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Optimality, accuracy, signal detection theory, incentives, experiment

JEL codes:
D8, D83, Y08

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Abstract

When making a decision under uncertainty, individuals aim to achieve optimality. In general, an accurate decision is optimal. However, in real life situations asymmetric stakes induce an unusual divergence between optimality and accuracy. We highlight this optimality-accuracy trade-off and study its origins using two experiments on perceptual decision making. We use Signal Detection Theory as a normative benchmark. The first experiment confirms the existence of an optimality-accuracy trade-off with a leading role of accuracy. The second experiment explains this trade-off by the concern of people for being right.

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1 Introduction

When making a decision, individuals try to reach an optimal solution, i.e. one that maximizes expected payoffs. Most of the time, aiming to take the accurate decision leads to optimality. However, some cases of decision under uncertainty may imply a divergence between optimality and accuracy. In such circumstances, individuals should give away some accuracy to reach optimality. However, individuals may not consider this unusual divergence between accuracy and optimality and adopt an accuracy-maximizing behavior instead of the optimal one. Aiming to choose correctly instead of optimally induces an optimality-accuracy trade-off. This paper is composed of two experimental studies pursuing two complementary objectives. The first study aims to highlight the existence of the optimality-accuracy trade-off and to test its robustness in a pure-loss decision framework. The second study enables a direct evaluation of the role played by the value of being correct in the observed optimality-accuracy trade-off.

In a general setting, let's study an individual who has to make a decision in an uncertain environment. Depending on the state of nature, his decision leads to two different outcomes that can be classified either as success or error. He receives a signal on the current state of nature, however this signal is noisy. Uncertainty blurs the decision-to-outcome relation resulting in a loss of control from the individual on the final outcome. We distinguish two alternative strategies: the optimal decision strategy and the accuracy maximizing strategy. We define optimality as the behavior that uses the decision criterion maximizing expected payoffs. An accurate behavior is defined as maximizing the success rate. To make optimal decisions, the individual should evaluate the outcome of the possible decisions for each state and assessing which decision is the most appropriated. Alternatively, the individual can try to maximize his odd of making the correct decision. With similar payoffs for all kind of successes and errors in the different states of nature, both strategies lead to the exact same behavior. However introducing state dependent differences between success and errors lead to a divergence. As a result, a naive individual may be driven away from the optimality by trying to maximize accuracy. From this divergence results a tension between these two opposed behaviors in which the optimality-accuracy trade-off takes its roots. The higher the asymmetry, the higher the consequences caused by this departure from optimality.

While we may find many situations in which the optimality-accuracy trade-off arises (e.g. response to a warning of danger, military decisions during conflicts, trading decisions on a volatile market), we choose to describe extensively this situation using a medical decision context. This medical decision-making framework has been previously used by economists, by example, to understand both diagnosis decision by practitioners (Karni, 2009; Berger et al., 2013) or patients and health care providers choice of treatments (Bleichrodt and Pinto, 2005; Hansen and Østerdal, 2006)[1]. A doctor having to determine if a patient suffers from an illness based on ambiguous symptoms when no further tests are able to suppress ambiguity[2]. As symptoms are not clear enough, the doctor is uncertain about the patient's condition. Four outcomes can arise from this situation depending on the patient health (being sick or not) and the doctor diagnosis (providing a treatment or not). If the patient is sick, correctly diagnosing the disease and incorrectly identifying the patient as healthy leads to large differences in consequences as it increases the patient's probability of recovering. Additionally, the doctor benefits from a positive reputation effect of being able to help patient to recover, it decreases the cost of treatments for the patients and limits the negative externality of being sick for other individuals (especially if the disease can be transmitted). If the patient is healthy, the difference in impact between a correct and incorrect diagnosis is less salient. The patient is treated with potential side effects when it is useless and this useless treatment negatively impacts the budget of social security systems. Using the scope of the optimality-accuracy trade-off, the doctor wants to be correct but at the same time it is important for him to take into account the asymmetrical stakes between overtreatment and undertreatment. To engage in the optimal decision process, he has to give up part of its accuracy when the patient is not sick in order to increase his accuracy when being confronted to a sick patient. How does he behave? Is his decision more driven by a search for accuracy or is he able to approach the optimal decision process? Does the self-rewarding effect of being correct prevent him from approaching this optimal decision process?

The optimality-accuracy trade-off might play a crucial role in each decision under uncertainty involving different rewards for successes and errors pattern. To the best of our knowledge and despite its important questions about efficiency, experts' behaviors and payment schemes, the trade-off has never been extensively analyzed in the economic literature. We argue that this results from a methodological difficulty. As an answer, our approach is based on a computational model used in cognitive sciences. Using a perceptual task and a Signal Detection model, we study the optimality-accuracy trade-off and investigate the decision processes involved. Signal Detection Theory (SDT hereafter; Green and Swets (1966), Wickens (2001)) offers a normative benchmark to understand how individuals make decisions under uncertainty. Individuals face a discrimination task in which they have to identify if a signal is present in a noisy environment. SDT provides theoretical foundations to identify the main components of the decision. It allows to

[1] See Felder and Mayrhofer (2011) for a review of medical decision-making from an economic perspective or Wakker (2008) for an historical evolution of the field.

[2] Alternatively, this situation can be transposed to the decision of doing a new test with an additional cost either for the patient or in terms of monetary costs.

disentangle the impact of the stimulus itself on the decision from the impact of the decision strategy. Applying this framework to the optimality-accuracy trade-off, it offers precise predictions of the expected behavior as well as estimations of potential treatments effects. Using a narrow set of assumptions, SDT enables to compute decision criteria based on observed decisions and provides a powerful tool to evaluate the decisions resulting from an optimal or an accurate decision process[3].

In the first experiment, we provide empirical findings on how people react to the optimality-accuracy trade-off by varying incentives at a treatment level to compare situations with a difference between optimality and accuracy to situations with no difference. We also investigate the impact of a pure-loss framework on the decisions by confronting individual to negative earnings for both successes and errors. The impact of loss aversion on economic decisions has been extensively studied (Tversky and Kahneman, 1991; Wakker, 2010). However, to our knowledge, the optimality-accuracy trade-off has been highlighted only in mixed gain-loss framework but never in a pure-loss frame (Maddox et al., 2003b). It is interesting to see whether this trade-off involving uncertainty is affected by decision under losses. We elicit loss attitudes under risk and under ambiguity to study how preferences matter in this loss context. To fulfil this objective, we manipulate payoffs for the different outcomes of the decision. By varying incentives, we capture a wide range of decisions in the framework of medical decision-making that differ regarding i) how doctors value their patients well-being, ii) the level of the fixed part of the remuneration, iii) reference points manipulations induced by the environment (*e.g.* every-day medicine, humanitarian crisis, war situations).

This first experiment reveals a decision strategy that lies between the optimal and accuracy maximizing strategies. However their intrinsic motivation is still to determine. Do individuals carry out an actual trade-off between seeking for the higher payoff or the higher success rate? Are individuals seeking for optimal decisions and cannot escape from a naive decision process leading to too much accuracy? Therefore, the second experiment compares incentivized to non-incentivized decisions to investigate how important is the value of being right as an explanation of the optimality-accuracy trade-off. We obtain that the value of being right is playing a major role in the departure from optimality. Therefore, the trade-off observed is not only the consequence of a difficulty to reach optimality, but also to a search for accuracy.

[3] SDT is a common tool for analyzing medical decision-making in the medical literature. See Metz (2008) for a review.

2 Theoretical background and hypotheses

2.1 Signal Detection Theory

SDT provides a general framework to describe and analyze perceptive decisions made under uncertainty. One of its strength is to allow to disentangle what comes from the task itself from what is involved by the decision process. Facing an uncertain situation, the observer has to detect a noisy signal. SDT separates human decision-making into discrimination (the difficulty of the task) and criterion (the decision process used). In "signal states", the signal adds up to some noise, making its discrimination difficult. In "noise states", only noise remains and no signal is present. Facing a stimulus, the individual gathers some evidence about the hypothetical presence of the signal. When signal evidence reaches a certain threshold, the individual concludes that the signal is present, otherwise he decides in favor of noise only. Depending on his answer and on the state of nature, four scenarios can thus emerge: reporting signal when the signal is present ("hit"), reporting signal when the signal is absent ("false alarm"), reporting that signal is absent when it is present ("miss"), and finally correctly identifying that the signal is absent ("correct rejection"). To formally define the problem, we consider a state of nature Θ that takes value in $\{0, 1\}$. The observer makes a decision D taking value in the same space. Table 1 summarizes the four possible outcomes.

	$\Theta = 1$	$\Theta = 0$
$D = 1$	Hit	False Alarm
$D = 0$	Miss	Correct Rejection

Table 1: Outcomes of a signal-in-noise decision.

The first range of information used to make a decision is given by the evidence received from the stimuli by the observer, X. The observer evaluates the likelihood of receiving this evidence for each state of nature. SDT assumes that X is a random variable taking its value in $\mathbb{R}$. Moreover for any two values of X it is possible to determine which one gives the highest likelihood of facing the signal. By convention for higher X, the state of nature "signal" is more likely. Thus:

$$\frac{\partial}{\partial X}\left(\frac{\mathbb{P}(X|\Theta = 1)}{\mathbb{P}(X|\Theta = 0)}\right) > 0$$

Additionally, SDT assumes that it exists a threshold such that if the amount of evidence exceeds it, the observer will always choose sigma. Let's assume that the decision maker (DM) is rational and there exists two levels of evidence for which the DM is making two different decisions. If for a level of evidence X_1 the observer is answering signal, for all level of evidence $X = X_1 + \epsilon_1$ with ϵ_1 arbitrary small, he will also answer signal, as signal is even more likely. As it exists X_2 such that the observer is answering noise, it exists ϵ_2 such if $X = X_2 - \epsilon_2$ the observer is answering noise. The minimal X verifying this constraint defines the decision threshold. Thus, the choice of response is made by applying a simple decision criterion to the magnitude of the evidence (Figure 1 - a and b) :

$$\exists\, \lambda \in \mathbb{R} \text{ s.t. } D = \mathbb{1}(X > \lambda) \tag{1}$$

The second range of information used by the DM is provided by the payoffs associated to each of the outcomes. The payoff matrix, Π, gives each outcome's payoff, $\Pi : \Theta \times D \to \mathbb{R}$.

The decision is made by combining the two information ranges, thus $D : \mathbb{R}^2 \to \{0, 1\}$. It is possible to summarize the decision strategy using a criterion β based on the amount of evidence and the payoff matrix, $\beta : \Pi \to \mathbb{R}$.

$$D(X, \Pi) = \mathbb{1}\left(\frac{\mathbb{P}(X|\Theta = 1)}{\mathbb{P}(X|\Theta = 0)} > \beta(\Pi)\right) \tag{2}$$

Two criteria stand out: the optimal Bayesian criterion and the accuracy maximizing criterion (Figure 1 - c). An optimal observer will act as a Bayesian observer. To make his decision, he will compare the difference in the payoffs between a correct and an incorrect answer in both states of nature with the relative likelihood of the two states. The decision criterion β^* maximizing the expected payoff of the decision is defined as follows:

$$\beta^*(\Pi) = \frac{\Pi(0,0) - \Pi(0,1)}{\Pi(1,1) - \Pi(1,0)}$$

.

Alternatively, a DM maximizing his probability of giving a correct answer will always answer the most likely outcome. The decision criterion β^a maximizing the probability of success is thus independent of Π:

$$\forall\, \Pi \;\; \beta^a(\Pi) = 1$$

In order to estimate a criterion based on decisions, one needs to assume a distribution of perceived evidence by the observer. Standard SDT assigns a Gaussian distribution of different means and variances for the random variables representing evidence coming from a noise (X_n or $X|\Theta = 0$) or a signal (X_s or $X|\Theta = 1$) (Gold and Shadlen, 2001, 2007). In this distribution, the key parameter is the difference in means between the signal and the noise: the discrimination (d'), as represented in Figure 1 - d. The higher

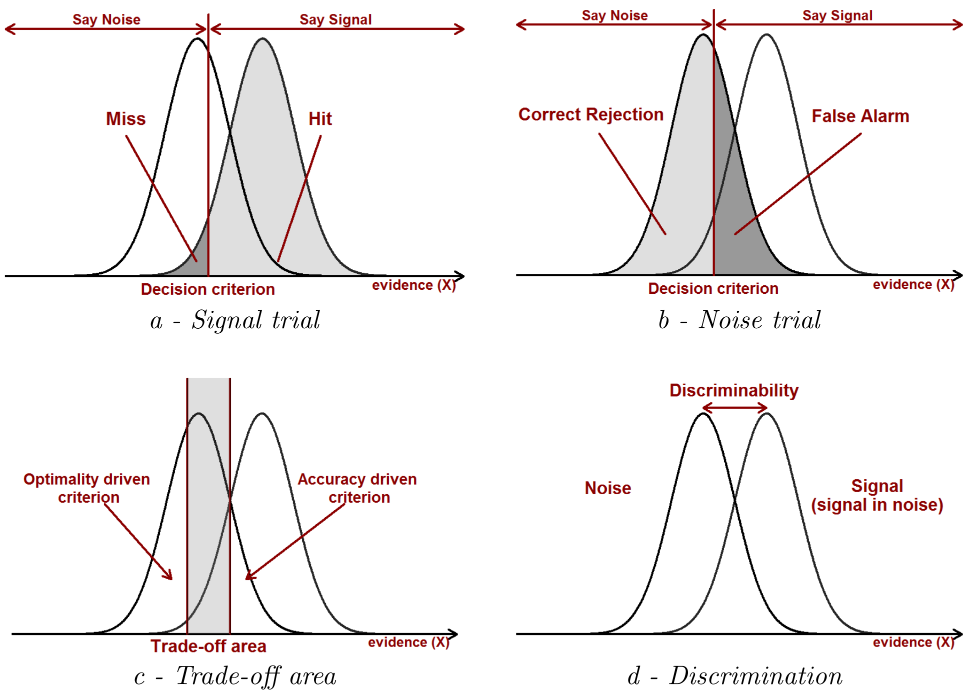


Figure 1: The different components of Gaussian equal variance SDT.

Reading note: Figure a and Figure b give the decision as a function of the criterion and the level of evidence. The shaded areas represent the corresponding probabilities of each outcome. Figure c plots the trade-off area i.e. the set of criteria between the optimal and the accurate criterion. Figure d represents discrimination based on the evidences coming from the noise and the signal.

the discrimination, the easier it is to discriminate the signal from the noise.

$$X_n \sim \mathcal{N}(0, \sigma_n^2) \text{ and } X_s \sim \mathcal{N}(d', \sigma_s^2)$$

To decrease the number of parameters it is possible to fix one of them. The convention is to set the variance of noise to 1. Additionally, the specification is commonly reduced to the equal variance model by assuming that the variance of the signal and that of the noise are the same ($\sigma_s^2 = \sigma_n^2 = 1$). The specification has the advantage of being easily interpretable with one parameter referring to the task difficulty (d') and the other referring to the decision strategy (β).

2.2 Related literature

The optimality-accuracy trade-off has been extensively studied in cognitive sciences. Various methods to induce an asymmetrical situation have been proposed, as well as different modelizations of these situations. While most of the studies are in psychology, some attempts to explain the observed behaviors have been proposed using an economic framework.

Using SDT, asymmetry is induced by manipulating either the probabilities of each state of nature (base rates) or the payoffs. Payoff matrix manipulations include a distortion of the asymmetry level (Pitz and Downing, 1967; Bohil and Maddox, 2001), the introduction of non-zero cost or a loss for some outcomes (Barkan et al., 1998; Maddox et al., 2003b; Maddox and Bohil, 2005), the multiplication of payoff matrices (Galanter and Holman, 1967; Maddox et al., 2003b) or combinations of the previous manipulations with different sensitivity levels (Bohil and Maddox, 2001, 2003). Facing these changes in incentives, individuals adjust their decision criterion, however they exhibit an under-optimal departure from optimality. The more salient the reward function, the better the adjustment. Introducing non-positive payoffs or decreasing the sensitivity has opposite consequences. This result is confirmed by introducing an asymmetry at the base rate level. When an option is more likely that another, individuals underestimate it. However, individuals tend to be closer from optimality facing base rate inequalities than equivalent payoff asymmetries (Maddox and Bohil, 1998; Maddox and Dodd, 2001; Maddox and Bohil, 2005). The present work complements existing researches on several points. First, we highlight the existence of the trade-off using a signal-in-noise task while previous studies implement two-alternative force choice (2AFC) task[4]. In real-life situations, high stakes are caused by the signal (*e.g.* a disease for a doctor, or danger for soldiers). Contrary to a 2AFC setting, a signal-in-noise framework enables us to reproduce the link signal/high stakes, increasing the external validity of the results. Secondly, we implement an innovative pure-loss framework to link the impact of losses on decisions to the optimality-accuracy trade-off reaction. The impact of losses on the trade-off has been highlighted only in mixed gain-loss frameworks but never in a pure-loss frame. However, the non-separability between the valuation of gain and loss reveals the importance to isolate losses from gains to study this impact (Wu and Markle, 2008).

Different explanations have been investigated to sort out the origin of this bias. The first category of explanations is based on the idea that, as individuals face multiple consecutive decisions, what matters most is not the *ex-nihilo* optimal solution but the path of optimization (Roth and Erev, 1995). Based on this idea, Erev (1998) states that the path of optimization does not converge to optimality, as a non-optimal decision may be positively rewarded increasing this strategy reinforcement. In the same modelization framework Myung and Busemeyer (1989) and Busemeyer and Myung (1992) find support for two different maximization processes, based either on a first or second order analysis of the criteria adjustment. The error correction model assumes that the magnitude of the stopping criteria is increased following an incorrect diagnosis while the hill climbing model states that the direction of adjustment changes after wrong answers. Thus, individuals would suffer from an outcome-biased decision process. As the decision is taken

[4]In 2AFC, the signal is always present and individuals have to choose its location between two options.

under uncertainty, a correct answer is not always an optimal answer. Overestimating the meaning of a correct answer would exhibit an outcome bias (Alicke et al., 1994; Baron and Hershey, 1988; Gino et al., 2010). Maddox and Bohil (2005) argue that the maximization process does not converge to optimality as the slope of the reward function in a neighborhood of the optimal solution is not steep enough to enable individual to reach optimality (flat-maxima hypothesis). If individuals initiate their maximization process at the equal-probability/equal-payoff solution, there maximization process would converge to an overly accurate solution.

A second category of explanations relies on the theory that participants emphasize accuracy over optimality. Several studies have concluded in a tendency for individuals to give over-accurate answers (Maddox and Bohil, 2003, 2004; Balci et al., 2011; Bogacz et al., 2006). Their approach is based on models comparison with a goodness-of-fit analysis. As a result, Maddox and Bohil (2003, 2004) argue that subjects attempt to maximize payoff on each trial, but erroneously believe that maximizing accuracy fulfils this objective. The priority of accuracy could also been interpreted as an induced value associated with successes. This importance of induced values has been first tackled by Smith (1976). In related setting based on unequal base rate, Siegel (1959) obtains that individuals classifying correctly the less likely outcome benefit from an additional non-monetary reward compared to correct classification of the more likely outcome. Our approach is based on a design enabling a direct evaluation of the value of being right and thus completes previous studies arguing for an over-representation of accuracy resulting from a biased search of optimality.

2.3 Hypotheses testing

Based on the results of the literature, our two studies aim to test a set of five hypotheses.

Study 1 enables to test the following hypotheses:

H 1.1. *The DMs' decision criterion is upper bounded by the accuracy driven decision criterion.*

H 1.2. *The DMs' decision criterion is lower bounded by the optimality driven decision criterion.*

Satisfying Hypothesis 1.1 and Hypothesis 1.2 gives the existence of the optimality-accuracy trade-off (cf. Figure 1 - c)[5].

H 1.3. *The DMs' decision criterion is closer to the accuracy driven decision criterion than to the optimality driven decision criterion.*

[5]The range of the bounds comes from the asymmetry toward signal; an asymmetry towards noise will reverse this range.

Hypothesis 1.3 investigates whether one of the two concepts may have a leading role in the trade-off. Accuracy maximization is a natural behavior and requires to assess only information coming from the stimuli. An optimal behavior requires also to assess information from the payoff matrix and to aggregate them optimally with stimuli information. It is thus a more sophisticated behavior and we hypothesise that it is harder to reach.

H 1.4. *The DMs' decision criterion and discrimination are affected by the decision under loss.*

Hypothesis 1.4 assesses the robustness of the previous hypotheses to decisions under loss.

If the optimality-accuracy trade-off takes its roots in a mixed valuation of accuracy and optimality, we can think of the DMs' target function as being an increasing function of both success and payoffs. Formally:

$$Target\ function = V(\mathbb{1}_{\{D=\Theta\}}, \Pi) \text{ with } \frac{\partial V}{\partial x} > 0 \text{ and } \frac{\partial V}{\partial y} > 0 \tag{3}$$

Alternatively, if individuals seek for the optimal decision rule but their maximization process is unconsciously biased towards accuracy, the target function is best represented by the usual payoff-based target function:

$$Target\ function = \tilde{V}(\Pi) \tag{4}$$

While both specifications could explain Study 1 results, Study 2 enables to directly identify which of the two specifications provides the best fit to observed behaviors. We implement situations with symmetric incentives between successes and errors and situations with no incentives on the quality of the decision. These two treatments induce two diametrically opposed criterion adjustments. In the incentivized symmetric context accuracy and optimality are perfectly aligned ($\beta^* = \beta^a = 1$), thus maximizing only payoffs or a combination of accuracy and optimality lead to the same decision strategy. With no incentives, the decision strategy obtained after maximizing the target function described in Equation 3 is not affected by the change. In fact, accuracy is still maximized by $\beta^a = 1$[6]. In contrast, a pure-payoff maximizer will approach random guesses are all decisions give him the same level of satisfaction. Thus, a major change in decision criterion should be observed. Therefore Study 2 is designed to assess Hypothesis 2.1. This hypothesis complete our hypotheses set.

H 2.1. *The optimality-accuracy trade-off is not only the consequence of a sub-optimal maximization process, but also a reaction to the intrinsic valuation of being right.*

[6]Even if the decision strategy is kept constant the effort invested may be different. This is captured by the discrimination term.

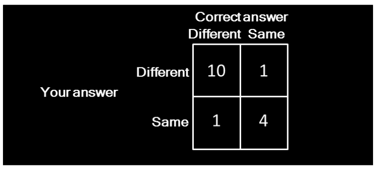
3 Design

Both experiments consist of series of individual perceptive decisions organized in a block/trial architecture. Each block represents a treatment while each trial represents a decision. To make a decision, subjects received two different information: a signal-in-noise stimuli and a payoff matrix. Using the stimuli, they form beliefs on whether the stimuli is a signal or a noise. The payoff matrix provided a matching rule between the four possible decision outcomes and the number of points earned in each case. By combining both information, they had to choose to answer either "noise" or "signal". Treatments corresponded to variations in the payoff matrix. Both studies uses the same stimuli but differ mainly regarding the treatments implemented. Additionally in Study 1, prior to the main section, we elicited attitudes toward risk, ambiguity and loss. This elicitation was not present in Study 2 as risk and loss attitudes are not central in this study. We reproduced the elicitation task of Dai et al. (2017) which is based on Eckel and Grossman (2008) method with the presentation proposed by Eckel et al. (2012). Appendix D details the elicitation method. At the end to both experiments, subjects had to answer a standard demographic questionnaire.

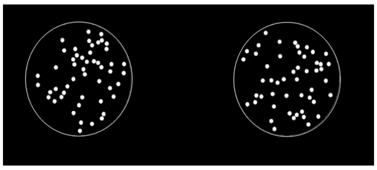
In this section, we first present the task, then the experimental procedures and our sample of subjects. Figure 2 gives an overview of the experimental design.

3.1 The stimuli

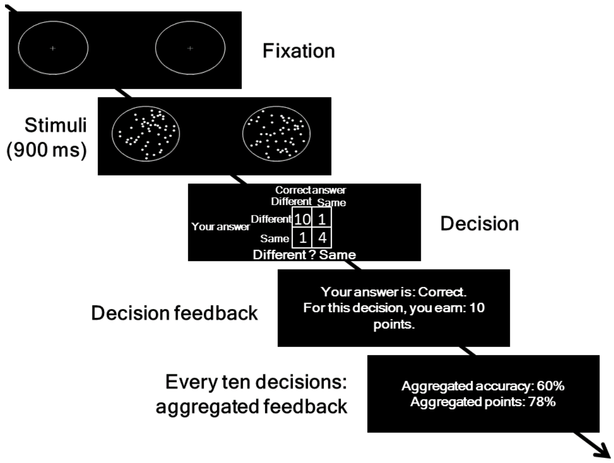
For both studies, we have used a variation of the visual task used by Hollard et al. (2016): a signal-in-noise stimulus. Dots were displayed in two circles during 900 ms. When signal was the correct answer ("signal trial"), one circle always contained 50 dots while the other contained more dots. The position of the target circle (on the left or right) was randomly chosen on each trial. When noise was the correct answer ("noise trial"), both circles contains the same number of dots (50). The short display time made counting dots impossible for subjects causing the uncertainty in the decision. To have a neutral framework noise was referred as "Same" and signal as "Different" during the experiment. Before and after the stimuli displayed, subjects were facing a fixation screen (the fixation screen was composed of both circles without dots but a cross in the middle of each one of them). The first fixation was used to direct subject's attention to the future location of the stimuli. The second one enhanced stimuli information processing after the end of the stimuli display. To increase control, we i) calibrated the task difficulty at the subject level, ii) randomly generated stimuli prior to the experiment by difficulty levels. The stimuli difficulty was given by the difference in numbers of dots between the two circles in signal trials (hereafter referred as x_c). The calibration of the difficulty of the task was



a - Payoff matrix (treatment dependent)



b - Stimuli (trial dependent)



c - Trial steps

Figure 2: Experimental design.

Reading note: (a) Payoff matrix: Subjects were informed of the payoff matrix at the beginning of treatments and this matrix was then displayed on the screen when they made their decision. (b) Example of stimuli. (c) Trial steps were: fixation, stimuli displayed (900 ms), decision and feedback. Every ten trials aggregated feedback constituted the last trial step.

done using a psychophysic staircase at the subject level in order to control for individual heterogeneity of vision abilities (Levitt, 1971)[7]. In this non-incentivized calibration period, subjects received only the stimuli information and had to determine if the stimuli were either in a noise or a signal state. Feedback on decision accuracy was provided after each decision. The targeted accuracy rate was 71%. This level was chosen for subjects to outperform random guesses (relevance of the stimuli) and to avoid being too close to perfect discrimination (relevance of the payoff matrix). For a same level of calibration, we presented the exact same set of stimuli to participants in each block by difficulty level. Stimuli were randomly generated prior to the experiment under constraints concerning dots spacing[8]. Noise and signal trial frequencies were controlled to be exactly equal and the sequence was reproduced from one block to another.

[7] The psychophysic staircase used was a one-up two-down staircase in which one dot was removed after two consecutive correct answers and one dot was added after one failure. The calibration ended when subjects had achieved 35 reversals in the staircase (a reversal means a change in the x_c's value). The number of dots difference x_c used in the experiment was computed as the mean dots number across the two last reversals of the staircase.

[8] All dots were of the same size (diameter 0.4°) and the average distance between dots was kept constant. They appeared at random positions inside two outline circles (diameter 5.1°) first displayed with fixation crosses at their centers at eccentricities of ± 8.9°.

3.2 Payoff matrices

To implement the asymmetrical framework, we let the base rates constant but manipulate the payoff matrices. Study 1 is based on 4 different matrices (one symmetric, three asymmetric) while Study 2 is based on two matrices (one symmetric and incentivized - same than Study 1 - and one flat). Both studies are within-subject experiments. The order of treatments is randomised at a subject level.

Study 1 - Study 1 aims to measure the difference in behaviors resulting from asymmetrical stakes. Out of the four payoff matrices used, three generate asymmetric earnings and one induces symmetric earnings. All asymmetries are biased toward signal to increase external validity[9]. Payoff matrices can be expressed using the two free parameters presented in Table 2. The m parameter introduces the optimality-accuracy trade-off by creating an asymmetry between both kinds of successes and x translates the payoff matrix. The "Symmetric Treatment" is our baseline and corresponds to $x = m = 0$. Subjects earn the same number of points when the correct answer is signal or noise. The "Asymmetric Low Gain Treatment" induces an asymmetry while staying as close as possible from the baseline: $x = 0$, $m = 3$. The "Asymmetric Loss Treatment" is the minimal translation from Low Gain Treatment inducing losses for all outcomes: $x = -11$, $m = 3$. The "Asymmetric High Gain Treatment" is obtained from the Asymmetric Low Gain Treatment after a positive translation matching the norm of the translation between Loss and Low Gain Treatments: $x = 11$, $m = 3$. This design enables us to implement a pure-loss treatment as even with only incorrect answers subjects still obtain an overall positive payment.

	$\Theta = 1$	$\Theta = 0$
$D = 1$	**7+x+m**	**1+x**
$D = 0$	**1+x**	**7+x-m**

Table 2: Study 1 - Payoff matrix.

Study 2 - Study 2 consists of the previous baseline and a new flat payoff matrix as described in Table 3. This payoff matrix enables to have a flat payment with minimal departure from the baseline treatment. For sake of clarity, Study 2's treatments are referred as "Symmetric Incentivized Treatment" and "Flat Treatment".

3.3 Feedback

To help subjects in their decision-making process, we provided two types of feedback to subjects. We aimed not to influence participants to consider more the stimuli or the

[9] As an example in cancer detection, security control or response to warning of danger, the signal situation is respectively a tumor, a harmful individual or a threat. They are the high stakes situations.

	$\Theta = 1$	$\Theta = 0$
$D = 1$	**7**	**1**
$D = 0$	**1**	**7**

a - Incentivized Treatment

	$\Theta = 1$	$\Theta = 0$
$D = 1$	**4**	**4**
$D = 0$	**4**	**4**

b - Flat Treatment

Table 3: Study 2 - Payoff matrix

payoff matrix. Thus, we gave them a feedback on the stimuli - if their decisions were correct or incorrect - and a feedback on the payoff matrix - number of points earned for the decision. Additionally to these trial-by-trial feedback, subjects received every 10 decisions two aggregated feedback. First, we showed their accuracy rate for the last 10 decisions. Second, we provided an aggregated point feedback indicating how close they were from optimality in terms of points accumulation during the last 10 decisions[10]. Our aggregated point feedback has the valuable characteristic of reflecting the performance of subjects without being influenced by any endowment effect. Feedback effects have been highlighted in perception problems using for example objective, optimal or delayed feedback (Maddox and Bohil, 2001; Maddox et al., 2003a; Ell et al., 2009). Including an accuracy feedback was important to limit the formation of biased beliefs on performances. The optimality feedback motivation is two-fold. First, it balances accuracy and optimality at a feedback level. Secondly, as experiments are based on payoff manipulations, it was important to ensure that subjects were assessing correctly the impact of their decisions. The optimality feedback works as a recall on the payoff implication of each decision.

3.4 Experimental procedures

All sessions of both studies were conducted at the Queensland University of Technology (QUT) in September 2016. Subjects were students from QUT and were enrolled using ORSEE (Greiner, 2015). Studies have been programmed using MATLAB with the Psychophysics Toolbox version 3 (Brainard, 1997) and have been achieved on computers of resolution 1920×1080. Points earned in 10%[11] of their decisions were converted into payments at a rate of 8 $points = AUD$ 1. The first study was 90 minutes long and paid in average AUD 27.0. The second study was half as long and paid in average 10.5 AUD. In

[10] With x the actual number of points earned, y the number of points earned if all answers would have been incorrect, z the number of points earned if all answers would have been correct; the aggregated point feedback (apf) is given by the following formula:

$$apf = \frac{x - y}{z - y} \mathbb{1}\{z > y\} + \mathbb{1}\{z = y\}$$

[11] There are 20 paid decisions out of 200 in Study 1 and 10 paid decisions out of 100 in Study 2. The number of decisions paid per block was controlled to be equal.

total 84 subjects participated in these studies across 3 sessions per study. The 41 subjects involved in Study 1 were on average 22.5 years old, 56% of them were males. The 43 subjects involved in Study 2 were on average 23.2 years old, 63% of them were males.

4 Methodology and results

We present the methodology used to analyze experimental data in Subsection 4.1. For both studies, we combine model-based results (Subsection 4.2.2, Subsection 4.3.2) and model-free analysis (Subsection 4.2.1, Subsection 4.3.1) to provide an extensive discussion of our hypothesis set.

4.1 Methodology

Estimations and model predictions based on SDT - Empirically, SDT enables to compute estimators of the decision criterion and the discrimination based on the observer's hit rate (HR) and false alarm rate (FAR). For n decisions, divided in n_s signal trials and n_n noise trials, we have:

$$HR = \frac{\sum_{i=1}^{n_s} \mathbb{1}(D_i = 1)}{n_s} \text{ and } FAR = \frac{\sum_{i=1}^{n_n} (1 - \mathbb{1}(D_i = 1))}{n_n}$$

.

The probabilities of hit (P_H) and false alarm (P_{FA}) are given by (proof in Appendix A):

$$P_H = \mathbb{P}(D = 1 | \Omega = 1) = 1 - \phi(\frac{log(\beta)}{d'} - d'/2) \tag{5}$$

$$P_{FA} = \mathbb{P}(D = 1 | \Omega = 0) = 1 - \phi(\frac{log(\beta)}{d'} + d'/2) \tag{6}$$

Hit or false alarm rates equal to 0 or 1 prevent robust estimations. Following the recommendations from Brown and White (2005), we use the $log-linear$ correction proposed by Hautus (1995) for estimations:

$$HR_C = \frac{0.5 + \sum_{i=1}^{n_s} \mathbb{1}(D_i = 1)}{n_s + 1} \text{ and } FAR_C = \frac{0.5 + \sum_{i=1}^{n_n} (1 - \mathbb{1}(D_i = 1))}{n_n + 1}$$

.

By finding the couple of parameters $(\hat{\beta}, \hat{d'})$, the most likely to have produced the actual HR_C and FAR_C, we are able to predict SDT parameters based on observed data (left side of Figure 3).

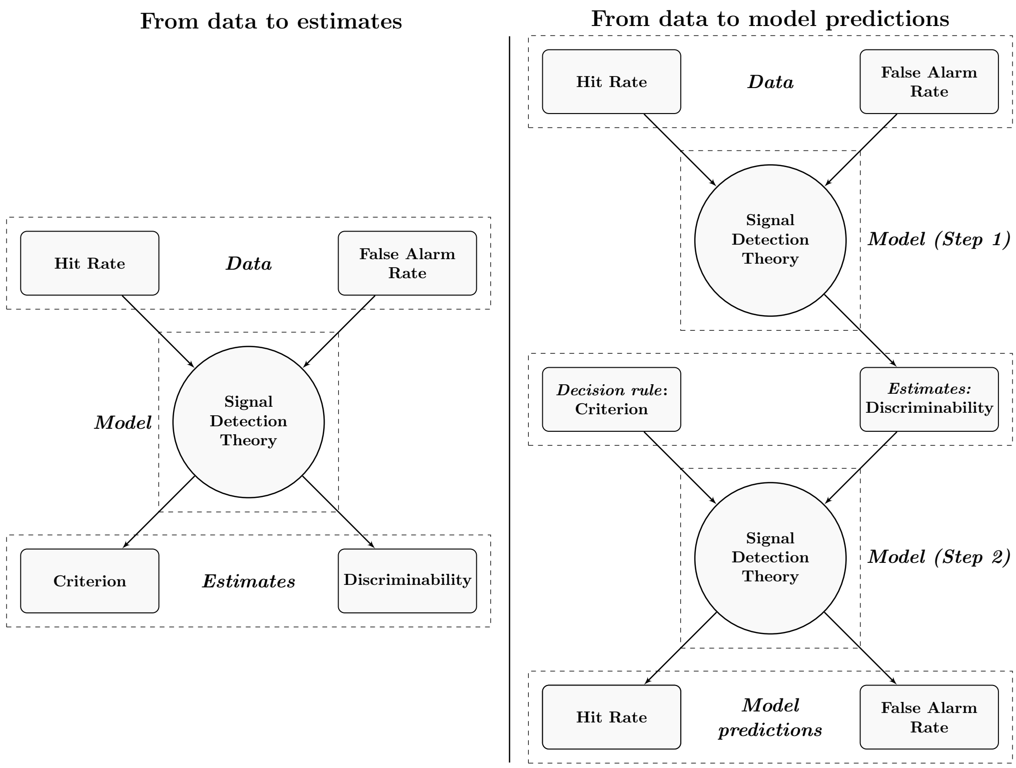


Figure 3: Discrimination and criterion estimations based on SDT modelisation.

To produce model predictions, we start from a couple (β, d') to compute a couple $(\hat{P}_H, \hat{P}_{FA})$, by inverting Equation 5 and Equation 6. As we are interested in SDT-based predictions of optimal and accurate behaviors, we use a two-step approach. We first estimate $(\hat{\beta}, \hat{d}')$ then replace $\hat{\beta}$ by their theoretical values from optimal or accurate behaviors and compute the couple $(\hat{P}_H, \hat{P}_{FA})$ (right side of Figure 3). Based on $\hat{P}_H$ and $\hat{P}_{FA}$, we are able to derive the predicted success probability $(\hat{P}_S)$ and number of points $(\hat{N}_P)$:

$$\hat{P}_S = \frac{\hat{P}_H + (1 - \hat{P}_{FA})}{2}$$

$$\begin{aligned}\hat{N}_P &= \hat{P}_H \times \Pi(1,1) + (1 - \hat{P}_H) \times \Pi(1,0) + (1 - \hat{P}_{FA}) \times \Pi(0,0) + \hat{P}_{FA} \times \Pi(0,1) \\ &= \hat{P}_H[\Pi(1,1) - \Pi(1,0)] + \hat{P}_{FA}[\Pi(0,1) - \Pi(0,0)] + \Pi(1,0) + \Pi(0,0)\end{aligned}$$

We predict behaviors for the two opposed components at the origin of the optimality-accuracy trade-off: β^* for the optimality driven behaviors and β^a for the accuracy driven behaviors (Section 2). For the symmetric treatment $\beta^* = 1$ and for asymmetric treatments $\beta^* = \frac{1}{3}$. For all treatments $\beta^a = 1$.

Estimations at a decision level - Previously presented estimations rely on aggregation of data by the computation of response rates. This methodology has the drawback of decreasing our statical power by summarizing all decisions made by an individual to a single measure. As an answer, we complement these analyses by estimations at the decision level. We use Generalized Estimating Equations (GEE) (Zeger and Liang, 1986). It is a quasi-likelihood based method (McCullagh and Nelder, 1989) designed to study clustered and repeated data. Compared to mixed-effect models, it has the valuable characteristics of i) providing population-average estimates instead of subject-specific estimates ii) not to require distributional assumptions (Hubbard et al., 2010). It is thus pertinent to use GEE to lead analyses at a decision level as it provides a flexible method for computing standard errors robust to individual clustering. Model selection in GEE do not rely on the standard index of goodness-of-fit: the Akaike Information criterion (AIC) and the Bayesian Information criterion (BIC) (Akaike, 1973; Schwarz et al., 1978) as GEE is non-likelihood-based. We use the quasi-likelihood criterion (QIC) (Pan, 2001). Model selection is accomplished by selecting the model minimizing the QIC. GEE estimation method, the selected specification and the index of goodness-of-fit are formally detailed in Appendix B.

4.2 Results - Study 1

To investigate Hypothesis 1.1 to Hypothesis 1.4, Study 1 results are first assessed on a model-free base before estimating the quality of predictions at a subjects/treatments level and finally at a decision level. Model-free analysis are mainly dedicated to evaluate the model-free Hypothesis 1.4 on decision under loss.

4.2.1 Model-free analysis at a decision level

Table 4 presents the estimations results[12] (for descriptive statistics see Table 1 of the Appendix).

Dependent variables - Four variables are relevant for analyzing subjects' behaviors. First, the variable "success" is equal to 1 for correct decisions and 0 for incorrect ones. Subjects have a 67.3% success rate validating the pre-task calibration (targeted value 71%). The variable "hit" is equal to success for signal trials while "false alarm" is error for noise trials. To link these variables to the SDT estimates and thus to our hypotheses set, the success variable is the local equivalent of the discrimination parameters. The cross-analysis of hit and false alarm gives us a local indicator on the decision criterion if both variables do not have opposite effects. The last variable of interest is the response time. We measure the response time as the time between the beginning of the stimuli display (lasting 900 ms) and the decision. We removed some outliers decisions which presented some abnormal long response times[13].

[12] Effects are estimated with and without control variables. The reference treatment is the Asymmetric High Gain Treatment as it enables to highlight the main impacts.

[13] Response times are, by definition, lower-bounded by 0 however they are not upper-bounded. Thus

Independent variables - To explain these behaviors, we use four different types of variables. Our main interest is to estimate the impact of the treatment on behavior, each treatment matching an indicative variable (Symmetric, Asymmetric Low Gain, Asymmetric High Gain, and Asymmetric Loss). The second set of variables is given by the attitudes toward loss and ambiguity. Subjects are clustered according to three modalities (averse, neutral or loving) concerning their loss attitudes under risk and uncertainty as well as their uncertainty attitudes under gain and loss[14]. Finally, we control for trials number within each treatment and the two most common demographic variables (gender and age).

Results: weak supports for Hypothesis 1.1 and Hypothesis 1.2 - The treatment variable is weakly relevant in explaining successes and response times (Fisher test, p-values respectively equal to 0.094 and 0.066). However, the variance inequality is not rejected for hit and false alarm (Fisher test, p-values respectively equal to 0.120 and 0.225). It can be explained by the fact that the sample is split in two to study these last two variables. As predicted by Hypothesis 1.1 and Hypothesis 1.2, successes are positively affected by the symmetric treatment. Interestingly the effect is driven by the false alarm rate but not by the hit rate. It means that individual were performing better in noise trials without decreasing their performance in signal trials. It may come from the fact that individuals were more confident in answering noise when having high subjective probabilities of facing a noise trial. The Asymmetric Low Gain Treatment is associated with more successes however the effect is, this time, driven by the hit rate. This low gain framework may involve less pressure on participants as all digits are lower. Thus, it could enhance performances by improving signal detection without sacrificing accuracy for noise detection.

Result: no support for Hypothesis 1.4 - The Loss Treatment has no influence on the decision outcomes (Fisher test, p-values: hit: 0.411, false alarm: 0.803 and success: 0.760)[15]. However in the Loss Treatment, subjects took more time to make their decisions. It is in line with previous research that have suggested that polarity and numerical magnitudes of negative numbers are represented separately and thus associated to higher response times (Tzelgov et al., 2009; Blair et al., 2012).

some really large response times have been recorded (until 36 times the mean of the sample). We can think of two reasons for abnormal response times. First, subjects could have introspected themselves for a long time. Second, they could have been distracted from the task or they have felt the need to use some rest before answering. In the second case, the time before answering cannot be interpreted as a response time because this time was not dedicated to the decision. As outliers have important effects on statistical results, we have chosen to remove outliers in case they do not reflect proper response times. We have used repeated Grubbs' tests (Grubbs, 1950). It tests if the hypothesis of normality can be rejected and remove the values the farthest from the mean. By applying this method to our sample until the normality hypotheses is not rejected at a one percent level, we exclude 2% of data (164 out of 8200 observations) and reduce the ratio between the mean value and the maximum value to 2.5.

[14]Refer to Appendix D for more details.

[15]This result is robust when reducing the analysis to only asymmetric treatments.

Additional results - Analyzing the attitude toward risk, loss and ambiguity, we note that only loss attitudes under ambiguity explains performances. Subjects exhibiting loss aversion under ambiguity have lower false alarm rate and higher success rate while loss loving subjects have lower hit rate. These better performances have been achieved as a result of higher response times.

It raises the question: does loss aversion (under ambiguity) induces different behaviors in the Loss Treatment? The cross effect of the Loss Treatment and loss aversion under ambiguity has a significant influence on the false alarms (Fisher test, p-value: 0.017) and response times (Fisher test, p-value: 0.097). Being loss averse (under ambiguity) increases response times more in the Loss Treatment and being loss lover (under ambiguity) also increases more the false alarm rate in this treatment (see Table 3 of the Appendix). We conclude that when subjects are loss averse under ambiguity and confronted to loss, ambiguity or both, they invest more cognitive resources in the task and also achieve a higher performance level. The fact that attitudes toward ambiguity are significant while attitudes toward risk are not is in line with the empirical differentiation of attitudes toward risk and ambiguity (Cohen et al., 2011). Finally, we do not observe a learning effect during the experiment as the trial number has no effect on decisions. The significant negative trend on response times could be explained by the additional time needed by subjects to get used to the new payoff matrix at the early stage of each treatment.

4.2.2 Model-based analysis

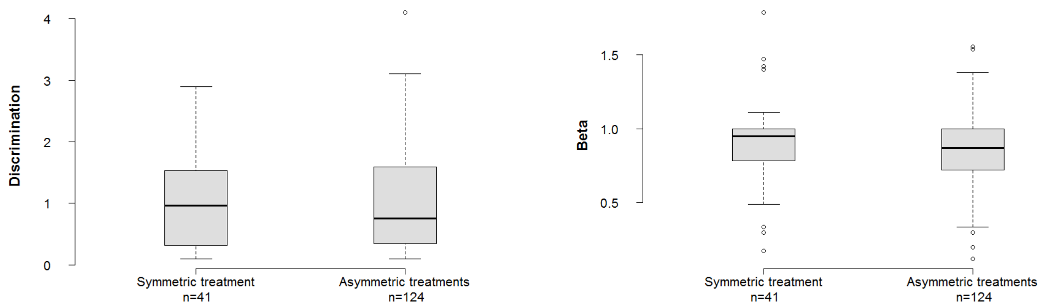
This subsection is dedicated to studying the three model-based hypotheses: Hypothesis 1.1, Hypothesis 1.2 and Hypothesis 1.3. To conclude, we oppose asymmetric treatments (trade-off existence) to the symmetric treatment - baseline (trade-off absence). We first provide an analysis of the distribution of SDT estimates, then a comparison between model predictions at a subject-treatment level and at a decision level.

SDT estimates

Level of analysis and model specification - The strength of SDT relies on the possibility to disentangle the impact of the task difficulty from the decision rules. In theory the task difficulty is the same for all treatments. Empirically, effort, learning, tiredness or other some random components of the decision process may induce differences in the subjects' capacity to discriminate. As the estimation of criteria relies on estimations of discrimination, if variations in discrimination are not totally random it may affect the quality of criteria's estimations. In order to control for these variations, we compute criteria and discrimination for each subject and each treatment. Parameters are estimated by maximum-likelihood using the Gaussian specification of SDT and constraining parameters on their definition set ($d' \in \mathbb{R}^+$). This methodology is reproduced in all model-based

	Dependent variable:							
	Hit		False Alarm		Success		Response time	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatments								
Symmetric	-0.000	-0.000	-0.256^{**}	-0.264^{**}	0.136^{**}	0.139^{**}	0.049	0.050
	(0.101)	(0.105)	(0.122)	(0.128)	(0.069)	(0.070)	(0.034)	(0.034)
Asymmetric Low Gain	0.203^{**}	0.211^{*}	-0.105	-0.109	0.145^{**}	0.148^{**}	0.016	0.017
	(0.103)	(0.108)	(0.097)	(0.100)	(0.062)	(0.063)	(0.036)	(0.036)
Asymmetric Loss	0.140	0.145	-0.097	-0.101	0.114	0.116	0.076^{**}	0.078^{**}
	(0.096)	(0.099)	(0.109)	(0.112)	(0.078)	(0.079)	(0.038)	(0.039)
Individual Variables								
Loss Averse Under Risk		-0.040		0.021		-0.024		0.050
		(0.158)		(0.219)		(0.150)		(0.084)
Loss Lover Under Risk		0.235		0.450		-0.148		0.178
		(0.250)		(0.274)		(0.214)		(0.143)
Loss Averse Under Ambiguity		0.345		-0.525^{**}		0.434^{**}		0.200^{*}
		(0.241)		(0.207)		(0.179)		(0.118)
Loss Lover Under Ambiguity		-0.522^{*}		0.152		-0.292		0.224
		(0.301)		(0.243)		(0.198)		(0.171)
Ambiguity Averse Under Gain		-0.093		0.082		-0.076		-0.164
		(0.277)		(0.256)		(0.226)		(0.136)
Ambiguity Lover Under Gain		-0.128		-0.096		-0.007		-0.179
		(0.282)		(0.248)		(0.210)		(0.127)
Ambiguity Averse Under Loss		0.130		-0.219		0.168		0.105
		(0.168)		(0.226)		(0.166)		(0.104)
Ambiguity Lover Under Loss		0.359		-0.039		0.174		-0.002
		(0.289)		(0.272)		(0.228)		(0.099)
Male		0.642^{***}		-0.015		0.291^{*}		-0.066
		(0.186)		(0.181)		(0.150)		(0.075)
Age		-0.052^{***}		0.018		-0.033^{***}		0.009
		(0.012)		(0.014)		(0.010)		(0.006)
Other								
Trial Number		-0.001		0.0004		0.001		-0.003^{***}
		(0.003)		(0.003)		(0.002)		(0.001)
Constant	0.944^{***}	1.662^{***}	-0.337^{**}	-0.474	0.627^{***}	0.966^{***}	1.470^{***}	1.271^{***}
	(0.134)	(0.370)	(0.134)	(0.500)	(0.100)	(0.352)	(0.047)	(0.218)
Observations	4,100	4,100	4,100	4,100	8,200	8,200	8,036	8,036
QIC	4,747.184	4,685.312	5,500.676	5,479.842	10,381.830	10,351.390	$-9,091.792$	$-8,726.823$
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 4: Study 1 - Model-free impacts of the treatments, the risk attitudes, demographics and trial number.



a - Discrimination *b - Criteria*

Figure 4: Study 1 - Estimated discrimination and criteria.

Reading note: (a) - distribution of the estimated discrimination (a) and β criteria (b) for symmetric and asymmetric treatments. Interquartile ranges are represented by the horizontal lines.

analyses.

Results - Discrimination and criteria medians are lower for asymmetric treatments (Figure 4). However, we are unable to prove that neither the discrimination (p-value = 0.813[16]) nor the criteria (p-value = 0.402) are statistically lower for asymmetric treatments.

The direct analysis of criteria and discrimination does not allow us to conclude on Hypothesis 1.1, Hypothesis 1.2 or Hypothesis 1.3. This lack of direct results may come from different factors. First, this approach is conservative as by aggregating information, we decrease substantially our statistical power. Second, we do not use the full potential of SDT as we do not take into account its predictive power concerning accuracy maximization or optimality. To better understand the optimality-accuracy trade-off, we provide a comparison of model predictions and observed data.

Comparison to model predictions at a subject-treatment level

Level of analysis and specification - We first compute the mean ratio between the two model predictions (accuracy driven and optimality driven) and observed data at a subject-treatment level. It enables us to evaluate if we are in presence of either over-accuracy or under-accuracy. Additionally, we tackle the question of a potential efficiency loss due to the optimality-accuracy trade-off.

Result: support for Hypothesis 1.1 - Confronted to the optimality-accuracy trade-off, the observed success rate is 7.9% higher than the optimal accuracy rate (p-value < 0.001). It induces a decrease by 11.8% of the number of points accumulated (p-value < 0.001)[17]. Opposing the deviations from predictions in symmetric and asymmetric treatments, we

[16] Throughout the paper, statistical tests used to compared two samples are two-sided Mann-Whitney U tests unless specified otherwise. Tests are paired when balanced.

[17] To control for the differences in performance-based earnings from one treatment to another, we scale the earnings by subtracting the minimal number of points (i.e. payoff for errors) from the actual number of points.

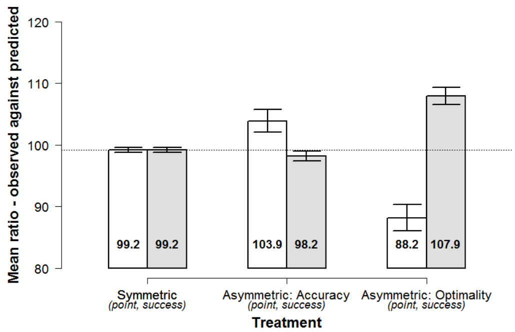


Figure 5: Deviations from accuracy-maximizing and optimal decision strategies.

Reading note: the mean ratio between observed and predicted decisions for the symmetric treatment and the asymmetric treatments are represented. White bars provide points comparisons and grey bars provide success rate comparisons. 95% confidence intervals are represented by the horizontal lines.

observe that subjects are closer from optimality in the symmetric framework for both accuracy rate and earnings (p-values < 0.001). We thus conclude that subjects are over-accurate leading to an efficiency loss.

Result: support for Hypothesis 1.2 - For asymmetric payoff matrices, the observed accuracy rate is 1.8% lower than the accuracy maximizing success rate (p-values < 0.001). This deviation from the accuracy maximizing decision strategy induces a 3.9% increase of subjects' earnings (p-values < 0.001). Again subjects are closer from predictions for earnings when there is no trade-off (p-value < 0.001). Concerning accuracy rates, the difference is not significant (p-value $= 0.156$). These analyses globally support that subjects deviate from the accuracy maximizing strategy toward the optimal strategy.

Result: support for Hypothesis 1.3 - Subjects are neither pure accuracy-maximizer nor optimal, however from which behavior do they differ the less? We observe that deviation from accuracy maximization toward optimality is weaker than the deviation from optimality toward accuracy both in term of success rate and points (p-values $<$ 0.001).

Comparison to model predictions at a decision level

We assess if previous findings are reproduced at a disaggregated level. We also investigate if model predictions are relevant in explaining data. Table 5 presents results for the four predicted variables based on the accuracy criterion and the optimal criterion[18].

Level of analysis and specification - Using GEE at a decision level, we test the predicted variables against the observed data including an indicative variable equal to one for the asymmetric treatment and a constant (a).

$$y_{obs} \sim y_{pred} + \mathbb{1}_{\{asymmetric\, treatment\}} + a$$

[18]All previous analysis are robust when adding controls in the regressions (see Appendix C).

The indicative term tells us whether there is an overestimation or an underestimation of the dependent variable for asymmetric treatments. The significativity of the prediction term assesses the relevance of model predictions. Finally, for each independent variable, we are able to assess whether the accuracy-based or the optimality-based predictions gives the best fit.

Result: support for Hypothesis 1.1 - For asymmetric treatments, optimality-based predictions overestimate the hit rate, the false alarm rate and payoffs. They underestimate the success rate. This over-accuracy ultimately results in sub-optimality.

Result: support for Hypothesis 1.2 - Accuracy-based predictions underestimate the number of hit, false alarm and payoffs for asymmetric treatments. It means that subjects are not pure-accuracy seeking. They are inclined to sacrifice some accuracy for the low stakes trials to increase their accuracy for high stakes trials.

Result: support for Hypothesis 1.3 - By comparing QIC criteria between both predictions rules, we notice that accuracy-based predictions systematically give a better fit to observed data. Thus data reveal an actual criterion closer to the accuracy-driven one rather than the optimal one.

Additional result - Each model predictions have a positive impact on its corresponding predicted variable at a 1% test level. Thus model predictions are relevant in predicting observed data.

	Dependent variable:							
	Hit		False Alarm		Success		Payoff	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hit Optimal	2.437***							
	(0.721)							
Hit Accuracy		5.475***						
		(0.577)						
False Alarm Optimal			2.345***					
			(0.244)					
False Alarm Accuracy				5.214***				
				(0.489)				
Success Optimal					4.960***			
					(0.161)			
Success Accuracy						5.216***		
						(0.162)		
Payoff Optimal							0.995***	
							(0.003)	
Payoff Accuracy								0.999***
								(0.003)
Asymmetric	−0.587***	0.166*	−0.811***	0.164*	0.284***	−0.013	−0.499***	0.185***
	(0.181)	(0.092)	(0.109)	(0.095)	(0.023)	(0.019)	(0.071)	(0.045)
Constant	−0.713	−2.728***	−1.336***	−2.277***	−2.585***	−2.754***	−0.012	−0.029*
	(0.480)	(0.380)	(0.099)	(0.179)	(0.100)	(0.103)	(0.021)	(0.017)
Observations	4,100	4,100	4,100	4,100	8,200	8,200	8,200	8,200
QIC	4,729.084	4,437.071	5,176.933	5,131.568	9,725.253	9,707.624	20,804.750	20,723.280
Technical note:								*p<0.1; **p<0.05; ***p<0.01

Table 5: Study 1 - Impacts of model predictions on observed behaviors.

Reading note: for each dependent variable, we present the causal effect of the corresponding predicted variable based on either optimal decision (odd numbers) or accuracy maximization (even numbers) strategies.

4.3 Results - Study 2

Study 2 tackles the question summarized in Hypothesis 2.1: does the value of being right contribute to the observed optimality-accuracy trade-off? The answers lies in the difference of behavior between the Incentivized and the Flat Treatment. If subjects are pure-payoff maximizer, their decisions should approach random guesses in the Flat Treatment. Otherwise, this difference reflects the marginal utility of being accurate compared to the marginal utility of payoffs. The smallest the difference, the higher the relative marginal utility. In line with the progression undertaken to investigate Study 1 results, Study 2 results are first assessed on a model-free base before estimating the quality of predictions at a subjects/treatments level and finally at a decision level.

4.3.1 Model-free analysis at a decision level

Level of analysis and specification - We use GEE equations to regress the treatment and controls on hits, false alarms, successes and response times[19]. Control variables are the trial number, the gender and the age of participants[20]. Results are given in Table 6, additional descriptive statistics are to be found in Table 2 of the appendix.

Result: subjects outperform random guesses but still decrease their success rate in the Flat Treatment - In the Flat Treatment subjects' success rates decrease. This result is driven both by a decreasing hit rate and an increasing false alarm rate. On average, the success rate decreases from 68.4% to 63.8% (p-value = 0.001). We reject the hypothesis that the true mean success rate in the Flat Treatment is equal to 50% at all common test level (binomial-test, p-value < 0.001).

Result: response times decreased in the Flat Treatment - Individuals make their decisions more quickly in the Flat Treatment compared to the Incentivized Treatment ($mean_{incentivized} = 1730ms$, $mean_{flat} = 1512ms$, p-value = 0.001). It confirms that they are sensitive to change in payoff matrices. Additionally, as in Study 1 individuals' response times decrease along treatments.

Conclusion: support for Hypothesis 2.1 - Subjects have on average outperformed random guesses. Thus we cannot find evidence for a pure-payoff maximization. However their accuracy has decreased from the Incentivized to the Flat Treatment. It shows that when the monetary reward is withdrawn from the value of being right, this value is not strong enough to induce, by itself, the same level of cognitive investment. It is confirmed by the analysis of response times. Based on these considerations, it is not possible to

[19]For the same reason than in Study 1, response times are corrected using a repeated Grubbs' test. 1.6% of the sample is considered as being outliers (68 observations out of 4300).

[20]Two participants entered an incoherent age (< 3), we assigned them the mean age of all other participants.

reject Hypothesis 2.1 as no criterion shift is highlighted and subjects are involved in an accuracy-seeking behavior in the Flat Treatment.

	Dependent variable:							
	Hit		False Alarm		Success		Response Time	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatments								
Flat Treatment	−0.195**	−0.195**	0.221**	0.221**	−0.208***	−0.208***	−0.218***	−0.218***
	(0.090)	(0.090)	(0.096)	(0.097)	(0.059)	(0.059)	(0.067)	(0.067)
Controls								
Trial number		−0.003		−0.001		−0.0001		−0.003***
		(0.003)		(0.003)		(0.002)		(0.001)
Male		−0.195		−0.126		−0.007		0.013
		(0.224)		(0.160)		(0.151)		(0.076)
Age		0.006		0.001		0.003		−0.006
		(0.018)		(0.026)		(0.014)		(0.007)
Constant	0.885***	0.954*	−0.665***	−0.585	0.773***	0.734*	1.641***	1.853***
	(0.125)	(0.538)	(0.086)	(0.637)	(0.089)	(0.378)	(0.048)	(0.176)
Observations	2,150	2,150	2,150	2,150	4,300	4,300	4,222	4,222
QIC	2, 680.757	2, 693.269	2, 824.493	2, 845.693	5, 509.606	5, 529.835	−4, 896.076	−4, 859.644
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 6: Study 2 - Model-free impacts of the Flat Treatment, demographics and trial number.

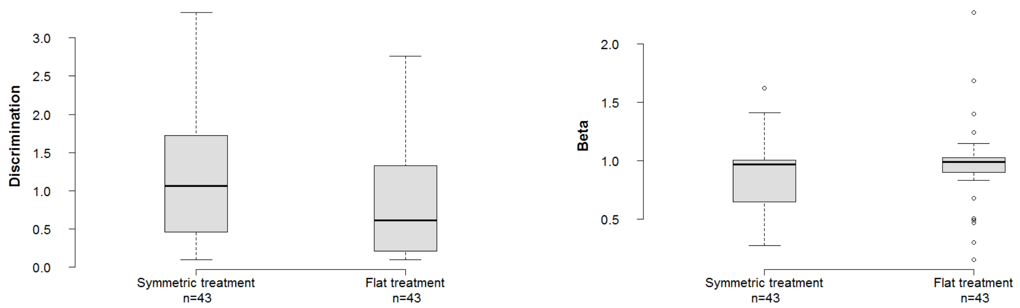
4.3.2 Model-based analysis

Model-based analysis at a cross subject-treatment level

Level of analysis and specification - Discrimination and decision parameters are computed at a cross subject-treatment level. If subjects were only maximizing rewards, their discrimination should be close from null and their decision criteria should approach a random distribution.

Results: decision criteria are not different between treatments and do not reflect random-guesses - We cannot reject the equality of criteria between treatments (p-value = 0.491). In the Flat Treatment, we notice much more extreme values than in the Incentivized Treatment; however more values are gathered around the median (Figure 6 - b). Using a Levene's test for equality of variance (Levene, 1960), we accept the treatments variance equality hypothesis (p-value = 0.718). We test criteria distribution using Kolmogorov-Smirnov tests. First, we compared criteria from both treatments. We do not reject the hypothesis of equal distribution at all common test levels (p-value = 0.303). Then, we test criteria from the Flat Treatment against a uniform distribution of same range. We reject the hypothesis of equal distribution at 1% (p-value < 0.001).

Result: discriminations decrease in the Flat Treatment but stay above null discrimination - The discrimination is lower in the Flat Treatment (p-value < 0.001, Figure 6 - a). The number of subjects with minimal discrimination increase by one from the incentivized to the Flat Treatment (14% against 16% of $\hat{d}'$).



a - Discrimination *b - Criteria*

Figure 6: Study 2 - Estimated discrimination and criteria.

Reading note: Distribution of the estimated discrimination (a) and β criteria (b) for Incentivized and Flat Treatments. Interquartile ranges are represented by the horizontal lines.

Conclusion: support for Hypothesis 2.1 - Once again, SDT enables us to disentangle the decision strategy from the discrimination. We find no difference in decisions strategy between treatments and a non-random strategy for the Flat Treatment. We explain the decreasing discrimination in the Flat Treatment compared to the Incentivized Treatment by a decrease in the effort level. Subjects invested less cognitive resources when monetary rewards were suppressed. However, the value of being right has kept discrimination above a random-guess level. To complete the spectrum of analysis, we assess the robustness of previous conclusions at a decision-level analysis.

Model-based analysis at a decision level

Level of analysis and specification - Following the level of analysis and specification of Subsection 4.2.2, we produce decision predictions based on estimated discrimination and theoretical β. In Study 2 only $\beta_a = 1$ can be used as reference[21] . The GEE regressions of forecast variables against observed variables is given in Table 7[22]. We are mainly interested in studying to which extent the accuracy-maximizing criterion (β_a) is relevant for predicting behaviors in the Flat Treatment.

Result: accuracy maximizing predictions explain behaviors in both treatments with a better fit for the Incentivized Treatment - We notice that all predictions are explaining actual behaviors. Additionally the Flat Treatment variable has no explanatory power. It means that the initial hypothesis made for predicting data ($\beta = \beta^a$) is relevant to explain data for treatments with and without incentives. Finally, we have computed the quality of fit by clustering data according to treatments. The Incentivized Treatment is better

[21]Under the hypothesis of mixed valuation of optimality and accuracy subjects should use this criterion in both treatments. Under the hypothesis of pure-payoff maximization, it is impossible to compute a unique reference criterion as subjects are supposed to behave randomly.

[22]Predictions are produced for hits, false alarms and successes. Payoffs are not predicted as by definition observed and predicted data are the same for at least half of the sample.

fitted than the Flat Treatment[23].

Conclusion: support for Hypothesis 2.1 - Data being explained by accuracy-maximization predictions reinforces previous findings on the role played by the value of being right in the optimality-accuracy trade-off. Higher deviations from predictions in the Flat Treatment are identified consistently with the decreasing level of effort in non-incentivized treatments.

	Dependent variable:		
	Hit	False Alarm	Success
	(1)	(2)	(3)
Predicted Hit	5.987***		
	(0.595)		
Predicted False Alarm		3.894***	
		(0.472)	
Predicted Success			4.843***
			(0.134)
Flat Treatment	0.058	0.051	0.0005
	(0.089)	(0.078)	(0.019)
Constant	−3.158***	−1.896***	−2.521***
	(0.404)	(0.147)	(0.088)
Observations	2,150	2,150	4,300
QIC Flat	1,309.000	1,400.000	2,708.000
QIC Incentive	1,176.000	1,332.000	2,521.000
Technical note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Study 2 - Impacts of model predictions on observed behaviors.

Reading note: for each dependent variable, we present the causal effect of the corresponding predicted variable based on either accuracy maximization or optimal decision strategies.

5 Discussion and Conclusion

In most situations, seeking for accuracy is relevant to achieve optimality. However, when stakes are asymmetric significant departures from accuracy must be achieved to approach optimality. As a consequence, an optimality-accuracy trade-off arises.

Based on a multi-level analysis, the first study confirms the existence of the optimality-accuracy trade-off using a signal-in-noise discrimination task. In fact, answer patterns exhibit a deviation from accuracy in the direction of optimality but do not approach the optimal solution. This tendency is so pronounced that we observe a leading role of accuracy in the trade-off[24]. Based on a pure-loss framework, we reject the hypothesis of an impact of losses on the trade-off behavior and extend previous findings based on a mixed gain-loss framework (Maddox et al., 2003b). It seems that in this perceptual

[23] All previously described results are robust to controls (see Appendix C).

[24] Subjects seem to be aware of this behavior. In a question at the end of Study 1, 80% of them report that they tried to maximize their accuracy rates rather than their payoffs.

task, individuals react less to reference-point manipulations than in preferences tasks (*e.g.* lotteries). This lack of effect is even more remarkable that we do not implement a loss framing but real monetary losses in the experiment. Additionally, we note a causal impact of loss attitudes under ambiguity on decisions in the Loss Treatment. The second study investigates if attitudes toward the optimality-accuracy trade-off could be impacted by the value of being right. Our approach, based on an original design enabling to directly tackle this question, provides new insights and contrasts with previous results (Maddox and Bohil, 2003, 2004). In line with the leading role of accuracy, our multi-level evaluation of the value of being right reveals that it plays a central role in the trade-off solution. When removing all monetary incentives, we obtain that individuals are driven by a search for accuracy.

One limitation of this result is that we cannot exclude a potential experimenter demand effect (Zizzo, 2010). The search for accuracy might be linked to an internal pressure for subjects to perform a task in a laboratory setting. While we do not have a control for this effect we doubt that it drives our result. First, subjects performed the Incentivized and the Flat Payoff Treatments in a same session. This should decrease the pressure felt by subjects to perform the non-incentivized task by comparison of both treatments. We can argue that real-life situations are quite similar with internal or external pressure to succeed even without rewards. Thus, we conclude in favor of our accuracy seeking hypothesis and that it is not possible to consider the trade-off only as an "*as-if*" behavior and that individuals intrinsically value the fact of being right. The non-monetary utility of success has been highlighted in other contexts. Thinking about how individuals behave in contests, this same idea of induced utility of success has been obtained referred as the joy of winning (Mago et al., 2013; Price and Sheremeta, 2011). To extend such findings in an individual setting is interesting as this utility is not driven by competition and the seek for out-performing our counterparts but only by internal challenge and self-ego.

In this paper, we consider that individuals evaluate the payoffs in terms of explicit rewards. However, one can assume that individuals instead assess the utility of these rewards. Introducing such subjective weightings of the rewards will affect the optimal criterion. It is possible to redefine optimality as a subjective optimality instead of an objective one. As subjective utility functions are typically concave, it involves a shift of the optimal criterion toward the accurate criterion. This explanation of the trade-off has been previously investigated by Ackermann and Landy (2015). They manipulate payoffs and base rates to compare decision criteria with Prospect Theory optima. However, even with this approach, the optimality-accuracy trade-off is still observed. While we do not choose to express our analysis in terms of weighting functions, our results tend to give low support to the importance of an utility-based approach. First, individual preferences toward risk, ambiguity and loss have a low explanatory power on observed behaviors, while if subjective utility was playing a key role in the decision process, we should observed important effects. Then, Ackermann and Landy (2015) state that the framing of decisions should affect the criterion placement in a Prospect Theory framework. Our design allows us to test and reject this claim as we cannot identify any effect on the criterion during decisions under losses.

Individuals under-react to payoff incentives. The intrinsic motivation of being successful seems to exceed the monetary motivation. However, emphasizing the monetary consequences of actions over the actual successes or errors may decrease the induced efficiency-loss. Note that our setting implies that all the monetary incentives are supported by the decision maker himself. It could be interesting to see how the trade-off is affected by a more social framework where decisions affect either the payoffs of one other subject (patient-practitioner relationship) or a whole group of subjects (externality). One can expect the trade-off to be affected toward more optimality with previous evidences that making decisions for others affects risk preferences (Chakravarty et al., 2011), loss aversion (Andersson et al., 2014), time discounting (Albrecht et al., 2011) and cooperation (Vermeer et al., 2016).

Identifying the optimality-accuracy trade-off and understanding its reasons, as this paper attempts, is a basic prerequisite to change behaviors toward more optimality. In a decision support tool perspective, it opens the question to know how to develop policies to correct the decision process and how to inverse the trade-off in favor of optimal-driven behaviors.

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Appendix

A Hit and false alarm probabilities

We demonstrate Equation 5 and Equation 6. First, we can easily write the P_H and P_{FA} in function of the criterion λ described in Equation 1.

$$\begin{aligned} P_H &= \mathbb{P}(X_s > \lambda) \\ &= 1 - \phi(\lambda - d') \\ P_{FA} &= \mathbb{P}(X_n > \lambda) \\ &= 1 - \phi(\lambda) \end{aligned}$$

Then, we need to express P_H and P_{FA} in function in function of the criterion $log(\beta)$:

$$\begin{aligned} log(\beta) &= log\left(\frac{f_s(\lambda)}{f_n(\lambda)}\right) \\ &= log\left(\frac{1}{\sqrt{2\pi}}exp(-\frac{1}{2}(\lambda - d')^2)\right) - log\left(\frac{1}{\sqrt{2\pi}}exp(-\frac{1}{2}\lambda)^2\right) \\ &= d'(\lambda - \frac{1}{2}d') \end{aligned}$$

Thus:

$$P_H = 1 - \phi\left(\frac{log(\beta)}{d'} - d'/2\right)$$

$$P_{FA} = 1 - \phi\left(\frac{log(\beta)}{d'} + d'/2\right)$$

B Generalized Estimation Equations

GEE is a quasi-likelihood method to study clustered data. To lead model selection, we rely on the quasi-likelihood criterion (QIC).

Formally, let's consider $y_i = (y_{1i}, ..., y_{iT})$ a vector of responses from n clusters with T observations for the i^{th} cluster, $i = 1, ..., n$. The expectation $\mathbb{E}(y_{it})$ is equal to μ_{it}. This expectation is related to reggressors through the mean-link function g:

$$g(\mu_{it}) = x_{it}^{\intercal}\beta$$

The variance of Y_{it} is given by:

$$var(y_{it}) = \phi a(\mu_{it})$$

With ϕ the common scale parameter and a the known variance function. To estimate the correlation between Y_{it}, GEE relies on a working correlation matrix $R_i(\alpha)$. The corresponding working covariance matrix of Y_i is thus given by:

$$V_i = \phi A_i^{\frac{1}{2}} R_i(\alpha) A_i^{\frac{1}{2}}$$

where A_i is the diagonal matrix with entries a_{it}. The estimates are the solution of the equation:

$$\sum_{i=1}^{K} \frac{\partial \mu_i^T}{\partial \beta} V_i^{-1}(y_i - \mu_i) = 0.$$

V_i is consistently estimated by the robust covariance estimator, V_r. It replaces the usual Fisher information matrix. Quasi-Likelihood methods benefit from yielding a consistent estimator of β even when $R_i(\alpha)$ is mis-specified (Liang and Zeger, 1986; Verbeke and Molenberghs, 2009). The most common hypothesis is thus to define the working correlation matrix as being equal to the identity matrix I. Under the independence assumption model, $\hat{\beta}$ is relatively efficient (Zeger et al., 1988; McDonald, 1993). This assumption is done in our estimations. Concerning the mean-link function, we use a binary logit function for binary responses and a Gaussian link for continuous ones.

Model selection is accomplished by selecting the model minimizing the QIC (Pan, 2001). Formally:

$$QIC(I) = -2Q(\hat{\beta}; I, \mathcal{D}) + 2trace(\hat{\Omega}_I \hat{V}_r)$$

where $\mathcal{D} = (y_1, x_1), ...(y_n, x_n)$ and $\hat{\Omega}_I = -\frac{\partial^2 Q(\hat{\beta}; I, \mathcal{D})}{\partial \beta \partial \beta'}|_{\beta = \hat{\beta}}$.

C Complementary results tables

C.1 Descriptive statistics

Statistic	Treatment	Mean (% or ms)	St. Dev.	Min (% or ms)	Max (% or ms)
Hit	B	71.12	14.83	37	98
	LG	74.88	13.78	44	98
	L	73.78	15.32	29	98
	HG	71.07	16.85	40	98
False Alarm	B	36.10	13.41	13	67
	LG	39.51	18.09	10	98
	L	39.71	18.34	13	98
	HG	42.02	20.33	2	98
Success	B	68.20	11.86	50	92
	LG	68.39	12.30	50	92
	L	67.71	13.43	34	92
	HG	65.17	14.70	42	100
Response Time	B	1.62	0.42	0.89	3.00
	LG	1.55	0.42	0.44	2.44
	L	1.69	0.61	0.37	3.95
	HG	1.55	0.38	0.73	2.58

Note: Baseline (B), Low Gain (LG), Loss (L) and High Gain (HG).

Table 1: Study 1 - Descriptive Statistics

Statistic	Treatment	Mean (% or ms)	St. Dev.	Min (% or ms)	Max (% or ms)
Hit	I	70.00	16.52	33	98
	F	65.95	15.53	33	98
False Alarm	I	34.60	12.29	10	56
	F	39.51	14.85	10	90
Success	I	68.42	12.82	42	96
	F	63.77	10.86	48	88
Response Time	I	1.65	0.34	1.16	2.84
	F	1.46	0.32	0.59	2.22

Note: Incentivized (I) and Flat (F).

Table 2: Study 2 - Descriptive Statistics

C.2 Model-free analysis

	Dependent variable:							
	Hit		False Alarm		Success		Response time	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cross-variables								
Asymmetric Loss × Loss Averse Under Ambiguity	−0.201	−0.204	−0.098	−0.098	−0.023	−0.023	0.164*	0.166**
	(0.216)	(0.221)	(0.228)	(0.229)	(0.144)	(0.145)	(0.084)	(0.084)
Asymmetric Loss × Loss Lover Under Ambiguity	−0.326	−0.333	0.432*	0.440*	−0.348	−0.350	0.047	0.048
	(0.319)	(0.324)	(0.258)	(0.260)	(0.216)	(0.217)	(0.117)	(0.116)
Treatments								
Symmetric	−0.000	0.000	−0.261**	−0.263**	0.137**	0.139**	0.049	0.050
	(0.101)	(0.104)	(0.125)	(0.127)	(0.070)	(0.070)	(0.034)	(0.034)
Asymmetric Low Gain	0.204*	0.210**	−0.108	−0.108	0.146**	0.148**	0.015	0.017
	(0.104)	(0.107)	(0.099)	(0.100)	(0.062)	(0.063)	(0.036)	(0.036)
Asymmetric Loss	0.313	0.320	−0.112	−0.113	0.186	0.187	−0.026	−0.027
	(0.202)	(0.205)	(0.210)	(0.211)	(0.123)	(0.124)	(0.080)	(0.079)
Individual Variables								
Loss Averse Under Ambiguity	−0.042	0.393	−0.512***	−0.500**	0.259	0.440**	0.127	0.159
	(0.249)	(0.255)	(0.199)	(0.218)	(0.179)	(0.189)	(0.101)	(0.114)
Loss Lover Under Ambiguity	−0.381	−0.441	0.184	0.043	−0.262	−0.204	0.151	0.212
	(0.238)	(0.283)	(0.305)	(0.241)	(0.181)	(0.190)	(0.153)	(0.162)
Loss Averse Under Risk		−0.040		0.021		−0.024		0.050
		(0.158)		(0.219)		(0.150)		(0.084)
Loss Lover Under Risk		0.235		0.451		−0.149		0.178
		(0.250)		(0.274)		(0.214)		(0.143)
Ambiguity Averse Under Gain		−0.093		0.083		−0.076		−0.164
		(0.277)		(0.256)		(0.226)		(0.136)
Ambiguity Lover Under Gain		−0.128		−0.097		−0.007		−0.179
		(0.283)		(0.248)		(0.211)		(0.127)
Ambiguity Averse Under Loss		0.130		−0.220		0.168		0.105
		(0.168)		(0.226)		(0.166)		(0.104)
Ambiguity Lover Under Loss		0.359		−0.039		0.174		−0.003
		(0.290)		(0.272)		(0.228)		(0.099)
Male		0.642***		−0.015		0.291*		−0.066
		(0.186)		(0.181)		(0.150)		(0.075)
Age		−0.052***		0.018		−0.033***		0.009
		(0.012)		(0.014)		(0.010)		(0.006)
Other								
Trial Number		−0.001		0.0004		0.001		−0.003***
		(0.003)		(0.003)		(0.002)		(0.001)
Constant	1.028***	1.621***	−0.070	−0.472	0.518***	0.949***	1.374***	1.297***
	(0.209)	(0.381)	(0.178)	(0.491)	(0.147)	(0.355)	(0.087)	(0.213)
Observations	4,100	4,100	4,100	4,100	8,200	8,200	8,036	8,036
QIC	4,758.649	4,688.881	5,423.710	5,478.697	10,322.740	10,352.040	−8,985.641	−8,728.611
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 3: Impacts of the cross-variable Asymmetric Loss Treatment × loss attitudes under ambiguity.

C.3 Model-based analysis

	Dependent variable:							
	Hit		False Alarm		Success		Payoff	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hit Optimal	1.834*** (0.697)							
Hit Accuracy		5.059*** (0.565)						
False Alarm Optimal			2.545*** (0.251)					
False Alarm Accuracy				5.772*** (0.479)				
Success Optimal					4.962*** (0.155)			
Success Accuracy						5.258*** (0.157)		
Point Optimal							0.995*** (0.003)	
Point Accuracy								0.998*** (0.003)
Asymmetric	−0.433** (0.183)	0.163* (0.092)	−0.890*** (0.122)	0.163* (0.097)	0.283*** (0.025)	−0.013 (0.019)	−0.498*** (0.071)	0.185*** (0.045)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Constant	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,100	4,100	4,100	4,100	8,200	8,200	8,200	8,200
QIC	4,628.860	4,416.117	5,151.926	5,104.202	9,725.096	9,708.939	20,759.370	20,699.830
Technical note:								*p<0.1; **p<0.05; ***p<0.01

Table 4: Study 1 - Impacts of model predictions on observed behaviors with controls.

Reading note: for each dependent variable, we present the causal effect of the corresponding predicted variable based on either accuracy maximization or optimal decision strategies.

	Dependent variable:		
	Hit	False Alarm	Success
	(1)	(2)	(3)
Predicted Hit	5.960*** (0.601)		
Predicted False Alarm		3.940*** (0.478)	
Predicted Success			4.850*** (0.134)
Flat Treatment	0.059 (0.086)	0.050 (0.078)	0.001 (0.019)
Controls	YES	YES	YES
Constant	YES	YES	YES
Observations	2,150	2,150	4,300
QIC flat	1,325.000	1,412.000	2,707.000
QIC Incentive	1,177.000	1,332.000	2,523.000
Technical note:			*p<0.1; **p<0.05; ***p<0.01

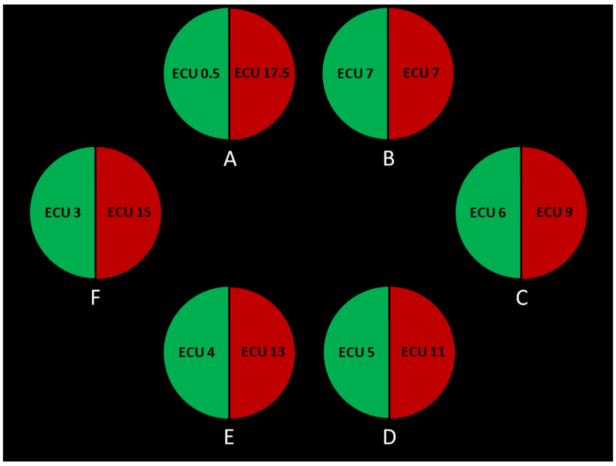
Table 5: Study 2 - Impacts of model predictions on observed behaviors with controls.

Reading note: for each dependent variable, we present the causal effect of the corresponding predicted variable based on either accuracy maximization or optimal decision strategies.

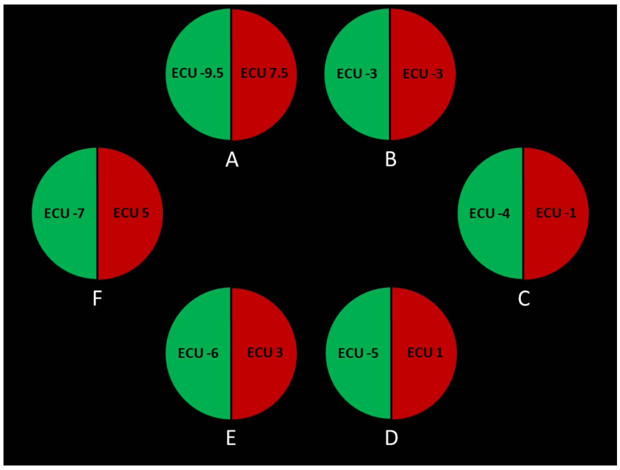
D Elicitation of attitudes toward risk, ambiguity and losses

Design - The elicitation task is composed of four successive lotteries decisions. Subjects have to select a two-outcome lottery out of six possibilities. Lottery sets differ from one another regarding likeliness of each outcome and the fact that outcomes can induce a loss. For decisions 1 and 2 (Figure 1 - a and b), each outcome is equally likely - decisions under risk. For decisions 3 and 4 (Figure 1 - c and d), the probability of each outcome varies between 30% and 70% - decisions under ambiguity. For decisions 1 and 3 losses are impossible while some outcomes result in losses for the two other decisions. Outcome earnings are constructed as follow: moving clockwise the expected payoff and its variance increase, exception made of the last lottery (A) for which only the variance of the payoff is higher compared to the previous one (F). For decisions involving losses, an endowment is allocated to subjects such that lotteries outcome more the endowment is equal to the corresponding gain framing. Experimental currencies (ECU) are used for this task. We randomly select one of the four decisions for payment (2 *ECU* = *AUD 1*).

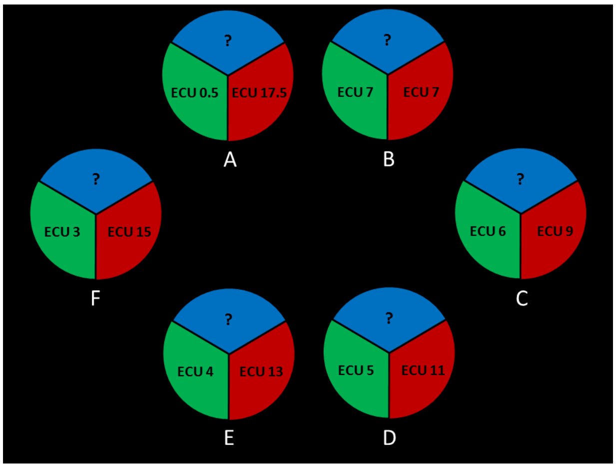
Methodology - Based on subjects' answers, we derive their attitudes toward loss under risk and under ambiguity and their attitude toward ambiguity under loss and gain. All variables defined takes three modalities: averse, neutral or lover. They are computed by two-by-two choices comparison. To define the loss aversion under risk, we compare lotteries with and without losses (decision 2 and decision 1). By comparing the lotteries under ambiguity (decision 3 and 4), we obtain the loss aversion under ambiguity. The ambiguity aversion is defined by comparison to risk aversion. Thus to find the ambiguity under gain, we compare the lotteries in gain under ambiguity and under risk (decision 3 and decision 1). Finally, to compute the ambiguity under loss, we compare decisions under loss (decision 2 and 4).



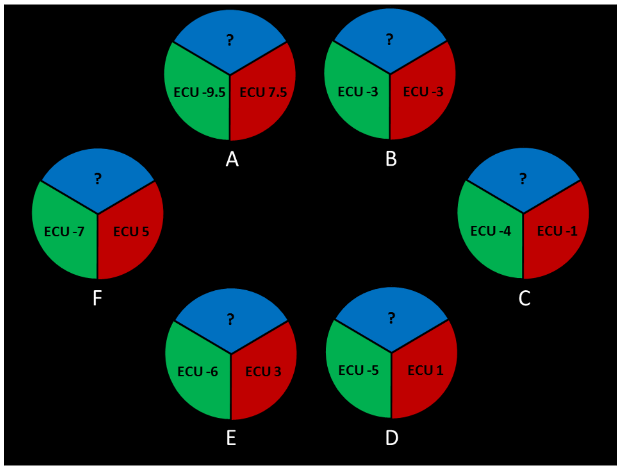
a - Decision 1 (gain, risk)



b - Decision 2 (loss, risk)



c - Decision 3 (gain, ambiguity)



d - Decision 4 (loss, ambiguity)

Figure 1: Lottery-based decisions used to elicit attitudes toward risk, ambiguity and losses.

E Written instructions given to participants

E.1 Study 1

Task 1

General information:

- Four sets of lotteries will be presented to you. For each set, you will have to choose one lottery out of six possibilities.
- Each lottery is composed of two different payoffs.
- When you select a lottery, you earn either the payoff on the left or on the right.

Proceeding:

- First lottery: No losses possible (no endowment), 50% of chance for the two different payoffs.
- Second lottery: Losses possible (endowment), 50% of chance for the two different payoffs.
- Third lottery: No losses possible (no endowment), between 30% and 70% of chance for the two different payoffs.
- Fourth lottery: Losses possible (endowment), between 30% and 70% of chance for the two different payoffs.

Task 2

General information:

- Determine if both circles contain either the same or a different number of dots.
- If you think that they contain the same number of dots, press the key $\boxed{\downarrow}$ on your keyboard.
- If you think that they contain a different number of dots, press the key $\boxed{\uparrow}$ on your keyboard.

For each decision, four outcomes are possible:

		Correct answer	
		Different	*Same*
Decision	*Different*	Success when different	Failure when similar
	Same	Failure when different	Success when similar

- To each possible outcome is associated a certain number of points.
- Your objective is to maximize the number of points earned.

Feedback:

- After each decision you will know if you were right or wrong and the number of points earned for this decision.
- Every 10 decisions, you will have:
  - An aggregated accuracy feedback: the percentage of correct answer during the last 10 decisions.
  - An aggregated point feedback: how close you are from the highest number of points compared to the lowest number of points accumulated during the last 10 decisions.

Steps:

- First training period without points.
- Second training period with points.
- Paid part: 4 blocks of 50 decisions. Points pattern are fixed within each block.

Earnings

Additionally to the AUD5 of show-up fee, you will receive:

First part:

- One of the chosen lottery will be randomly selected. You will be paid according to its result.
- Payoffs are in ECU.
- The conversion rate between ECU and AUD is:

$$2\ ECU = AUD1$$

Second part:

- Five decisions randomly selected in each block.
- Your payment is the sum of all points accumulated during the 4*5 selected decisions.
- Losses will occur but they will be more than compensated by your gains even in the worst case scenario.
- The conversion rate between points and AUD is:

$$8\ points = AUD1$$

E.2 Study 1

Task

General information:

- Determine if both circles contain either the same or a different number of dots.
- If you think that they contain the same number of dots, press the key $\boxed{\downarrow}$ on your keyboard.
- If you think that they contain a different number of dots, press the key $\boxed{\uparrow}$ on your keyboard.

For each decision, four outcomes are possible:

		Correct answer	
		Different	*Same*
Decision	*Different*	Success	Failure
	Same	Failure	Success

- To each possible outcome is associated a certain number of points.

- Your objective is to maximize the number of points earned.

Feedback:

- After each decision you will know if you were right or wrong and the number of points earned for this decision.
- Every 10 decisions, you will have:
  - An aggregated accuracy feedback: the percentage of correct answer during the last 10 decisions.
  - An aggregated point feedback: how close you were from the highest number of points during the last 10 decisions.

Steps:

- First training period without point.
- Second training period with points.
- Paid part: 2 blocks of 50 decisions. Points patterns are fixed within each block.

Earnings

Additionally to the AUD5 of show-up fee, you will receive:

- Five decisions randomly selected in each block.
- Your variable payment is the sum of all points accumulated during the 2*5 selected decisions.
- The conversion rate between points and AUD is:

$$8\ points = AUD1$$