period and jointly over

\(^7\)When values of \(t\) are in line with estimates from the literature, the model of Camerer, Ho, and Chong (2004) assigns non-negligible probability only to players up to step 4 or 5. Because step \(k > 0\) players perfectly optimize, overall they use only a small set of actions. Thus, the model attributes actions outside this set to step 0 players, who are assumed to randomize their play. This approach is not very convenient for games with a large action set and in which subjects’ observed play is fairly dispersed, as our TD.

\(^8\)See Rogers, Palfrey, and Camerer (2009) for a model which relaxes both assumptions.

\(^9\)Such an action is not rationalizable but, as one can see in figure 1, it seems somehow salient. Also Arad and Rubinstein (2012) adopt a similar specification for the behavior of level 0 players in a game which bares some similarities with the TD and has a salient action.

\(^10\) Equation (7) is not invariant to the scale of payoffs. For instance, premultiplying \(U(x)\) by a constant is equivalent to a correspondent decrease in \(\mu\). Changes in \(\alpha\) imply not only a variation in the curvature of the utility function but also in the magnitude of payoffs. The normalization controls for this scale effect. Note that the normalization would also cancel out any loss aversion parameter one may think of as premultiplying the utility in the loss treatment.

\(^11\)This controls for the fact that equation (7) is also not invariant to shifts in the claim space.
the five periods under the restriction that $\alpha$ is constant. Estimations obtained with the two methodologies yield fairly similar result, which is encouraging. Table 1 reports estimates of the joint model, while estimates of the separate model are in table 2 in section B of the appendix. Both tables also contain estimates under the risk-neutrality restriction ($\alpha = 1$).

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Estimates of $\alpha$ confirm the qualitative predictions of section 2 about the curvature of the utility function in the gain and loss domain. Besides, using a likelihood-ratio test, we are able to reject risk-neutrality in favor of risk-lovingness in the loss treatment at the 1 percent significance level. In the gain treatment, we reject risk neutrality in favor of risk aversion at the 5 percent level. Overall, table 1 and 2 suggest that the risk-neutrality restriction usually imposed in the literature might be justified for games played in the gain domain, but less so for games played over losses.

As expected, estimates of $w$ decrease across periods in both treatments. Estimates of $\mu$ decrease in the gain treatment but not in the loss treatment, and overall, are larger in the latter. Thus, evidence seems to corroborate also the hypothesis that behavior is noisier when losses are at stake. At the same time, estimates of $t$ show no clear pattern. Because $t$ measures subjects’ sophistication, one might argue it is also a measure of noise. In this view, the model lacks a precise metric for a formal test. Moreover, we suspect the model might fail to perfectly identify $t$ and $\mu$ separately. This might call for further identifying restrictions, such as imposing that the distributions of steps do not vary over periods (i.e., a constant $t$).
In periods 6 through 10 of both the loss and the gain treatment, we let subjects play the TD with \( R = 0.5 \). First of all, this allows us to test whether subjects in our main treatments behave in line with previous studies, that is, whether a lower reward/punishment parameter leads to higher average claims (e.g. Capra, Goeree, Gomez, and Holt (1999)). In addition, the \( R = 0.5 \) provides a testing ground for the model we estimated in the previous section. In a sense, we are able to evaluate its accuracy in out-of-sample forecasts. Finally, we can simulate the model with \( R = 0.5 \) and re-estimate all parameters.

Figure 3 depicts the observed (smoothed) distribution of claims from periods 6 through 10 of the gain and loss treatment. Average net claims are 6.55 and 5.91 respectively. We do not report per-period averages as, differently from the \( R = 3 \) case, they are fairly stable over periods. In both treatments, we confirm previous findings that reducing \( R \) increases average claims. More interestingly, observed claims are higher in the gain treatment than in the loss treatment.

To explain this finding, recall from section 3 that the effect of risk preferences on behavior becomes small as \( R \) shrinks. Thus, noise takes the center stage. As estimates of the previous section indicate, noise is higher in the loss domain. Thus, the model may well give rise to less cooperation than in the gain treatment. We know that for constant noise, a decrease in \( R \) leads to an increase in average claims (Capra, Goeree, Gomez, and Holt, 1999). But for high average claims, the now dominant noise effect flattens the theoretical distribution of actions and thereby pushes average predicted claims away from the upper bound toward the middle of the action distribution. Indeed, using the parameter estimates of period 5 in table 1, we find that when \( R = 0.5 \) our model predicts average net claims of 6.89 in the gain treatment and 5.6 in the loss treatment.

12Given the payoffs structure of the TD, when \( R = 0.5 \) normalized utility takes the form \( U(z) = z^{0.4-2.5z} \).
13We invariably let subjects play the \( R = 0.5 \) part after our main treatments which stipulates \( R = 3 \). This means that the skeptical reader may want to take the results of this section with a grain of salt as they may be susceptible to order effects. At the same time, however, we have every reason to believe that order effects are small and working against the relationship we uncover. In particular, (Capra, Goeree, Gomez, and Holt, 1999) find that in within subject sequential treatments in which \( R \) was varied, higher (lower) claims in an initial treatment lead to slightly higher (lower) claims in the following treatment. Since the loss treatment at \( R = 3 \) yields higher claims then the gain treatment, an order effect would therefore be more likely to give rise to a bias that counteracts what we find in periods 6 to 10.
In line with claim 3 and the previous observation, we expect the risk preference parameter not to be well identified when re-estimating the model with $R = 0.5$. Estimates of the joint model are in table 3 in section B of the appendix. In both treatments, the likelihood is rather flat in $\alpha$ and, as a consequence, we cannot reject risk neutrality. Moreover, estimates of the other parameters and theoretically predicted averages do not seem to vary with different values of $\alpha$.

8 Loss avoidance and the gain-loss treatment

In addition to our two main treatments, we implemented a gain-loss treatment. The treatment differs from the other two in that subjects were paid a participation fee of 8 euros and admissible claims now lay between -5 and 0. We had 34 subjects participating in the two sessions of this treatment and $R$ was again set at 3 euros. If our framing was ineffective or subjects did not treat losses and gains differently, the gain-loss treatment would again be identical to the two main treatments. In the gain-loss treatment positive payoffs as well as negative payoffs are possible and it may therefore be thought of a hybrid between our other two treatments. Furthermore, if the participation fee of 8 euros does in fact pin down the reference point at 8, the gain-loss treatment allows us to observe behavior around the reference point, not just behavior approaching it from the right or left direction as in the gain and the loss treatments respectively.

Our risk preference based explanation of the experimental results from the two main treatments implies that average claims in the gain-loss treatment should lie between average claims in the loss and the gain treatment. And indeed, this is what happens, with the observed distribution of net claims in Figure 4a peaking at around 5, as opposed to 6 in the loss treatment and 3 in the gain treatment. This result allows us to rule out an explanation of our main treatment effect that relies on a fixed change in behavior that arises as soon as losses of any size are possible in favor of an explanation, like ours, in which the scale of possible losses matters.

In order to devise a more stringent test of whether the observed behavior is consistent with prospect theory, we use the experimental data to estimate a variation of our cognitive model in which the utility function takes the following form:

$$U(z) = e^{-\delta[-\ln(\frac{z}{10.9})]^\gamma}.$$  (8)

Prelec (1998) originally introduced this functional form to study probability weights. For our purposes, it has a number of desirable properties. First, $U(0) = 0$ and $U(10.9) = 1$, as in the normalization we used in the main treatment. Second, while the function is monotonic, it may take a large number of shapes, including not only a convex or concave curve but also an S-shape and an inverted S-shape. Third, when the function takes an S-shape its point of inflection may be placed anywhere along the horizontal axis, depending on the parameter values.

Prospect theory makes a clear prediction regarding the shape of an individual’s utility or value function: it is S-shaped and its gradient is highest at the reference point, which in our case is $z = 8$. Instead of assuming a piecewise defined S-shaped utility function (with two parameters measuring respectively risk attitudes in the gain and loss domain) and pinning down the predicted reference point at the outset, this functional form allows us to test whether the
S-shape with maximal gradient around the reference point provides the best fit for the model of our experimental game in a large class of possible functions. Put differently, we test whether prospect theory’s S-shaped value function and a reference point at \( z = 8 \) emerge endogenously from estimating underlying preferences on our model.\(^{14}\)

Our estimates are in table 4 in section B of the appendix. The parameters of the utility function that yield the best fit are \( \gamma = 3 \) and \( \delta = 17 \) and Figure 4b plots the estimated utility function. Even if its inflection point is slightly lower than the \( z = 8 \) we predicted, the utility bears a remarkable resemblance to what prospect theory would suggest. Besides, we can reject risk-neutrality (i.e., \( \gamma = 1 \) and \( \delta = 1 \)) at the 1 percent level.

![Empirical distribution](image1.png) ![Estimated utility function](image2.png)

(a) Empirical distribution  
(b) Estimated utility function  

Fig. 4  Gain-loss treatment

To understand how a reference point of \( z = 8 \) implies the pronounced peak in the frequency of observed claims at \( x = 5 \), note that the S-shaped utility function around the reference point implies a rapid increase in value that a subject attaches to small increases in earnings around the reference point. She will therefore be very keen to avoid earning less than \( z = 8 \) and facing a noisy distribution of potential claims by her opponent. That is, she may act almost as if to maximize her chance of not earning less than \( z = 8 \). This, in turn, is achieved by playing \( x = 5 \), since in all cases in which her opponent submits a higher claim, she will receive \( z = 5 + R = 8 \).

Note that as a consequence of having subjects’ reference point lie within the range of attainable earnings, the frequency of claims around \( x = 5 \) in the gain-loss treatment is much higher than the peak of the claims distribution in the loss treatment.

Subjects in the gain-loss treatment play to avoid losses and this loss avoidance follows naturally from prospect theory’s value function and noisy decision making. The mechanism we emphasize may therefore be viewed as a microfoundation for loss avoidance as an equilibrium selection principle, which Cachon and Camerer (1996) document in the context of a coordination game.

9 Testing confounding effects

We are currently conducting further experimental sessions which we expect to complete by April 2014. Again, subjects play in either a gain or loss treatment which closely resemble our two main treatments described at section 4. However, the new design exploits the payoff structure

\(^{14}\)Our function has no kink and that we are therefore abstracting from loss aversion.
of the traveller’s dilemma to also elicit the risk preferences, social preferences and degree of sophistication of subjects. This will allow us to test for whether differences in these parameters across subjects impact on a subject’s actions in the hypothesized ways. Furthermore, each treatment consists of 10 periods of play to determine whether our main treatment effect persists over a longer horizon.

10 Conclusion

We demonstrate that the behavior of experimental subjects in strategic interactions may be drastically different when payoffs are framed as losses rather than gains. Since we have to rely on framing payoffs as losses, rather than inflicting real losses on subjects, the difference in behavior we observe is likely to provide a lower bound of what would be observed if real losses are at stake. Since the cooperative effect of losses we find is sizable and there is a multitude of situations in which individuals interact over payoffs that are negative or fall short of expectations, our findings are likely to be of economic relevance. Using the example of the TD we have argued that our understanding of strategic interactions over losses may be greatly aided by insights from individual decision making. In this paper, diminishing sensitivity takes center stage and can account for observed behavior. In other settings, concepts such as loss aversion may facilitate the understanding of strategic behavior when losses are at stake. This is particularly likely to be the case when losses are incurred in one state of the world (e.g. an individual loses an auction) and gains are obtained in another (e.g. a subject wins an auction), rather than in situations in which all outcomes (as in our loss treatment) result in losses. In Delgado, Schotter, Ozbay, and Phelps (2008), for example, loss aversion can account for overbidding (a less cooperative outcome) in a first price auction. We think that the interpretation of many real world interactions may be aided by the marriage of prospect theory and game theoretical methods that allow for noisy behavior. We provide a first stab at this endeavor.
References


Appendices

A The traveller’s dilemma

The TD probably best captures a Bertrand model of imperfect price competition, such as that between two firms with differentiated products or capacity constraints, in which each firm has an incentive to undercut the other by an infinitesimal amount, but the penalty for posting the higher price is not as severe as in pure Bertrand competition. Our loss treatment may then be interpreted as an investigation of the competitive effects of sunk costs or worse than expected demand conditions. A few previous experiments have investigated related scenarios. Kachelmeier (1996) find that sunk costs have no effect in a double auction. On the contrary, Offerman and Potters (2006) find that auctioning off entry fees or imposing fixed sunk costs in a Bertrand oligopoly increases collusion among entrants. Buchheit and Feltovich (2011) investigate experimental behavior in two versions of the Bertrand-Edgeworth duopoly with exogenous entry costs. They find that market prices are first increasing and then decreasing in sunk costs. We think that some of these studies suffer from the framing and complexity inherent in their experimental games. In a very simple setting that is more abstract than previous studies, we find that if the cost of being underbid is sufficiently large, sunk costs are likely to lead to more cooperative outcomes and less competitive prices.

The TD was originally introduced as a striking example of conflict between intuition and game theoretic reasoning (Basu, 1994): for a very low reward/penalty parameter $R$ and a high upper bound the Nash equilibrium prediction that players’ actions should be clustered around the lower bound is counterintuitive. And indeed, experiments show that for low values of $R$ relative to the upper bound, claims are clustered around the highest possible claim (Goeree and Holt, 2001; Rubinstein, 2006, 2007; Becker, Carter, and Naeve, 2005). As the reward/penalty parameter grows larger, however, claims converge to the Nash equilibrium play (Capra, Goeree, Gomez, and Holt, 1999; Goeree and Holt, 2001). This pattern persists in the repeated version of the game (Capra, Goeree, Gomez, and Holt, 1999) and is robust to differences in the culture, age and background of experimental subjects (Rubinstein, 2006). Evidence from these experiments enabled us to pick a reward/punishment, $R$, that was sufficiently high to bring about Nash play in the gain treatment, for if we had unwittingly induced maximal cooperation in the gain treatment there would be nowhere left to go for average claims in the loss treatment.

Capra, Goeree, Gomez, and Holt (1999) explain the finding that average claims are decreasing in $R$ by making use of the quantal response equilibrium. To understand their logic, consider a player in the TD who faces a distribution of possible actions by her opponent. In situations in which her claim is the higher one, raising it further has no effect on payoffs. In situations in which her claim is the lower one, increasing the claim entails a trade-off. On the one hand, she benefits from raising the lower of the two claims. On the other hand, she risks crossing her opponent’s claim in which case she loses $2R$ because she forgoes her reward and is instead charged the penalty. Therefore, as $2R$ decreases, potential cost of raising one’s claim decreases, while the benefits remain unaltered. A similar logic is found in Baghestanian (2013), who shows

\[\text{Capra, Goeree, Gomez, and Holt (2002)}\] for an experiment in which firms engage in Bertrand competition and the firm setting the higher price has a non-vanishing market share. In this case, the size of the residual market is the counterpart of the reward parameter in the TD.
how models of cognitive hierarchies can explain this and other regularities in subjects’ behavior in the TD.

B Additional material

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Tab. 4  Estimates for the gain-loss treatment

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<th>$\delta$</th>
<th>$t$</th>
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Bienvenue au Laboratoire experimental de la Toulouse School of Economics et merci de votre participation. Toutes les données recueillies lors de cette expérience sont anonymes et seront utilisées à des fins scientifiques.

Dans cette expérience, vos revenus dépendent des décisions prises à la fois par vous et par les autres participants.

On vous a donné 11€ comme payement pour votre participation. L’expérience consiste en trois parties : vous allez débuter par la partie A. Partie A sera ensuite suivie de deux nouvelles expériences, appelées partie B et C. Il y a 5 tours dans chaque partie. Un seul tour parmi les 15 sera choisi au hasard pour le calcul de vos gains finaux. Si dans le tour sélectionné vous remportez des montants négatifs, vous devrez nous rembourser la somme correspondante en utilisant une part de 11€ qui vous ont été données en début d’expérience.

Si vous avez des questions, exprimez-les dès le présent. À partir de maintenant vous n’êtes plus autorisés poser des questions publiquement. Si vous voulez poser une question pendant l’expérience, nous vous prions de lever votre main et nous y répondrons individuellement. Enfin, vous n’êtes pas autorisés à communiquer avec d’autres participants et ce jusqu’à la fin de l’expérience.

Nous vous prions de ne PAS tourner la page avant autorisation de notre part. Merci
Instructions pour partie A

Partie A consiste en cinq tours identiques. Lors de chaque tour, vous allez être associé avec un autre participant de façon aléatoire. Vous ne pouvez être associé avec le même participant qu’une seule fois. Les décisions que vous et votre binôme/opposant prendrez détermineront vos gains respectifs pour ce tour.

À chaque tour, chacun de vous deux doit choisir un montant compris entre -8 et -3 inclus. Les nombres non entiers sont autorisés jusqu’à une décimale, par exemple une déclaration de -5.3 équivaut à moins 5 euro et 30 centimes. Votre gain sera déterminé de la façon suivante:

- Si les deux montants sont égaux, chacun de vous deux recevra le montant demandé.
- Si les deux montants sont différents, chacun de vous recevra le minimum des deux montants soumis. De plus, 3€ seront ajoutés aux gains de la personne ayant déclaré le plus petit montant et 3€ seront déduits des gains de la personne ayant déclaré le plus grand montant.

On vous rappelle que gagner un montant négatif correspond à une perte, et que des qu’on est face à des nombres négatifs, le nombre plus petit est celui qui a une valeur absolue le plus élevée (donc, par exemple, -3.5 est plus petit que -3.4).

Par exemple, si vous et votre binôme choisissez -4, chacun d’entre vous gagnera -4€ (donc perdra 4 euro). Si vous choisissez -4.8 et votre binôme -4.5, vous gagnerez -4.8€ + 3€ = -1.8€, et votre binôme gagnera -4.8€ - 3€ = -7.8€. Si vous choisissez -3.2 et votre binôme -3.5, vous gagnerez -6.5€ et votre binôme -0.5€. Assurez-vous maintenant que vous avez bien compris comment les gains présents dans les exemples sont calculés.

Une fenêtre interactive va maintenant apparaître sur votre écran et partie A va débuter.

Nous vous prions de ne PAS tourner la page avant autorisation de notre part. Merci.
Instructions pour partie B

Partie B consiste en cinq tours identiques. Lors de chaque tour, vous allez être associé avec un autre participant de façon aléatoire. Vous ne pouvez être associé un même participant qu’une seule fois, et vous ne seriez pas associé quelqu’un avec lequel vous avez été associé en partie A. Les décisions que vous et votre binôme/opposant prendrez détermineront vos gains respectifs pour ce tour.

À chaque tour, chacun de vous deux doit choisir un montant compris entre -8€ et -3€ (-8 et -3 inclus). Les nombres non entiers sont autorisés jusqu’à une décimale, par exemple une déclaration de -5.3 équivaut à moins 5 euro et 30 centimes. Votre gains son déterminé de la façon suivante:

Si les deux montants sont égaux, chacun de vous deux recevra le montant demandé.

Si les deux montants different, chacun de vous recevra le minimum des deux montants soumis. De plus 0.5€ seront ajoutés aux gains de la personne ayant déclaréle plus petit montant et 0.5€ seront déduits des gains de la personne ayant déclaré le plus gros montant.

On vous rappelle que gagner un montant negatif correspond à une perte, et que dès qu’on est face à de nombres negatifs, le nombre plus petit est celui qui a une valeur absolu le plus eleve (donc, par exemple, -3.5 est plus petit que -3.4).

Par exemple, si vous et votre binome choisissez -4, chacun d’entre vous gagnera -4€ (donc perdra 4 euro). Si vous choisissez -4.8 et votre binome -4.5, vous gagnerez -4.8€ + 0.5€ = -4.3€, et votre binome gagnera -4.8€ - 0.5€ = -5.3 €. Si vous choisissez -3.2 et votre binome -3.5, vous gagnerez -4€ et votre binome -3€. Assurez-vous maintenant que vous avez bien compris comment les gains présentes dans les exemples sont calculés.

S’il vous plait, attendez la permission de l’expérimentateur avant de appuyer sur continuer sur votre écran, et partie B débutera.

Nous vous prions de ne PAS tourner la page avant autorisation de notre part. Merci
Instructions pour partie C

Partie C consiste en cinq tours identiques. Lors de chaque tour, vous allez être associé avec un autre participant de façon aléatoire. Vous ne pouvez être associé avec le même participant qu’une seule fois, et vous ne seriez pas associé quelqu’un avec lequel vous avez été associé en partie A ou B. Les décisions que vous et votre binôme/opposant prendrez détermineront vos gains respectifs pour ce tour.

A chaque tour, chacun de vous deux doit choisir un montant compris entre $-8$ et $-3$ ($-8$ et $-3$ inclus). Les nombres non entiers sont autorisés jusqu’à une décimale, par exemple une déclaration de -5.3 équivaut à moins 5 euro et 30 centimes. Votre gains sont déterminés de la façon suivante:

Si les deux montants sont égaux, chacun de vous deux recevra le montant demandé.

Si les deux montants différent, chacun de vous recevra le minimum des deux montants soumis. De plus, $3$ seront ajoutés aux gains de la personne ayant déclaré le plus petit montant et $0.5$ seront déduits des gains de la personne ayant déclaré le plus gros montant.

On vous rappelle que gagner un montant négatif correspond à une perte, et que des que on est face à deux nombres négatifs, le nombre plus petit est celui qui a une valeur absolue le plus élevée (donc, par exemple, -3.5 est plus petit que -3.4).

Par exemple, si vous et votre binôme choisissez -4, chacun d’entre vous gagnera -4€ (donc perdra 4 euro). Si vous choisissez -4.8 et votre binôme -4.5, vous gagnerez -4.8€ + 3€ = -1.8€, et votre binôme gagnera -4.8€ - 0.5€ = -5.3 €. Si vous choisissez -3.2 et votre binôme -3.5, vous gagnerez -4€ et votre binôme -0.5€. Assurez-vous maintenant que vous avez bien compris comment les gains présents dans les exemples sont calculés.

S’il vous plaît, attendez la permission de l’expérimentateur avant de appuyer sur continue sur votre écran, et partie C débutera.