UMR 8184
Thema
THéorie Économique, Modélisation et Applications

THEMA Working Paper n°2018-10
Université de Cergy-Pontoise, France

The price for instrumentally valuable information

Roxane Bricet

UNIVERSITÉ de Cergy-Pontoise

CNRS CENTRE NATIONAL DE LA RECHERCHE SCIENTIFIQUE

March 2018

The price for instrumentally valuable information*

Roxane Bricet†

March, 2018

Abstract

In this article, I propose an experimental design to measure the value of instrumental information in a model-free setup. In particular, this study provides operating instructions to test Blackwell's ranking of informative structures under risk and under ambiguity. Drawing on Ellsberg's two-color thought experiment, the subject faces three different types of choice situations: simple risk, compound risk and ambiguity. The original experiment is modified by enabling the agent to observe random draws with replacement so that he can learn about the composition of the urns. The proposed design allows to estimate the value of signals that differ in their informativeness and how it relates to ambiguity attitudes.

Keywords: Value of Information, Ambiguity, Blackwell's theorem, Reduction of Compound Lotteries, Ellsberg paradox, Experiment, Prince.

JEL Classification Codes: C91, D81, D83

---

*I would like to thank Eric Danan and Ani Guerdjikova for helpful suggestions and detailed comments throughout the redaction of this article. This research has been conducted as part of the project Labex MME-DII (ANR11-LBX-0023-01).

†Université de Cergy-Pontoise, THEMA. 33, boulevard du Port, 95011 Cergy-Pontoise Cedex, France. Email: roxane.bricet@u-cergy.fr.

1 Introduction

1.1 Motivation

In most decision situations, the available information is insufficient to allow agents to predict the outcome of an action with full confidence. However, a Decision Maker (henceforth, DM) who can observe statistical information in the form of data generated by the true probabilities will become increasingly confident in his personal estimates. Hence, subjective beliefs may converge to objective probabilities through statistical learning. In this paper, I focus on the subsequent question: How do agents value instrumental information?

While statistical observations are theoretically not valuable for simple risky prospects (e.g., betting on the result of the toss of a fair coin), it might inform decisions under compound risk. Consider the decision situation in which the state of the world is unknown but drawn from a known and well-defined distribution function. For instance, suppose that you have to bet on the result of the toss of a coin which is chosen uniformly at random between a fair one and a biased coin that comes up tails with objective probability 9/10. Since data collection might inform on the true state of the world (the coin that is tossed), the value of information under compound risk is a worthwhile question. However, empirical evidence on the valuation of informative signals in such risky framework is missing.

As opposed to risk, a decision situation is characterized by ambiguity when the agents are not able to derive a unique and additive probability measurement from the informational context (Knight, 1921). This is the case when the probability distribution over the states of the world cannot be inferred from the available data. Suppose, for instance, that you are asked to bet on the result of the toss of a coin but now, you have no clue on the fairness of the coin. While the study of choice under ambiguity has been one of the main topics in decision theory over the last decades, the related question of the value of information that mitigates or resolves ambiguity has attracted seemingly less attention.

Therefore, this paper is intended to further investigate how DMs value instrumental information under *uncertain* decision contexts — the word 'uncertainty' is used, here, as a general concept that encompasses both compound risk and ambiguity. To answer this research question, I provide an operational experimental design which allows to estimate the reservation price of agents for informative signals on the objective probability structure of uncertain prospects. Discriminating between different relevant signals requires the definition of a sorting criterion depending on their informativeness. This is provided by Blackwell's (1951, 1953) seminal papers in which he proposes a ranking of information structures independent of beliefs. According to his equivalence result, experiment I (i.e., a sampling procedure) is more "Blackwell-informative" than experiment II if the former is more valuable than the latter for all expected-utility maximizers. Li and Zhou (2016) extend Blackwell's equivalence result to a general class of ambiguity-averse preferences. It can be inferred from their analysis that both ambiguity-averse and ambiguity-loving DMs should place higher value on informative data as its degree of informativeness increases. This paper aims at improving understanding about the pricing of informative signals by ambiguity-sensitive agents. For ambiguity-neutral DMs who behave in accordance with Subjective Expected Utility (SEU) theory, it provides also experimental assessments of the Blackwell result, which lacks empirical evidence.

The main contribution of this research is to provide a unified Blackwell's experimental framework to measure the value of information in uncertain settings. Next, the effect of the informativeness on the value of the signal can be estimated and examined in the light of Blackwell equivalence result and its extension. With my design, it is also possible to gain insight into the link between the value of information and ambiguity attitudes, which has not been addressed in the literature so far to the best of my knowledge. At last, this research is conducted in a model-free set-up. Since I do not restrain the analysis to a particular class of non-EU preferences, it provides a general testing context.

The design proposed here is an extension of Ellsberg's (1961) two-color experiment when samples of draws with replacement are available. In a laboratory experiment, the subject is asked to consider gambles on three different urns containing 100 (blue or red) balls each. The first urn contains 50 blue and 50 red balls (simple risk); the number of blue balls in the second urn is uniformly distributed between 0 and 100 (compound risk); the composition of the third urn cannot be deduced from an objective distribution function (ambiguity). The gambles offer the participant to bet on his preferred color without information (for all urns) and with information (for the last two urns). Especially, the Certainty Equivalents (CEs) are estimated for different number of random draws, where weakly-informative signals contain small number of draws and highly-informative signals consist of large number of draws. This design intends to simulate a realistic process of accumulation of information. The first urn serves as a benchmark: it allows to distinguish between attitudes toward risk and ambiguity and to study agents' ability to reduce compound lotteries. While controlling for ambiguity attitudes, this design enables experimental assessments of: (*i*) the value attributed to informative signals and (*ii*) the individual ranking of signals of different informativeness. One key feature of the design relies on the sequence of the bet: the subject is asked to announce his signal-contingent strategy *before* observing the draws. Indeed, Li et al.'s (2016) statement requires full commitment to hold. It is motivated by the fact that an ambiguity-averse DM might be dynamically inconsistent and the inner conflict between ex-ante and ex-post preferences could make him reject information in the absence of commitment (Siniscalchi, 2011).

The novelty of the approach also lies in the payment procedure: the choices of participants are incentivized according to the Prince mechanism, recently proposed by Johnson *et al.* (2015). Therefore, I depart from the related literature that incentivizes decisions with the standard techniques (Random-Incentive-System, Becker-DeGroot-Marschak) even though these mechanisms have been criticized for their inability to induce truthful revelation of preferences in ambiguous contexts (see, e.g., Bade, 2015; Baillon *et al.*, 2015). The features of Prince allow to overcome inherent drawbacks of other techniques and, thus, ensure incentive-compatibility of experimental choice questions.

The remainder of the paper proceeds as follows. Related literature is reviewed next. Section 2 presents the experimental design. Section 3 discusses the theoretical background and its requirements. Section 4 concludes. Appendix A explains how the described signals can be compared with respect to their informativeness in Blackwell's sense. Appendix B displays a full set of the instructions of the experiment.

1.2 Related literature

Marinacci (1999) presents a relevant mathematical framework for learning under ambiguity and derives a Law of Large Number that applies to non-additive probabilities in the context of capacities. In 2002, he studies the particular case of learning by sampling with replacement from the same ambiguous urn and shows that ambiguity resolves asymptotically. Most recently, Marinacci and Massari (2017) generalize the previous result to the case in which the DM have misspecified prior beliefs over the decision problem and they prove that ambiguity may still fade away under standard assumptions. Besides, Epstein and Schneider (2007) and Zimper and Ma (2017) generalize the Bayesian learning model within the decision-theoretic framework of Gilboa and Schmeidler (1989) Maxmin Expected Utility (MEU) preferences. So far, the theoretical literature fails to provide suitable conditions that apply to a general class of ambiguity preferences and thus it does not ensure that ambiguity would systematically resolve with experience.

Blackwell (1951, 1953) defines an informativeness ranking of data structures. According to his main theorem, structure I is more "Blackwell-informative" than structure II if II is a garble[1] of I. For any decision problem and subjective prior, the expected loss supported by the DM from choices based on I is at least as low as the expected loss resulting from choices based on II. Hence, I is preferred to II. However, Wakker (1988) shows that violation of the Independence Axiom (as formulated by Von Neumann and Morgenstern, 1944) might lead to the existence of decision situations in which information-aversion is exhibited, in contradiction to Blackwell's theorem. The rationale for this phenomenon lies in the typical non-compliance with the commutativity principle of non-EU maximizers and their subsequent violations of dynamic consistency. Moreover, Siniscalchi (2011) and Epstein and Ji (2017) study the dynamics of information acquisition under ambi-

[1] A garble is a transformation from one informative structure to another which adds noise to the original structure. See Appendix A for a formal definition of a garble.

guity. The resulting optimal stopping problem is solved and they show that rejection of learning opportunities can be optimal for an ambiguity averse agent given a small cost of information (Epstein and Ji, 2017) or even when the information is freely available (Siniscalchi, 2011). Çelen (2012) was the first to apply Blackwell's ranking to ambiguity-sensitive preferences in the case of MEU preferences. Further, Heyen and Wiesenfarth (2015) draw on Çelen's framework and provide a definition of the value of information that is compatible with recursive utility and thus respects dynamic consistency. Lately, Li and Zhou (2016) show that Blackwell's equivalence result holds for a general class of ambiguity-averse preferences, under reduction and commitment.

The literature on the value of information and ambiguity is limited. Using Machina's (2004) concept of almost-objective acts, Quiggin (2007) shows that ambiguity aversion may be defined in terms of the value of information. He states that, for expected utility preferences, the value of information with respect to almost-objective acts is asymptotically equal to zero. Snow (2010) studies the value of information in a particular adaptation of the smooth ambiguity model (Klibanoff *et al.*, 2005). His analysis relies on a particular definition of greater ambiguity in terms of mean-preserving spreads. Given this framework, he proves that ambiguity averters (lovers) are willing to pay to obtain (avoid) information that lessens ambiguity while leaving the decision maker's expectations unchanged[2]. Similarly, Eichberger and Guerdjikova (2013) study preferences for information precision in an adaptation of the Maxmin Expected Utility model. Increasing the number of observations while keeping frequencies constant enhances the precision of information in an objective sense and therefore the informativeness of the data. Controlling for the frequency of observations, they show that the value attributed to precise sets of observations rises with greater ambiguity aversion. Although this theoretical literature provides compelling insights, the experiment presented in this paper leads to a substantially different analysis since additional information affects both the ambiguity perceived by the DM and his expectations.

[2]Besides, Snow (2010) also states that the value of information which *resolves* ambiguity increases with greater ambiguity and with greater ambiguity aversion. Note that, in this paper, I will only consider information that *reduces* ambiguity.

Reviewing the most recent experimental research on ambiguity, Trautmann and Van De Kuilen (2015) point out that there are only few experimental studies on how learning influences ambiguity attitude, and how ambiguity attitude may affect the decision to experiment and learn. Regarding the effect of information on beliefs and ambiguity attitudes, the existing studies display particularly mixed evidence. Nicholls *et al.* (2015) find that statistical learning does not reduce the number of violations of the basic Savage's sure-thing principle compared to a control group. On the other hand, Baillon *et al.* (2017) observe that subjects' beliefs move towards Expected Utility with more information although substantial deviations remain even in their maximum information condition. Moreno and Rosokha (2016) estimate a behavioral model of belief updating in a three-urns design closed to mine. They note that learning behavior in the compound urn is consistent with Bayesian updating whereas participants tend to overweigh additional information in ambiguous frameworks. As predicted by Prospect Theory, Abdellaoui *et al.* (2016) report that subjects tend to be more ambiguity-averse for likely events and more ambiguity-loving for rare events when subjects can learn about the composition of an ambiguous urn. Moreover, they find that participants exhibit less ambiguity-sensitive behavior as the sample size increases although statistical learning does not allow to preclude ambiguity-nonneutral preferences. On the contrary, Ert and Trautmann (2014) show that sampling completely reverses traditional patterns of preferences: they observe ambiguity-aversion with low frequencies and ambiguity-seeking with high frequencies.

Regarding the preferences for information, Trautmann and Zeckhauser (2013) report that subjects forgo opportunities to learn about an ambiguous urn in favour of the risky urn, even in an extreme learning experience (complete resolution of ambiguity). Ambuehl and Li (2018) find that subjects underreact to the increase of informativeness of data and they have a strong preference for information that entirely resolves ambiguity. Further, Eliaz and Schotter (2010) report that experimental subjects are willing to pay for information that will not affect their decision (non-instrumental information). This result contrasts with Hoffman (2016) who finds that agents exhibit significant overconfidence about their knowledge, inducing low demand information.

So far, some recent papers have examined the influence of information on ambiguity attitudes, but experimental evidence regarding the effects of ambiguity attitudes on the willingness to pay for additional information is clearly missing. This research aims at providing a relevant framework to study this open question.

2 Experimental design

2.1 Stimuli

The experimental design draws on Ellsberg's (1961) two-color urns experiment. In this experiment, the participants are shown three opaque bags. They are informed that each of the three bags contain 100 balls and that balls can be either blue or red. The subjects could win a fixed amount of money by betting on the color of their choice to be blindly drawn from a bag by themselves. More specifically, the gambles on the color of the ball pay 15€ if the color of the drawn ball matches the color of the bet, 5€ otherwise. The composition of the first bag is perfectly known to the subjects or equivalently *certain*: it contains exactly 50 blue balls and 50 red balls. The exact proportions of balls in the second and third bags remain unknown but they differ with respect to the delivered description of their composition. The participants know that the composition of the second bag is determined using a uniform distribution over the 101 possible bags containing 100 balls, the composition of this bag is then *risky*. The composition of the third bag, however, is *ambiguous* in the sense that there is no such objective distribution device that defines the proportions of balls: the number of blue (or red) balls in the bag is determined by a number drawn from a pool of 200 numbers ranging from 0 to 100, with no hints on the frequencies of each number in the pool except that each number appears at least once. For the sake of brevity, in the rest of the paper, the three bags are referred to as the certain bag, the risky bag and the ambiguous bag respectively[3]. Subsection 2.2 provides a detailed description of the procedure to generate the bags. Since the composition of the certain bag is known, objective probabilities can be easily inferred and betting on a color from this bag relates to simple risky prospects.

The risky and ambiguous bags refer to different ways to generate uncertainty in the lab. The former have been substantially used in the experimental research (e.g., Becker and Brownson, 1964; Maafi, 2011). Although this transparent technique enhances the trust of participants in the experimental design, this condition may not be perceived as real ambiguity. Indeed, the prospects related to this bag result from a compound lottery which allows subjects who satisfy the Reduction Of Compound Lotteries (ROCL) axiom to use second-order objective probabilities to inform their beliefs. Recent empirical studies display contradictory findings on the link between ambiguity attitudes and multiple-stage lotteries. For instance, Halevy (2007) finds equivalence between ROCL and ambiguity-neutrality, whereas ambiguity-sensitive agents generally fail to reduce compound lotteries. Moreover, Halevy *et al.* (2008) and Seo (2009) provide axiomatizations which explicitly relate attitudes towards ambiguity and two-stage lotteries while accomodating Halevy's (2007) findings. On the other hand, Abdellaoui *et al.* (2015) report contrasting empirical evidence: they find that a substantial share of ambiguity-neutral agents violates the ROCL axiom while most of the subjects who successfully reduce two-stage lotteries exhibit non-neutral ambiguity attitudes[4]. Finally, the strategy used to generate the third bag (ambiguous bag) described previously can be viewed as an attempt to create an ambiguous condition with a tractable and credible device that prevents subjects from using probability reduction.

Such "three-urns" design has been previously implemented in two other articles, Yates and Zukowski (1976) and Chow and Sarin (2002), who study standard Ellsberg-type preferences without learning. They found evidence that the two-stage lottery occupies an intermediate position: it is usually preferred to the ambiguous prospect but less attrac-

[3]During the experimental sessions, note that one should refer to bags with neutral labels such as bag A, bag B and bag C.

[4]See also Attanasi *et al.* (2014) who conduct an experimental study on ambiguity attitudes using bets with unknown probabilities, as well as compound lotteries, when preferences are specified within the smooth ambiguity model (Klibanoff *et al.*, 2005).

tive than the simple one-stage objective lottery. Therefore, combining both strategies to generate uncertainty in this experiment allows me to estimate the differential effects of this distinct types of uncertainty on the value of information while relating to existing sparse research.

The experiment consists of three stages: in the first stage, the participant's attitude towards risk is estimated, this preliminary step is necessary to disentangle risk attitude from ambiguity attitude in the subsequent data analysis; in the second stage, the individual reservation price for information about the uncertain bag is elicited for varying degrees of informativeness; the third stage replicates the questions of the second stage on the ambiguous bag. All subjects participate to each stage in that order.

Stage 1. In this stage, the participant deals with the certain bag. First, he has to choose the color of the ball on which to bet to be drawn from this bag. Then, he is asked to express preferences between the bet on the color of the ball previously chosen and different sure amounts. He is presented with a series of 10 binary choices where the sure amounts is increased in order to elicit the subject's Certainty Equivalent (CE, defined as the sure amount equally desirable as the gamble) for such risky prospect (CE_C). The CE is reported using a Multiple-Price List (MPL). More precisely, in each row of the MPL, the participant has to single out his preferred option between Option 1: "Bet on the color of the ball" or Option 2:"x€", with x taking the 10 equally spaced values between 5.50 and 14.50. The monetary amounts rise moving down the table while the bet remains the same. Figure 1 provides an example of such MPL. By linear interpolation, the CE is taken as the mid-point of the two sure amounts for which the subject switched preferences. Moreover, to avoid inconsistent answers resulting from multiple switching points, a computer program enforces the monotonicity of revealed preferences by allowing at most one switching point from the gamble to the sure amount. More specifically, the filling of the table is automated: by ticking a box of a line of the table, the boxes corresponding to the bet are automatically ticked for the lines above and the boxes corresponding to the sure amount are automatically ticked for the lines below[5].

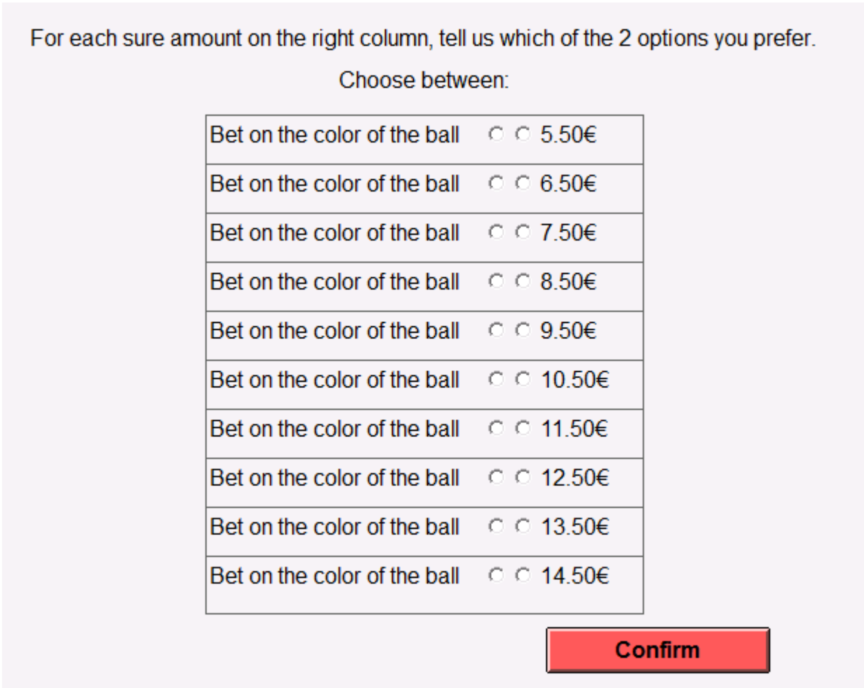


Figure 1: Example of MPL

Stage 2. In the second stage, the participant has to consider bets on the risky bag. This stage consists of two successive phases:

Non-informational phase. First, the subject is asked to select a color on which to bet for a draw from the risky bag. Then, the CE for the related prospect is elicited when no information is available ($CE_{R,0}$). The CE is estimated via a similar procedure as in stage 1: the subject has to fill out a MPL with 10 binary choices between a bet on the color of the ball to be drawn from the risky bag and a sure gain.

Informational phase. Next, the participant is asked to consider different informational situations in which a sample of random draws with replacement from the risky bag is available. This phase consists of 5 informational situations corresponding to datasets

[5]See Chapter 2 for a thorough discussion on the advantages of the MPL as compared to other valuation methods and on the automatic filling of the table.

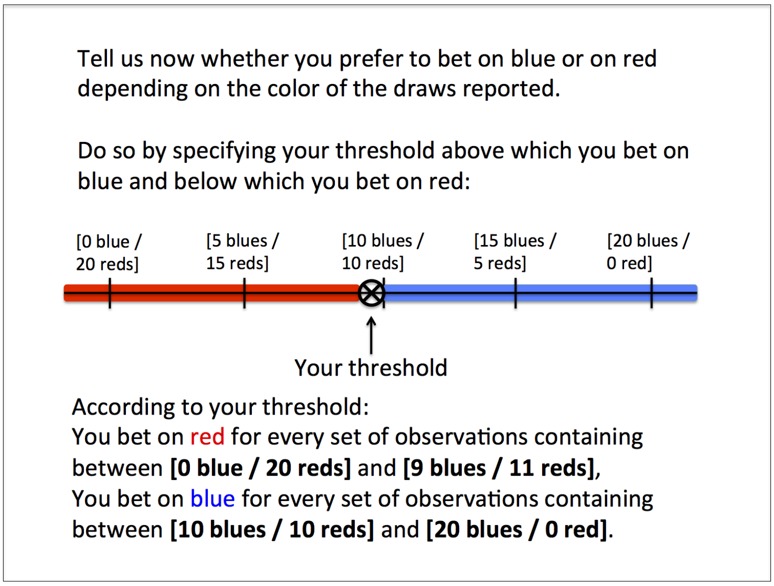


Figure 2: Example of a slider when the dataset contains 20 draws

of 5 different lengths ranging from weakly-informative for small number of draws to highly-informative for large number of draws. The number of draws (d) are fixed and $d \in \mathcal{D} = [1; 5; 20; 50; 200]$. For each informational condition: First, the subject has to announce his color-betting strategy conditional on the resulting draws of the dataset. There, he specifies the particular signal, i.e., the minimum number of blue draws out of the d draws and the corresponding maximum number of red draws, above which he chooses to bet on a blue ball to be drawn and below which his bet goes on red. The subject selects this threshold ($t_{R,d}$) using an horizontal slider as proposed in Figure 2. Then, the subject is asked to fill out a MPL with 10 binary choices between a bet on the color of the ball to be drawn from the risky bag conditional on the information and a sure gain. Hence, the CE ($CE_{R,d}$) is elicited via the aforementioned procedure.

Stage 3. The last stage replicates the phases of stage 2 on the ambiguous bag. Thus, this stage starts with the non-informational phase which serves to elicit the CE for the ambiguous prospect without information ($CE_{A,0}$). The signal-contingent strategies ($t_{A,d}$) and the CEs associated to the informative signals ($CE_{A,d}$) are collected for the

5 different lengths of datasets ($d \in \mathcal{D}$) specified above in the subsequent informational phase.

Table 1 summarizes the structure of the experiment, the tasks performed by the participant and the experimental variables collected. The informational phases proceed by increasing the degree of informativeness of the dataset and the participant never receives information on color of the draws nor feedback about his decisions until the end of the experiment. Indeed, delivering information on the draws throughout the course of the experiment would progressively alter the experimental variables as the participant learns about the composition of the risky and ambiguous bags. Since this experiment is not meant to study the dynamics of learning under ambiguity, each decision has to be taken in isolation. Therefore, subjects make all choices before having observed the signals and the ex-post strategies implemented in the payment stage correspond to the ex-ante optimal strategies (*full commitment*). Indeed, the generalization of Blackwell equivalence result by Li and Zhou (2016) requires full commitment to all signal-contingent strategies (this requirement is discussed in Subsection 3.2).

Bag	Information	Tasks	Variables
Stage 1			
Certain	No	Select the color of the bet & Fill out the MPL	CE_C
Stage 2			
Non-informational phase			
Risky	No	Select the color of the bet & Fill out the MPL	$CE_{R,0}$
Informational phase			
Risky	$d = 1$	State the threshold & Fill out the MPL	$t_{R,1}$; $CE_{R,1}$
	$d = 5$	State the threshold & Fill out the MPL	$t_{R,5}$; $CE_{R,5}$
	$d = 20$	State the threshold & Fill out the MPL	$t_{R,20}$; $CE_{R,20}$
	$d = 50$	State the threshold & Fill out the MPL	$t_{R,50}$; $CE_{R,50}$
	$d = 200$	State the threshold & Fill out the MPL	$t_{R,200}$; $CE_{R,200}$
Stage 3			
Non-informational phase			
Ambiguous	No	Select the color of the bet & Fill out the MPL	$CE_{A,0}$
Informational phase			
Ambiguous	$d = 1$	State the threshold & Fill out the MPL	$t_{A,1}$; $CE_{A,1}$
	$d = 5$	State the threshold & Fill out the MPL	$t_{A,5}$; $CE_{A,5}$
	$d = 20$	State the threshold & Fill out the MPL	$t_{A,20}$; $CE_{A,20}$
	$d = 50$	State the threshold & Fill out the MPL	$t_{A,50}$; $CE_{A,50}$
	$d = 200$	State the threshold & Fill out the MPL	$t_{A,200}$; $CE_{A,200}$

Table 1: Structure of the experiment

2.2 Procedures

Composition of the bags

Regarding the technical aspect of the composition of the bags, the certain bag contains 50 blue balls and 50 red balls as announced. The risky and ambiguous bags contain 100 balls each, balls being either blue or red, but in unknown proportions. This experimental design relies on the results of Li and Zhou (2016) which require a fully supported prior on the set of balls. If the set of priors of the DM reduces to a singleton, i.e., if the DM is certain about the composition of the bag, the information might be of no value to him (as, e.g., is the case for a max-min EU maximizer). Hence, the method for generating the bags has to make explicitly clear that the risky and ambiguous bags in the experimental sessions can be any bag out of the 101 possible bags containing 100 blue or red balls. To do so, the composition of the risky bag is determined as follows: 101 chips numbered from 0 to 100 are presented so that the subject can check for the presence of every number. After verification, they are thrown in an opaque bag. A participant blindly draws one numbered chip out of the 101 chips of the bag. Next, a fair external device (toss of a coin) is used to determine if the number of the drawn chip corresponds to the quantity of blue balls or the quantity of red balls in the risky bag. Hence, each color can be selected with an objective probability of 50%. With this two-stage technique, the probability to draw a blue ball is the same as the probability to draw a red ball which equals 50% — although nothing ensures that the subjects achieve to calculate them.

The composition of the ambiguous bag follows a different procedure: A second set of 101 chips numbered from 0 to 100 are presented to the subjects. After checking, they are thrown in an opaque bag. Another 99 numbered chips are added to the previous pool of chips but the chips of this second set can take any number between 0 and 101 and multiple chips can have the same number. The numbers of this second set of chips are not observed by the subject. Both pools of chips are shuffled jointly and a participant blindly draws one numbered chip out of the 200 chips of the bag. Next, a coin is tossed to determine if the number of the drawn chip corresponds to the quantity of blue balls or the quantity of red balls in the ambiguous bag.

This method allows to generate uncertainty about the composition of the risky and ambiguous bags while inducing the subject to consider the entire set of possible bags. It is pretty straightforward to implement a transparent procedure to determine the composition of the risky bag. On the other hand, the authors usually choose to remain silent about the method to generate the ambiguous bag in the lab and describe it only as being filled with blue and red balls *in unknown proportions* (e.g., Halevy, 2007; Chow and Sarin, 2002). However, when the experimenter holds private information on the composition of the bag, the participants are more inclined to distrust the experimenter, suspecting him to have generated the bag in a way to save them money. The participation of subjects in the composition of the bag allows to minimize suspicion by ensuring that the bag is truly not-manipulated by the experimenter. For instance, in Trautmann and Zeckhauser (2013), each subject filled his own bag by blindly drawing balls from a bag whose composition is known. Ideally, the composition of the bag is unknown to everyone, reducing potential "comparative ignorance" effects (Fox and Tversky, 1995) in which the presence of an informed agent reduces the desirability of the prospect. Therefore, in this experiment, the number of the drawn chips and the result of the tossing of the coins remain secret to the participants and the experimenter until the end of the session.

Incentive device

At the end of the session, one question of the experiment, corresponding to one row out of the 13 MPLs of the experiment, is played for real according to the Prince incentive mechanism (Johnson *et al.*, 2015). The key component of this mechanism design relies on the timing of the random selection of the question that serves for payment: contrary to most standard techniques, the question is selected at the beginning of the experiment and provided to the participant in a sealed envelope. Each subject knows about the content of all envelopes in the session but does not know the content of his own. Two examples of envelope content are provided in Figures 3 and 4. At the end of the session, the envelope is opened and the choice of the subject is performed. There are 3 different types of options: (i) if the preferred option was a sure amount, the subject receives the sure gain; (ii) if the preferred option was a bet without information, he randomly draws one ball from the bag involved in the bet and if the color of the ball matches the color chosen before, he receives 15€, otherwise he gets 5€; (iii) if the preferred option was a bet with information, the computer generates a sample of d random draws with replacement from the ambiguous bag; the result of the draws is compared to the threshold t_d announced by the subject and the winning color of the bet is deduced; then the participant randomly draws one ball from the ambiguous bag and if the color of the ball matches the color stated before, he receives 15€, otherwise he gets 5€. While the usual Random-Incentive-System (RIS, first introduced by Savage, 1954) and Becker-DeGroot-Marschak (BDM, 1964) mechanisms have been blamed for their inability to induce truthfull-telling for non-expected-utility maximizers and for the subsequent violations of incentive-compatibility in ambiguous contexts (Bade, 2015), the Prince device allows to overcome inherent drawbacks of existing techniques and ensures subjects that truthful revelation of preferences is in their best interest[6].

In this experiment, there are 13 MPLs, each containing 10 rows. In sum, this experiment consists of 130 binary choices. Hence, there are 130 envelopes numbered 1-130 in random order, such that each envelope contains one of the 130 questions. At the beginning of the experiment, these envelopes are randomly distributed to subjects without replacement. At the very end of the experiment, each participant receives a list describing all envelopes which avoids deception by allowing him to verify that his envelope has correct content.

Option 1 : Bet on the color of the ball to be drawn from **bag A**.	Option 2 : **8.50€**.

Figure 3: An example of envelope content (certain bag)

[6]see Chapter 2 for a complete description of the Prince mechanism in a similar framework.

Option 1 : Bet on the color of the ball to be drawn from **bag B** with a sample of **200 random draws** with replacement.	Option 2 : **12.50€**.

Figure 4: An example of envelope content (risky bag)

Proceedings

The experiment starts with an oral presentation of the instructions[7]. When the explanation reaches the relevant points, the composition of the risky and ambiguous bag are determined through the method described before and each subject randomly picks one sealed envelope that serves for payment. After the instructions, a comprehension questionnaire is implemented to test subject's understanding of the experiment. Then, the participant performs the tasks of the experiment using the computer in front of him. After that, he is asked to complete a short form including basic socio-demographic variables (age, gender, studies). The last screen of the experiment invites him to reach the experimenter's office with his envelope to proceed for payment.

Each experimental session should not last more than 1 hour including payment. The maximum payoff is 15€ and the minimum payoff equals 5€. The show-up fee (usually 5€) is included in the gambles payoff because agents seem to pay more attention to their decisions and make less errors when the monetary incentives are high (see for instance Lévy-Garboua *et al.*, 2012). There is no particular subject requirement to participate. The experiment can be easily programmed with the experiment software z-Tree (Fischbacher, 2007). Finally, the design allows within-subject as well as between-subject analysis.

[7]See Appendix B for a full set of instructions.

2.3 Experimental measures

Symmetric prior

With the elicitation of the signal-contingent strategies $(t_{R,d})_{d\in\mathcal{D}}$ and $(t_{A,d})_{d\in\mathcal{D}}$, it is possible to test for the existence of individual symmetric priors regarding the composition of the risky bag and the composition of the ambiguous bag. In this framework, the symmetry of beliefs seem to be pretty natural. Especially, the DM may think about the bags as follows: "The number of red balls in it can be any number between 0 and 100. My information is completely symmetric, and there is no reason to believe that there are more red balls than [blue] balls or vice versa. Hence, if I were to adopt a prior probability over the composition of the [bag], from [0:100] to [100:0], I should choose a symmetric prior. That is, the probability that there are 3 red balls should be equal to the probability that there are 97 red balls, and so forth." (Gilboa and Marinacci, 2016, p392). Moreover, since the composition of the risky bag is objectively drawn from a uniform distribution over the entire range of possible bag composition, subjects who successfully perform ROCL should postulate that the probability to draw a blue ball is precisely 50%. Therefore, a DM who reduces compound lotteries or has a symmetric prior should bet on blue for any set of observations containing more than 50% of blue draws and bet on red otherwise (with indifference at 50%). The same strategy is optimal for the ambiguous bag, as long as the DM has a symmetric prior. Given the transparency and credibility of the random drawing experimental procedures, any other signal-contingent strategy can be taken to imply an asymmetric prior belief.

Ambiguity-aversion

The aversion to ambiguity is estimated within the standard Ellsberg framework where the DM is confronted with a binary choice between a prospect on the known urn and a prospect on the ambiguous urn. Thus, the following ambiguity-aversion index based on certainty equivalents (Sutter *et al.*, 2013) can be calculated for each subject:

$$I_{AA} = \frac{CE_C - CE_{A,0}}{CE_C + CE_{A,0}} \tag{1}$$

I_{AA} is the normalized measure of the difference between the CE for the certain bag and the CE for the ambiguous bag without information. For instance, $CE_C > CE_{A,0}$ means that the ambiguous bag is less attractive than the certain bag for a color-bet, denoting ambiguity-aversion. Since CE_C and $CE_{A,0}$ can take values in the interval $[5; 15]$, I_{AA} ranges from -$\frac{1}{2}$ to $\frac{1}{2}$, where $\frac{1}{2}$ refers to extreme ambiguity-aversion and $-\frac{1}{2}$ indicates extreme ambiguity-loving. Hence, the participants are classified according to the sign of their index: ambiguity-averse for strictly positive I_{AA}, ambiguity-neutral for I_{AA}=0 and ambiguity-lover for strictly negative I_{AA}[8]. The denominator of the index accounts for the fact that a 1€-difference should weigh more heavily for those who report low CEs than for those who announce high CEs.

Second, it is possible to study the ability of participants to reduce compound lotteries, although the detailed description of the connection between reduction/non-reduction and ambiguity neutrality/non-neutrality is an issue outside the scope of this paper[9]. There, the following index can be calculated :

$$I_{ROCL} = \frac{CE_C - CE_{R,0}}{CE_C + CE_{R,0}} \tag{2}$$

which is the normalized measure of the difference between the CE for the certain bag and the CE for the risky bag without information. In the spirit of Abdellaoui *et al.* (2015) and Halevy (2007), if the subject's preferences satisfy ROCL, he should treat both associated prospects as equivalent and value them equally, then $I_{ROCL} = 0$. On

[8]Note that one cannot distinguish between an ambiguity-lover and a neutral agent with an asymmetric prior regarding the composition of the ambiguous bag. Indeed, both agents might strictly prefer the ambiguous bag and thus get a strictly positive I_{AA}. However, this appears to be only a minor disadvantage of this tractable index because symmetric beliefs are the most reasonable class of beliefs given the setting of the experiment. Moreover, the design allows to test for the symmetry of prior and provides hence a further insight on the beliefs.

[9]Notwithstanding, the calculus of these two indexes allows to relate and compare the results of this experiment with Halevy (2007) and Abdellaoui *et al.* (2015, see Table 5).

the contrary, if participants fail to reduce compound lotteries, the reported CE for the certain bag differs from the CE for the risky bag, which yields $I_{ROCL} \neq 0$. Moreover, this index informs on the distance between both CEs which is a relevant question. It allows to discriminate between participants who value both prospects almost equally and those whose valuations for these prospects differ significantly.

To summarize, if the DM's preferences and beliefs satisfy: (*i*) ROCL, (*ii*) the symmetry of priors on the composition of the bags, and (*iii*) ambiguity-neutrality, the theory predicts that the agent will be indifferent between the three bags, which implies: $CE_C = CE_{R,0} = CE_{A,0}$. If one of these 3 conditions is relaxed, one equality does not hold as described above.

Value of information

The value of information can be broadly defined as the amount a DM would be willing to pay to obtain information prior to making a decision. There is a particular amount below which he accepts to pay for information and above which he rejects the information. This threshold corresponds to the DM's reservation price for information which is the amount that makes him indifferent between making the decision with information (and hence paying the price) and making the decision without information. Although any DM should be able to announce his price in theory, such task is not easily comprehensible in practice and can be misunderstood. This relates concretely to answering the following question: "What is the price for information that makes you indifferent between the bet on the bag without information and the bet on the bag with information?", which is far from intuitive. Hence, a crucial operational issue related to this type of design concerns the elicitation of this price. Alternatively, the DM can be confronted with a series of binary choices between the bet without information and the bet with information at price p. Indeed, asking subjects to express such preferences is less cognitively demanding than asking them to reveal their indifference point. The price is varied so that the reservation price can be elicited, and the same process is replicated for different informative signals. I find this technique particularly heavy, potentially confusing and difficult to implement in the lab. Thus, it is not straightforward to find a convenient and tractable device that easily fits the intended purpose. In Eliaz and Schotter (2010) for instance, subjects, endowed with money, are asked if they want to pay a fee to obtain information on the bet at hand. In their experiment, the fee can take only 3 values ($.50; $2; $4) which does not allow to precisely identify the individual indifference point. Attanasi and Montesano (2012) proposes an operational design where the agent's reservation price for information is estimated through the BDM mechanism. However, the use of the BDM device to incentivize choices has met numerous critics for its opaqueness and its failure to induce truthful revelation of preferences[10]. In Ambuehl and Li (2018), the value of the informative structure is approximated via uncertainty equivalents. In particular, they define the agent's Willingness-To-Pay for an ambiguous prospect with information as the probability mixture over the gamble's best outcome and zero that generates indifference.

To summarize, a consensus on the method to estimate the DM's reservation price for information has not yet emerged. In this experiment, the value of information is estimated through CE measurements. The value of the prospect without information is elicited in the non-informational phase. The effect of information on the valuation of the prospect is estimated during the subsequent informational phase. Hence, it is possible to build the following individual measures:

$$V_R(d,0) = CE_{R,d} - CE_{R,0} \tag{3}$$

$V_R(d,0)$ is the value of the signal s_d containing d draws that informs on the risky bag. A strictly positive $V_R(d,0)$ denotes an increase in the attractiveness of the risky prospect, which means that the information is valuable to the DM. If the value of information is positive, is it increasing in the number of observations d? If Blackwell's theorem holds, then $V_R(d,d')$ defined by $V_R(d,d') = CE_{R,d} - CE_{R,d'}$ is positive for any $d > d'$.

$V_A(d,0)$ corresponds to the value of information in the ambiguous bag. It is given

[10] Bardsley *et al.* (2010) stresses the complexity of the BDM mechanism in Section 6.5. See also Karni and Safra (1987) and Bade (2015) for theoretical discussions.

by:

$$V_A(d,0) = CE_{A,d} - CE_{A,0} \tag{4}$$

As reviewed in the Introduction, theoretical results predict positive value for ambiguity-averse and ambiguity-loving agents (this last point is discussed more carefully in 3.3). As for $V_R(d,0)$, twofold analysis applies here: (*i*) the sign of $V_A(d,0)$, and (*ii*) the comparison with the value of signals containing more/less draws.

This may be also of interest to study the difference:

$$V_A(d,0) - V_R(d,0) = (CE_{A,d} - CE_{A,0}) - (CE_{R,d} - CE_{R,0}) \tag{5}$$

which measures the differential effect of signals of the same length on the ambiguous and risky bags. This question is especially relevant for those who perceive the risky bag as an intermediate condition between the certain bag and the ambiguous bag (Yates and Zukowski, 1976; Chow and Sarin, 2002). How does this difference depend on ambiguity-aversion as captured by the index I_{AA} calculated previously?

3 Theoretical background

3.1 Blackwell's framework

The design presented previously falls into Blackwell's framework in the sense that the different information structures used in this experiment are Blackwell-comparable. Indeed, the signal s_{d+1} which contains $d+1$ random draws with replacement from an unknown bag is more Blackwell-informative than the signal s_d which consists of d draws. As stressed by Gollier (2004, §24.3.2), such signal s_d can be obtained from signal s_{d+1} by using a 'garbling machine', which adds a noise uncorrelated with the true state of nature (i.e., the composition of the bag). This is equivalent to showing that there exists a garble of s_{d+1} which preserves the posterior probabilities of s_d on the states of the world. A short explanation is sketched here and the detailed discussion is relegated to Appendix A.

Consider now the more general problem in which the bag contains N balls, each ball being either blue or red. The proportions of balls are unknown and the composition of the bag can be parameterized by the number of blue balls, $k \in \{0, 1, ..., N\}$. Without information, the $N+1$ compositions are objectively equally likely inducing a uniform distribution on the states of the world. Hence, each composition is assumed to occur with a prior probability of $\frac{1}{N+1}$.

A signal is a sequence of random draws with replacement. For instance, the signal corresponding to the following sequence of draws: blue, red, blue, is denoted (brb). Assume that the DM obtains a signal of d draws from the bag. Among the d draws, a blue ball has been drawn d_b times and it follows that $d_b \in \{0, 1, ..., d\}$ and that a red ball has been drawn $d - d_b$ times. The joint probability of the state of the world k and the particular signal $(b...br...r)$ is given by:

$$\Pr\{\text{Bag } k, (b...br...r)\} = \frac{k^{d_b}(N-k)^{d-d_b}}{N^d(N+1)} \tag{6}$$

The conditional probability for this signal structure is hence:

$$\Pr\{\text{Bag } k \mid (b...br...r)\} = \frac{k^{d_b}(N-k)^{d-d_b}}{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}} \tag{7}$$

To show that this information structure is less informative than the one with $d+1$ draws, consider a DM, who obtains now a signal of $d+1$ draws, but a garbling machine replaces the last information of the sequence by b with probability $\frac{1}{2}$ and by r with probability $\frac{1}{2}$. For instance, reconsider the signal $(b...br...r)$ containing d draws described before for which a noisy information is added. This yields:

$$\Pr\left\{\text{Bag } k, (\underbrace{b...br...r}_{d \text{ draws}}\, b)\right\} = \Pr\left\{\text{Bag } k, (\underbrace{b...br...r}_{d \text{ draws}}\, r)\right\} = \frac{1}{2}\frac{k^{d_b}(N-k)^{d-d_b}}{N^d(N+1)} \tag{8}$$

The conditional probabilities are given by:

$$\Pr\left\{\text{Bag } k \mid (\underbrace{b...br...r}_{d \text{ draws}} b)\right\} = \Pr\left\{\text{Bag } k \mid (\underbrace{b...br...r}_{d \text{ draws}} r)\right\} = \frac{k^{d_b}(N-k)^{d-d_b}}{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}} \tag{9}$$

Hence the conditional probabilities are preserved with the adding of a noisy information and the signal structure obtained with the garbling on the $(d+1)$th draws is equivalent to the signal structure with d draws.

3.2 Commitment

It is well-known that non-EU preferences, especially ambiguity-sensitive preferences, might not comply with the Independence Axiom which implies dynamically inconsistent behavior (Siniscalchi, 2011). Dynamic consistency requires that ex-ante contingent choices coincide with ex-post preferences. However, in this experiment, there is no reason to assume that preferences before the realization of the draws match preferences after the observation of the signal. Within the MEU framework for instance, Epstein and Schneider (2003) axiomatize a recursive structure for utility which requires that each prior is updated in a Bayesian way and that the set of priors satisfy the restrictive *rectangularity* condition. Wakker (1988), Hilton (1990) and Safra and Sulganik (1995) prove that delaying the choices after the realization of the signal might lead to the existence of choice situations in which non-EU DMs exhibit information-aversion, inducing the Blackwell theorem to fail. In particular, Li's (2016) extension of Blackwell informativeness ranking does not apply in general. Hence, the theoretical framework requires full-commitment to all signal-contingent strategies. Since the experimenter cannot exert control over the way subjects form beliefs and the way they update their beliefs, dynamic consistency might not be achieved in this setting and experimental results are more robust with full-commitment.

3.3 Mixed strategies

From the proof of Theorem 1 in Li and Zhou (2016), it can be inferred that: if the signal s_d is more Blackwell-informative than the signal $s_{d'}$, then s_d is more valuable than $s_{d'}$ for all (ambiguity-neutral and ambiguity-nonneutral) DMs[11]. When the DM has the opportunity to observe an informative signal, he determines his optimal signal-contingent strategy. A necessary condition for the result of Li is the possibility to replicate this optimal strategy when observing a more Blackwell-informative signal. Hence, the value of information is always positive since one can always choose to not take into account the additional information. This is especially relevant for ambiguity-lovers who may be willing to pay to avoid information (Snow, 2010; Attanasi and Montesano, 2012). One way to proceed is to allow the agents to randomize their strategies, i.e., to play mixed strategies. Consider the following example: The DM observes a signal containing 5 draws. Assume that his optimal strategy is to bet on blue if the signal contains 3 or more blue balls and to bet on red otherwise. Hence, he bets on blue starting from the signal containing (3 blue / 2 red). He is then confronted with a more informative signal containing 6 balls but he wants to replicate his 5-draws optimal strategy. To this end, he rejects the additional information by randomly eliminating one draw from the 6-draws signal. His optimal strategy to bet on blue now starts at (3 blue / 3 red) with probability .5 and at (4 blue / 2 red) with probability .5.

Although appealing in theory, mixed strategies are difficult to implement in practice and it is not straightforward to find a tractable mechanism to elicit mixed strategies in the lab. Moreover, it is not judicious to offer subjects a random device to reduce the length of signals, since Bade (2015) has proved that ambiguity-averse agents may also use randomization devices to hedge, yielding contamination of the experimental data. In my experiment, subjects who want to avoid additional information should be able to *mentally* randomize. Therefore, my design departs slightly from the theoretical predictions since it does not allow subjects to explicitly state mixed strategies. This is motivated by the fact that adding mixed strategies would excessively complicate the

[11] The converse is not true and requires convexity of preferences to hold.

instructions while reducing the tractability of the design. Moreover, it would expose the experimenter to misclassification of subjects.

3.4 Predictions

Two hypotheses are derived from the theoretical literature reviewed in the previous sections and can be examined through the presented experimental setting:

H1. *Blackwell's equivalence result under compound risk* (Blackwell, 1951). To bet on the risky bag, the value of information is strictly positive and strictly increasing in the informativeness of the signal.

H2. *Blackwell's equivalence result under ambiguity* (Li and Zhou, 2016). To bet on the ambiguous bag, the value of information is strictly positive and strictly increasing in the informativeness of the signal.

The prediction H1 translates to the following experimental hypothesis: For all DM i, $0 < V_R^i(d,0) < V_R^i(d',0)$, for any $d, d' \in \mathcal{D}$ such that $d < d'$. H2 is equivalent to: For all DM i, $0 < V_A^i(d,0) < V_A^i(d',0)$, for any $d, d' \in \mathcal{D}$ such that $d < d'$. It is of interest to investigate further the effect of the introduction of ambiguity in the composition of the bag on the valuation of the signal. To this end, the difference $V_A^i(d,0) - V_R^i(d,0)$ provides the relevant measure.

Moreover, it is also possible to examine an additional hypothesis:

H3. *Value of information and attitudes towards ambiguity.* The value of information increases with ambiguity-aversion.

Thus, H3 is equivalent to the following statement: For any DM i and DM j $(i \neq j)$, if i is more ambiguity-averse than j $(I_{AA}^i > I_{AA}^j)$, then $V_A^i(d,0) > V_A^j(d,0)$, for all $d \in \mathcal{D}$. For ambiguity-averse DMs, some authors have argued that the value attributed to informative signals which *resolves* ambiguity increases with ambiguity-aversion (Snow, 2010; Attanasi and Montesano, 2012). H3 is intented to test the existence of such increasing relation when information *reduces* ambiguity.

4 Conclusion

Thanks to technological innovations, the mass of available information has been considerably increasing in the last decades, hence the individual valuation of information is an issue of particular interest in our modern societies. Drawing on Ellsberg's two-color experiment, I have proposed an experimental design to measure the value of information under compound risk and ambiguity in a model-free setup. The second objective of this paper is to provide an operational framework to test Blackwell equivalence result, which lacks empirical evidence. Moreover, once subjects' reservation price for information is elicited, it can be related to ambiguity attitudes. Finally, the 3-urns design proposed here allows to study the relation between reduction of compound lotteries and ambiguity attitudes which makes it possible to conduct further comparative analysis with Halevy (2007) and Abdellaoui *et al.* (2015).

References

Abdellaoui, M., Hill, B., Kemel, E. and Maafi, H. (2016). The evolution of ambiguity attitudes through learning.

—, Klibanoff, P. and Placido, L. (2015). Experiments on compound risk in relation to simple risk and to ambiguity. *Management Science*, **61** (6), 1306–1322.

Ambuehl, S. and Li, S. (2018). Belief updating and the demand for information. *Games and Economic Behavior*, **109**, 21–39.

Attanasi, G., Gollier, C., Montesano, A. and Pace, N. (2014). Eliciting ambiguity aversion in unknown and in compound lotteries: a smooth ambiguity model experimental study. *Theory and decision*, **77** (4), 485–530.

— and Montesano, A. (2012). The price for information about probabilities and its relation with risk and ambiguity. *Theory and decision*, **73** (1), 125–160.

Bade, S. (2015). Randomization devices and the elicitation of ambiguity-averse preferences. *Journal of Economic Theory*, **159**, 221–235.

Baillon, A., Bleichrodt, H., Keskin, U., l'Haridon, O. and Li, C. (2017). The effect of learning on ambiguity attitudes. *Management Science*.

—, Halevy, Y., Li, C. *et al.* (2015). Experimental elicitation of ambiguity attitude using the random incentive system. *University of British Columbia working paper*.

Bardsley, N., Cubitt, R., Loomes, G., Moffat, P., Starmer, C. and Sugden, R. (2010). *Experimental economics: Rethinking the rules*. Princeton University Press.

Becker, G. M., DeGroot, M. H. and Marschak, J. (1964). Measuring utility by a single-response sequential method. *Systems Research and Behavioral Science*, **9** (3), 226–232.

Becker, S. W. and Brownson, F. O. (1964). What price ambiguity? or the role of ambiguity in decision-making. *Journal of Political Economy*, **72** (1), 62–73.

Blackwell, D. (1951). Comparison of experiments. In *Proceedings of the second Berkeley symposium on mathematical statistics and probability*, The Regents of the University of California, University of California Press, pp. 93–102.

— (1953). Equivalent comparisons of experiments. *The annals of mathematical statistics*, pp. 265–272.

Çelen, B. (2012). Informativeness of experiments for MEU. *Journal of Mathematical Economics*, **48** (6), 404–406.

Chow, C. C. and Sarin, R. K. (2002). Known, unknown, and unknowable uncertainties. *Theory and Decision*, **52** (2), 127–138.

Eichberger, J. and Guerdjikova, A. (2013). Ambiguity, data and preferences for information–A case-based approach. *Journal of Economic Theory*, **148** (4), 1433–1462.

ELIAZ, K. and SCHOTTER, A. (2010). Paying for confidence: An experimental study of the demand for non-instrumental information. *Games and Economic Behavior*, **70** (2), 304–324.

ELLSBERG, D. (1961). Risk, ambiguity, and the Savage axioms. *The quarterly journal of economics*, pp. 643–669.

EPSTEIN, L. G. and JI, S. (2017). Optimal learning and Ellsberg's urns.

— and SCHNEIDER, M. (2003). Recursive multiple-priors. *Journal of Economic Theory*, **113** (1), 1–31.

— and — (2007). Learning under ambiguity. *The Review of Economic Studies*, **74** (4), 1275–1303.

ERT, E. and TRAUTMANN, S. T. (2014). Sampling experience reverses preferences for ambiguity. *Journal of Risk and Uncertainty*, **49** (1), 31–42.

FISCHBACHER, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental economics*, **10** (2), 171–178.

FOX, C. R. and TVERSKY, A. (1995). Ambiguity aversion and comparative ignorance. *The quarterly journal of economics*, **110** (3), 585–603.

GILBOA, I. and MARINACCI, M. (2016). Ambiguity and the bayesian paradigm. In *Readings in Formal Epistemology*, Springer, pp. 385–439.

— and SCHMEIDLER, D. (1989). Maxmin expected utility with non-unique prior. *Journal of mathematical economics*, **18** (2), 141–153.

GOLLIER, C. (2004). *The economics of risk and time*. MIT press.

HALEVY, Y. (2007). Ellsberg revisited: An experimental study. *Econometrica*, **75** (2), 503–536.

—, OZDENOREN, E. *et al.* (2008). Uncertainty and compound lotteries: Calibration.

Heyen, D. and Wiesenfarth, B. R. (2015). Informativeness of experiments for MEU—A recursive definition. *Journal of Mathematical Economics*, **57**, 28–30.

Hilton, R. W. (1990). Failure of Blackwell's theorem under Machina's generalization of expected-utility analysis without the independence axiom. *Journal of Economic Behavior & Organization*, **13** (2), 233–244.

Hoffman, M. (2016). How is Information Valued? Evidence from Framed Field Experiments. *The Economic Journal*, **126** (595), 1884–1911.

Johnson, C. A., Baillon, A., Bleichrodt, H., Li, Z., Van Dolder, D. and Wakker, P. P. (2015). Prince: An improved method for measuring incentivized preferences.

Karni, E. and Safra, Z. (1987). "Preference reversal" and the observability of preferences by experimental methods. *Econometrica: Journal of the Econometric Society*, pp. 675–685.

Klibanoff, P., Marinacci, M. and Mukerji, S. (2005). A smooth model of decision making under ambiguity. *Econometrica*, **73** (6), 1849–1892.

Knight, F. H. (1921). *Risk, uncertainty and profit.* New York: Dover Publications 2006.

Lévy-Garboua, L., Maafi, H., Masclet, D. and Terracol, A. (2012). Risk aversion and framing effects. *Experimental Economics*, **15** (1), 128–144.

Li, J. and Zhou, J. (2016). Blackwell's informativeness ranking with uncertainty-averse preferences. *Games and Economic Behavior*, **96**, 18–29.

Maafi, H. (2011). Preference reversals under ambiguity. *Management science*, **57** (11), 2054–2066.

Machina, M. J. (2004). Almost-objective uncertainty. *Economic Theory*, **24** (1), 1–54.

Marinacci, M. (1999). Limit laws for non-additive probabilities and their frequentist interpretation. *Journal of Economic Theory*, **84** (2), 145–195.

— (2002). Learning from ambiguous urns. *Statistical Papers*, **43** (1), 143–151.

— and Massari, F. (2017). Learning from ambiguous and misspecified models.

Moreno, O. M. and Rosokha, Y. (2016). Learning under compound risk vs. learning under ambiguity–an experiment. *Journal of Risk and Uncertainty*, **53** (2-3), 137–162.

Nicholls, N., Romm, A. T. and Zimper, A. (2015). The impact of statistical learning on violations of the sure-thing principle. *Journal of Risk and Uncertainty*, **50** (2), 97–115.

Quiggin, J. (2007). Ambiguity and the value of information: an almost-objective events analysis. *Economic Theory*, **30** (3), 409–414.

Safra, Z. and Sulganik, E. (1995). On the nonexistence of Blackwell's theorem-type results with general preference relations. *Journal of Risk and Uncertainty*, **10** (3), 187–201.

Savage, L. J. (1954). *The foundations of statistics*. New York: John Wiley and Sons.

Seo, K. (2009). Ambiguity and second-order belief. *Econometrica*, **77** (5), 1575–1605.

Siniscalchi, M. (2011). Dynamic choice under ambiguity. *Theoretical Economics*, **6** (3), 379–421.

Snow, A. (2010). Ambiguity and the value of information. *Journal of Risk and Uncertainty*, **40** (2), 133–145.

Sutter, M., Kocher, M. G., Glätzle-Rützler, D. and Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *The American Economic Review*, **103** (1), 510–531.

Trautmann, S. T. and Van De Kuilen, G. (2015). Ambiguity attitudes. *The Wiley Blackwell handbook of judgment and decision making*, **1**, 89–116.

— and Zeckhauser, R. J. (2013). Shunning uncertainty: The neglect of learning opportunities. *Games and Economic Behavior*, **79**, 44–55.

Von Neumann, J. and Morgenstern, O. (1944). *Theory of Games and Economic Behavior*. Princeton University Press.

Wakker, P. (1988). Nonexpected utility as aversion of information. *Journal of Behavioral Decision Making*, **1** (3), 169–175.

Yates, J. F. and Zukowski, L. G. (1976). Characterization of ambiguity in decision making. *Systems Research and Behavioral Science*, **21** (1), 19–25.

Zimper, A. and Ma, W. (2017). Bayesian learning with multiple priors and nonvanishing ambiguity. *Economic Theory*, **64** (3), 409–447.

A Proof: Blackwell's garbling

In this Appendix, I show that the information structure containing d random draws with replacement from the bag is a garble of the information structure with $d+1$ draws.

Formally, there are $N+1$ possible compositions of the bag containing N balls, and $\forall k \in \{0, N\}$, $\frac{k}{N}$ of balls are blue and $\frac{N-k}{N}$ of balls are red in Bag k. An information structure is a tuple (S, P) where $S := \{s_1, ..., s_{|S|}\}$ is a set of signals and $P_{|S|\times(N+1)}$ a matrix. In particular, p_{sk} is the probability that bag k be realized if signal s is observed, i.e., $p_{sk} := \Pr(k|s)$. Vector $p_{s.} = (p_{s1}, ..., p_{sN+1})$ gives the posterior probabilities conditional to signal s.

The information structure (S', P'), such that $S' := \{s'_1, ..., s'_{|S'|}\}$ and $P' = [p'_{s'k}]_{|S'|\times(N+1)}$, is a garble of information structure (S, P) if and only if there exists a Markov matrix[12] M such that:

$$P' = MP \tag{10}$$

$M = [m_{s's}]_{|S'|\times|S|}$ is the garbling matrix. The posterior distribution of the garbled information structure is given by:

$$q_{s'.} = \sum_{s=1}^{S} m_{s's} p_{s.} \tag{11}$$

Thus, all posterior probabilities in structure (S', P') are a convex combination of the posterior probabilities in structure (S, P).

Showing that the information structure containing d draws (S_d) is a garble of the information structure with $d+1$ draws (S_{d+1}) is equivalent to proving that there exists a garble of S_{d+1} which preserves the posterior probabilities of S_d on the states of the world. It then follows from Blackwell (1951) that the structure given by d draws with replacement is less informative than that containing $d+1$ draws.

Assumption: Each composition k occurs with a prior probability of $\frac{1}{N+1}$.

[12] M is a Markov matrix if and only if it is nonnegative and row-stochastic, i.e., $m_{ij} \geq 0$ and $\sum_j m_{ij} = 1$ for all i.

d draws

Suppose that the DM obtains a signal s_d of d draws from the bag. Among the d draws, a blue ball has been drawn d_b times and a red ball has been draws d_r times. It follows that $d_b \in \{0, 1, ..., d\}$ and $d_r = d - d_b$.

For instance,

$$\Pr\left\{\text{Bag } k, (\underbrace{b...br...r}_{d \text{ draws}})\right\} = \frac{1}{N+1} \underbrace{\frac{k}{N} ... \frac{k}{N}}_{d_b \text{ draws}} \underbrace{\frac{N-k}{N} ... \frac{N-k}{N}}_{d-d_b \text{ draws}} = \frac{k^{d_b}(N-k)^{d-d_b}}{N^d(N+1)}$$

With d draws, there are $\sum_{d_b=0}^{d} \binom{d}{d_b} = 2^d$ possible signals s_d.

The joint probability distribution of the state of the world (i.e., the composition of the bag) and the signal (i.e., the d draws from the bag) is:

	$(w...w)$	$(w...wb)$	...	$(w...wb...b)$	...	$(b...b)$	Total
Bag k	$\frac{k^d}{N^d(N+1)}$	$\frac{k^{d-1}(N-k)}{N^d(N+1)}$	...	$\frac{k^{d_b}(N-k)^{d-d_b}}{N^d(N+1)}$	...	$\frac{(N-k)^d}{N^d(N+1)}$	$t_k = \frac{1}{N+1}$
Total	$\frac{\sum_{k=0}^{N} k^d}{N^d(N+1)}$	$\frac{\sum_{k=0}^{N} k^{d-1}(N-k)}{N^d(N+1)}$	...	$\frac{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}}{N^d(N+1)}$	...	$\frac{\sum_{k=0}^{N} (N-k)^d}{N^d(N+1)}$	$T = 1$

The conditional probabilities for this signal structure are given by:

	$(w...w)$	$(w...wb)$	...	$(w...wb...b)$	...	$(b...b)$
$\Pr\{\text{Bag } k \mid s_d\}$	$\frac{k^d}{\sum_{k=0}^{N} k^d}$	$\frac{k^{d-1}(N-k)}{\sum_{k=0}^{N} k^{d-1}(N-k)}$	...	$\frac{k^{d_b}(N-k)^{d-d_b}}{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}}$	...	$\frac{(N-k)^d}{\sum_{k=0}^{N} (N-k)^d}$
Total	1	1	...	1	...	1

$d + 1$ draws

Suppose that the DM obtains a signal s_{d+1} of $d+1$ draws from the urn. Among the $d+1$ draws, a blue ball has been drawn d_b times and a red ball has been draws d_r times. It follows that $d_b \in [0, d+1]$ and $d_r = d + 1 - d_b$.

With $d+1$ draws, there are 2^{d+1} possible signals s_{d+1}.

The joint probability distribution of the state of the world and the signal is (i.e., the $d+1$ draws form the bag):

	$(w...ww)$	$(w...wb)$	...	$(w...wb...b)$	...	$(b...b)$	Total
Bag k	$\frac{k^{d+1}}{N^{d+1}(N+1)}$	$\frac{k^{d}(N-k)}{N^{d+1}(N+1)}$	...	$\frac{k^{d_b}(N-k)^{d+1-d_b}}{N^{d+1}(N+1)}$	...	$\frac{(N-k)^{d+1}}{N^{d+1}(N+1)}$	$\frac{1}{N+1}$
Total	$\frac{\sum_{k=0}^{N} k^{d+1}}{N^{d+1}(N+1)}$	$\frac{\sum_{k=0}^{N} k^{d}(N-k)}{N^{d+1}(N+1)}$	...	$\frac{\sum_{k=0}^{N} k^{d_b}(N-k)^{d+1-d_b}}{N^{d+1}(N+1)}$	...	$\frac{\sum_{k=0}^{N}(N-k)^{d+1}}{N^{d+1}(N+1)}$	1

The conditional probabilities for this signal structure are given by:

	$(w...w)$	$(w...wb)$	...	$(w...wb...b)$	...	$(b...b)$
$\Pr\{\text{Bag } k \mid s_{d+1}\}$	$\frac{k^{d+1}}{\sum_{k=0}^{N} k^{d+1}}$	$\frac{k^{d}(N-k)}{\sum_{k=0}^{N} k^{d}(N-k)}$	...	$\frac{k^{d_b}(N-k)^{d+1-d_b}}{\sum_{k=0}^{N} k^{d_b}(N-k)^{d+1-d_b}}$	...	$\frac{(N-k)^{d+1}}{\sum_{k=0}^{N}(N-k)^{d+1}}$
Total	1	1	...	1	...	1

Garbling machine

A garbling machine replaces the last signal by b with probability $\frac{1}{2}$ and by r with probability $\frac{1}{2}$. Such garbled signal is denoted s_{d+1}^{g}. Then:

	$(w...ww)$	$(w...wb)$	...	$(w...wb...bw)$	$(w...wb...bb)$	...	$(b...bw)$	$(b...bb)$	Total
Bag k	$\frac{k^{d}}{2N^{d}(N+1)}$	$\frac{k^{d}}{2N^{d}(N+1)}$	...	$\frac{k^{d_b}(N-k)^{d-d_b}}{2N^{d}(N+1)}$	$\frac{k^{d_b}(N-k)^{d-d_b}}{2N^{d}(N+1)}$	...	$\frac{(N-k)^{d}}{2N^{d}(N+1)}$	$\frac{(N-k)^{d}}{2N^{d}(N+1)}$	$t'_k = \frac{1}{N+1}$
Total	$\frac{\sum_{k=0}^{N} k^{d}}{2N^{d}(N+1)}$	$\frac{\sum_{k=0}^{N} k^{d}}{2N^{d}(N+1)}$	...	$\frac{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}}{2N^{d}(N+1)}$	$\frac{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}}{2N^{d}(N+1)}$	...	$\frac{\sum_{k=0}^{N}(N-k)^{d}}{2N^{d}(N+1)}$	$\frac{\sum_{k=0}^{N}(N-k)^{d}}{2N^{d}(N+1)}$	$T' = 1$

The conditionals for this signal structure are given by:

	$(w...ww)$	$(w...wb)$	...	$(w...wb...bw)$	$(w...wb...bb)$	...	$(b...bw)$	$(b...bb)$
$\Pr\left\{\text{Bag } k \mid s_{d+1}^{g}\right\}$	$\frac{k^{d}}{\sum_{k=0}^{N} k^{d}}$	$\frac{k^{d}}{\sum_{k=0}^{N} k^{d}}$	...	$\frac{k^{d_b}(N-k)^{d-d_b}}{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}}$	$\frac{k^{d_b}(N-k)^{d-d_b}}{\sum_{k=0}^{N} k^{d_b}(N-k)^{d-d_b}}$	...	$\frac{(N-k)^{d}}{\sum_{k=0}^{N}(N-k)^{d}}$	$\frac{(N-k)^{d}}{\sum_{k=0}^{N}(N-k)^{d}}$
Total	1	1	...	1	1	...	1	1

which is equivalent to the signal structure obtained with d draws from the bag.

Note that the conditional probability of obtaining signal i from the garbling machine given that the machine received signal j, m_{ij} is given by:

m_{ij}		Signal received by the machine							
		$(w...ww)$	$(w...wb)$	...	$(w...wb...bw)$	$(w...wb...bb)$	...	$(b...bw)$	$(b...bb)$
Signal delivered by the machine	$(w...ww)$	$\frac{1}{2}$	$\frac{1}{2}$	...	0	0	...	0	0
	$(w...wb)$	$\frac{1}{2}$	$\frac{1}{2}$	...	0	0	...	0	0
	...	...	...	...	...	...	...	...	...
	$(w...wb...bw)$	0	0	...	$\frac{1}{2}$	$\frac{1}{2}$	...	0	0
	$(w...wb...bb)$	0	0	...	$\frac{1}{2}$	$\frac{1}{2}$	...	0	0
	...	...	...	...	...	...	...	...	...
	$(b...bw)$	0	0	...	0	0	...	$\frac{1}{2}$	$\frac{1}{2}$
	$(w...wb)$	0	0	...	0	0	...	$\frac{1}{2}$	$\frac{1}{2}$

It is then possible to deduce the relationship between the structure with d useful draws and one garbled draw, the structure with $d+1$ draws and m_{ij}:

$$\begin{aligned}
\Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}}\right\} &= \Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}} w\right\}_{\text{garbling}} + \Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}} b\right\}_{\text{garbling}} \\
&= \frac{k^{d_b}(N-k)^{d-d_b}}{N^d(N+1)}
\end{aligned}$$

Moreover:

$$\begin{aligned}
\Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}}\right\} &= \frac{1}{2}_{\text{garble w}} \Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}} w\right\} + \frac{1}{2}_{\text{garble w}} \Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}} b\right\} \\
&\quad + \frac{1}{2}_{\text{garble b}} \Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}} w\right\} + \frac{1}{2}_{\text{garble b}} \Pr\left\{\text{Urn } k; \underbrace{w...wb...b}_{d \text{ draws}} b\right\} \\
&= 2\frac{1}{2}\frac{k^{d_b+1}(N-k)^{d+1-(d_b+1)}}{2N^{d+1}(N+1)} + 2\frac{1}{2}\frac{k^{d_b}(N-k)^{d+1-d_b}}{2N^{d+1}(N+1)} \\
&= \frac{1}{N^{d+1}(N+1)}\left[k^{d_b+1}(N-k)^{d-d_b} + k^{d_b}(N-k)^{d+1-d_b}\right] \\
&= \frac{1}{N^{d+1}(N+1)}\left[k^{d_b}(N-k)^{d-d_b}(k+(N-k))\right] \\
&= \frac{k^{d_b}(N-k)^{d-d_b}}{N^d(N+1)}
\end{aligned}$$

which is verified for all k and for all d_b. Hence, the information structure obtained with the garbling on the $(d+1)$th draws is equivalent to the signal structure with d draws. Thus, the structure S_{d+1} is more informative than the structure S_d.

B Instructions

Note: The sentences in brackets are not included in the instructions but inform the reader on the moment an action is performed.

— Start of Instructions —

Welcome everybody, and thank you for accepting our invitation to participate in this experiment. I am going to present the outline of the experiment, please pay close attention to this presentation.

First, some important rules which must be respected: It is important that the experiment takes place in silence, you are not allowed to communicate with other participants. The use of mobile phones and calculators is forbidden. No particular preliminary knowledge is needed to participate. As soon as the experiment starts, if you have any questions, please raise your hand and I will assist you.
Thank you in advance for your cooperation.

What do we do?
You are going to participate in an economic experiment on decision theory.
In this experiment, you will have to consider three opaque bags, A, B and C, each containing 100 balls. Each ball can be either blue or red.

The bags:
Bag A contains 100 balls and its composition is perfectly known. It contains exactly 50 blue balls and 50 red balls.

Bag B contains 100 balls and the proportions of blue and red balls are given by the following procedure: There are 101 chips numbered 0 to 100. [The chips are presented to the audience in increasing order so that everybody can easily check for the presence of every number.] These chips are thrown and shuffled in a bag. One of you is now asked to blindly draw one chip from this bag. [The chip is drawn and placed in an opaque box on the table in front of the room.]
Here is a coin. One of you is going to toss this coin and if it comes up heads, the number of the drawn chip determines the quantity of blue balls in bag B, the rest of the bag being filled with red balls. If the coin comes up tails, the number of the drawn chip determines the quantity of red balls in bag B, the rest of the bag being filled with blue balls. For instance, if the drawn chip is numbered 12 and the coin comes up tails, bag B is filled with 12 red balls and 88 blue balls; if the the coin comes up heads, bag B is filled with 12 blue balls and 88 red balls. The number of this chip and the result of the coin toss are kept secret until the end of the experiment. [At this point, the coin is tossed in an opaque box and placed on the table in front of the room.]

Bag C contains 100 balls and the proportions of blue and red balls are given by the following procedure: Here again, there are 101 chips numbered 0 to 100. [The chips are presented to the audience in increasing order so that everybody can easily check for the presence of every number.] These chips are thrown and shuffled in a bag. 99 secret numbered chips are added to the bag. These chips can take any number between 0 and 100 and multiple chips can have the same number. [The second set of numbered chips is thrown in the bag, while their numbering cannot be checked by the subjects.] One of you is now asked to blindly draw one chip from this bag. [The chip is drawn and placed in an opaque box on the table in front of the room.]
Here is a coin. one of you is going to toss this coin and if it comes up heads, the number of the drawn chip determines the quantity of blue balls in bag C, the rest of the bag being filled with red balls. If the coin comes up tails, the number of the drawn chip determines the quantity of red balls in bag C, the rest of the bag being filled with blue balls. The number of this chip and the result of the coin toss are kept secret until the

end of the experiment. [At this point, the coin is tossed in an opaque box and placed on the table in front of the room.]

THE GAMBLES:

During the experiment, you will be asked to consider gambles on bags A, B and C. Especially, you will have to place bets on the color of the ball to be randomly drawn from these bags. If the color of the drawn ball matches your selected color, you win 15€, otherwise you win 5€.

In some cases, you will be able to condition your decision on the revelation of observations from the bag. In such cases, a random ball is drawn from the bag, the color of the draw is reported and the ball is replaced in the bag. This operation, called a random draw with replacement, may be replicated.

The sets of observations provide information about bag B and bag C. They contain 1, 5, 20, 50 or 200 random draws with replacement.

THE ENVELOPES:

Before the beginning of the experiment, each of you will receive a **closed** envelope. Each envelope contains two options. These options differ depending on the envelopes. Your goal is to tell us which of the two options you prefer for each envelope of the experiment. At the end of the experiment, you will be rewarded depending on your envelope content and your choices of options.

Important: There are no "right" or "wrong" answers in this experiment, it is only a matter of preferences.

Here are some examples of envelope content:

Option 1 : Bet on the color of the ball to be drawn from **bag A**.	Option 2 : **8.50€**.

Each envelope is of a particular type indicated by a greek letter (alpha, beta, gamma...) in the envelope. There are 13 types of envelopes corresponding to 13 different types of questions.

Option 1 : Bet on the color of the ball to be drawn from **bag B** with a sample of **50 random draws** with replacement.	Option 2 : **12.50€**.

Option 1 : Bet on the color of the ball to be drawn from **bag C** with a sample of **200 random draws** with replacement.	Option 2 : **10.50€**.

The options contained in the different types of envelopes are given in the following table:

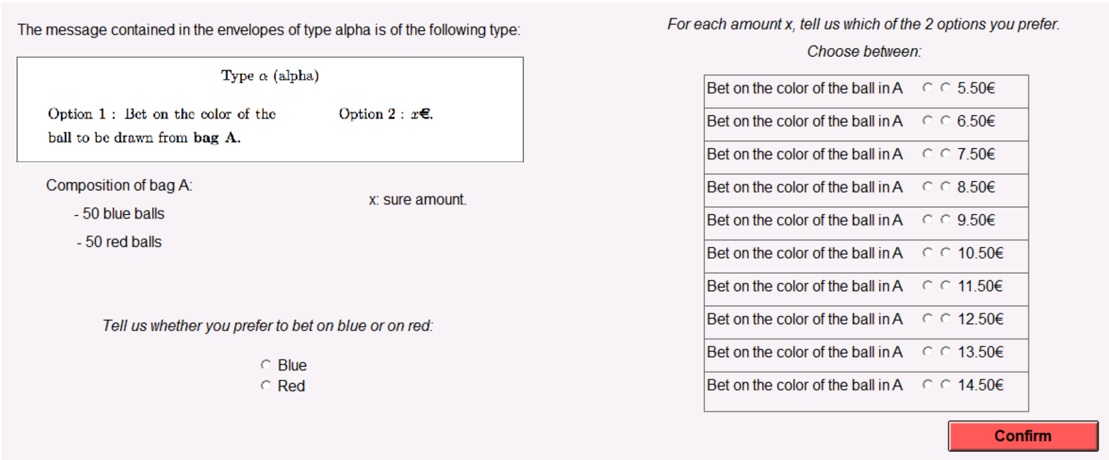
envelopes	option 1	option 2
α	bet on a ball from A	x€
β	bet on a ball from B	x€
γ	bet on a ball from B with 1 observation	x€
δ	bet on a ball from B with 5 observations	x€
ϵ	bet on a ball from B with 20 observations	x€
θ	bet on a ball from B with 50 observations	x€
ι	bet on a ball from B with 200 observations	x€
κ	bet on a ball from C	x€
λ	bet on a ball from C with 1 observation	x€
π	bet on a ball from C with 5 observations	x€
σ	bet on a ball from C with 20 observations	x€
ϕ	bet on a ball from C with 50 observations	x€
ω	bet on a ball from C with 200 observations	x€

We have 130 envelopes, 10 of each type. These envelopes are numbered from 1 to 130. Five of you are now asked to check their numbering.

With this established, I am going to walk among you and each of you will randomly draw one of the envelopes.

DO NOT OPEN YOUR ENVELOPE! Anyone who opens his envelope will be immediately excluded from the experiment and will not receive any financial reward.

During the experiment, the contents of the envelopes of type alpha will be presented to you as follows:



This question concerns bag A. Option 1 corresponds to the bet on the color of the ball to be drawn from bag A. If the color of the drawn ball matches the selected color, you win 15€, otherwise, you win 5€. Option 2 corresponds to a sure amount x in euros.

First, tell us whether you prefer to bet on a blue draw or on a red draw from bag A.

Second, fill out the table on the right. Here, for each amount x, tell us which of the two options you prefer. To this end, fill out the following table. In this table, each line describes the content of an envelope. For your convenience, the filling of this table is automated. When you tick a box of a line of the table, option 1 is automatically ticked for the lines above and option 2 is automatically ticked for the lines below. Thus, it is enough for you to tick a single box of the table to fill out every lines of the table.

Indeed, if for the first line of the table you choose option 1 "Bet on the color of the ball in A", tick option 1 on the first line of the table. Then, option 2 will be automatically ticked for the rest of the decisions, that is to say the lines 2 to 10. [During the oral explanations with slides, each pattern of answers should be illustrated with an example of a filled table.] If for the first line of the table, you choose option 2 "5.50€", tick option

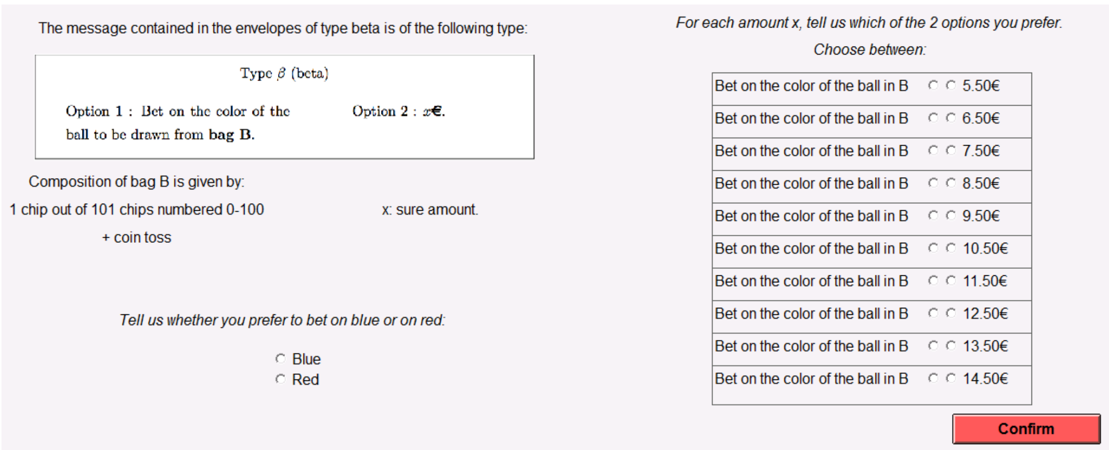
2 on the first line of the table. Then, option 2 will be automatically ticked for the rest of the decisions, that is to say for the lines 2 to 10.

You may also choose option 1 for the second line of the table. In this case, tick option 1 on the second line of the table. Option 1 will be automatically ticked for the line 1 of the table, and option 2 will be automatically ticked for the lines 3 to 10 of the table. Otherwise, you may choose option 2 for the second line of the table. In this case, tick option 2 on the second line of the table. Option 1 will be automatically ticked for the line 1 of the table, and option 2 will be automatically ticked for the lines 3 to 10 of the table.

And so on until the end of the table. You can choose option 1 for the tenth line of the table. In this case, tick option 1 on the tenth line of the table. Option 1 will be automatically ticked for the rest of the decisions, that is to say for the lines 1 to 9.

Note that you can revise your choice as many times as needed before confirming your choice and proceeding to the following question.

The contents of the envelopes of type beta will be presented to you as follows:


The message contained in the envelopes of type beta is of the following type:

Type β (beta)

Option 1 : Bet on the color of the ball to be drawn from **bag B**.

Option 2 : x**€**.

Composition of bag B is given by:

1 chip out of 101 chips numbered 0-100

+ coin toss

x: sure amount.

Tell us whether you prefer to bet on blue or on red:

Blue

Red

For each amount x, tell us which of the 2 options you prefer.

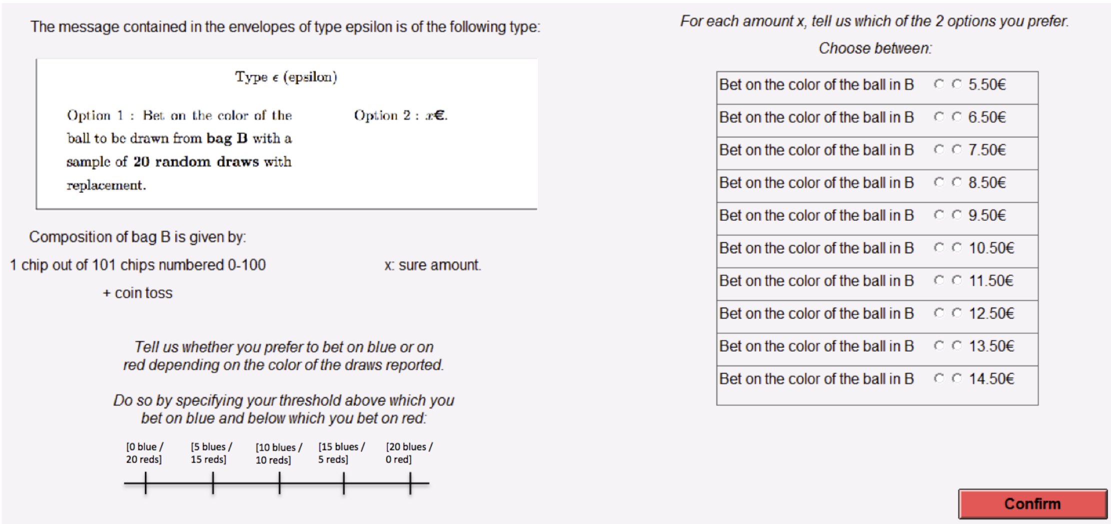
Choose between:

Bet on the color of the ball in B	5.50€
Bet on the color of the ball in B	6.50€
Bet on the color of the ball in B	7.50€
Bet on the color of the ball in B	8.50€
Bet on the color of the ball in B	9.50€
Bet on the color of the ball in B	10.50€
Bet on the color of the ball in B	11.50€
Bet on the color of the ball in B	12.50€
Bet on the color of the ball in B	13.50€
Bet on the color of the ball in B	14.50€

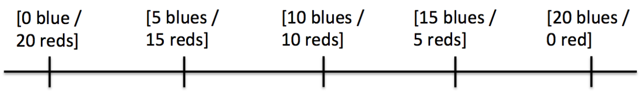
Confirm

This question concerns bag B. Option 1 corresponds to the bet on the color of the ball to be drawn from bag B. Option 2 corresponds to a sure amount x in euros. First, tell us whether you prefer to bet on a blue draw or on a red draw from bag A. Second, for each amount x, tell us which of the two options you prefer. Do so by filling out the table on the right as described previously.

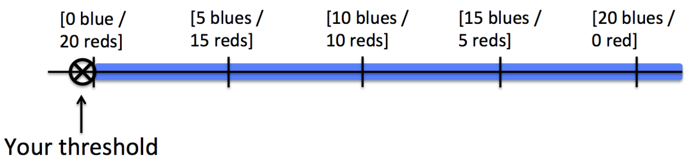
When observations from bag B are available, the contents of the envelopes will be presented to you a bit differently, for instance:



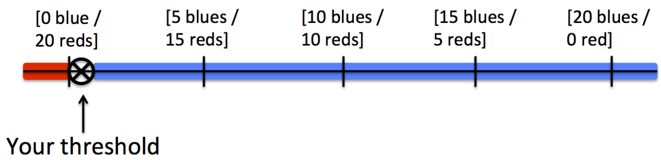
This is the content of envelope of type epsilon. Option 1 corresponds to the bet on the color of the ball to be drawn from bag B with a sample of 20 random draws with replacement. Option 2 corresponds to a sure amount x in euros. First, you announce whether you prefer to bet on blue or on red depending on the color of the draws reported. Here, you have to specify the threshold above which you bet on blue and below which you bet on red. You answer this question using a horizontal slider as below:



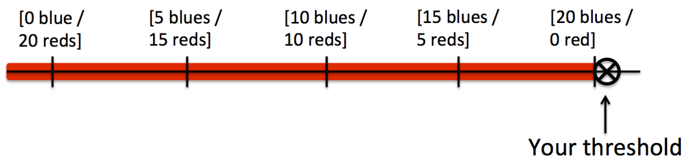
You are asked to place your threshold on this horizontal line. If you place your threshold below [0 blue / 20 reds], it means that you will bet on blue for every sets of observations containing 20 balls.



If you place your threshold between [0 blue / 20 reds] and [1 blue / 19 reds], it means that you will bet on red for a set of observations containing no blue ball while you will bet on blue for every sets of observations containing 1 and more blue balls.

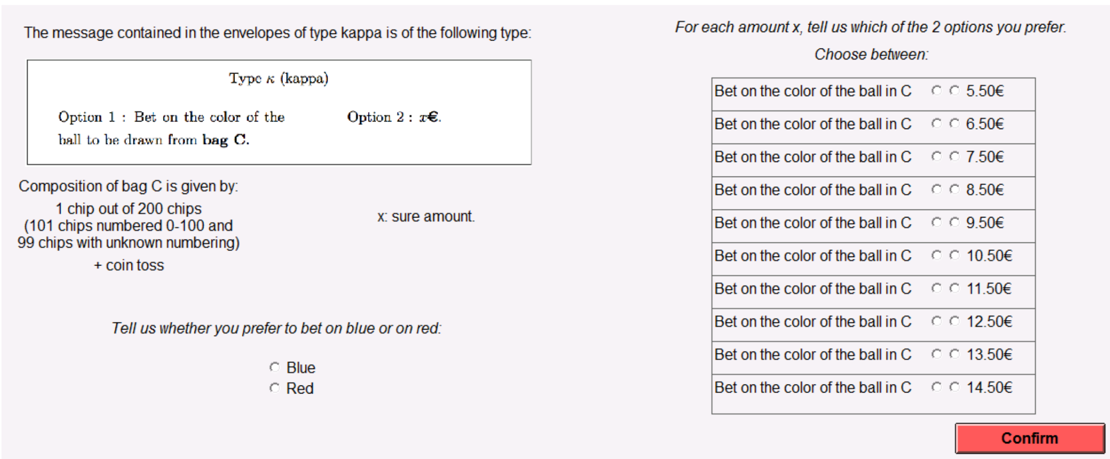


And so on until the last threshold: if your threshold is above [20 blues / 0 red], it means that you will bet on red for every sets of observations containing 20 balls.

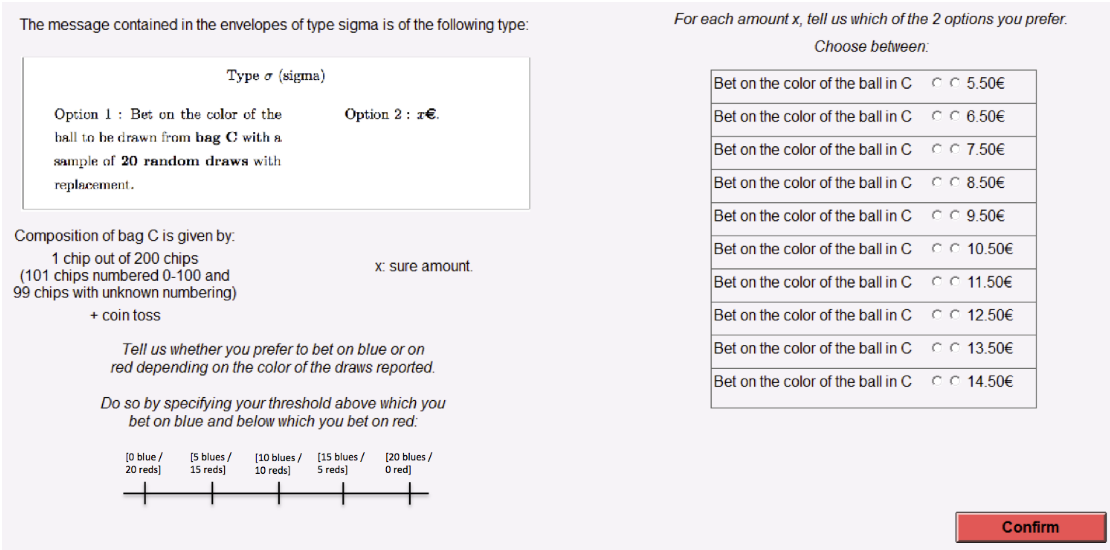


After that, fill out the table on the right. Here, for each amount x, tell us which of the 2 options you prefer.

Regarding bag C, the contents of the envelope of type kappa will be presented as follows:



When observations are available, you will face for instance:



Your payment:

In this experiment, the minimum gain is 5 euros and the maximum gain is 15 euros.

Reminder: There are no "right" or "wrong" answers in this experiment, it is only a matter of preferences.

Plan of the experiment:

Practically, you will answer the questions of the experiment using the computer in front of you.

First, you will be asked some comprehension questions to check your understanding of the instructions. Your answers to these questions do not affect your payment.

Then, the experiment on your choices of options will start. The experiment consists of 13 successive stages for 13 types of envelopes (13 different types of questions).

Finally, you will be asked to fill out a short complementary questionnaire to get to know you better. Your answers to these questions do not affect your payment.

The last screen will invite you to reach the experimenter's office to proceed for payment.

In the office of the experimenter:

I will open the envelope in front of you and I will just implement what you chose during the session.

If the option chosen during the session is a bet without observation of draws: the color that you selected for this specific question will be recalled and you will proceed to draw a ball at random from the bag involved in the bet. If the drawn ball matches the winning color, you win 15€; otherwise, you only win 5€.

If the option is a bet with observation of draws: the computer will generate a set of random draws with replacement from the bag involved in the bet. The threshold you announce for this particular question will be recalled and compared to the set of random draws to determine your winning color. Then you will proceed to draw a ball at random from the bag involved in the bet. If the drawn ball matches the winning color, you win 15€; otherwise, you only win 5€.

If the option is a sure amount x: you get the x€ gain.

Because you do not know the content of your envelope and because I will implement your choices, it is in your best interest to tell us your preferred option at each question. Indeed, if you tell us what you want, your preferred option will be the one implemented!

VERIFICATION:

At the end of the experiment, the two numbered chips and the two results of coin tosses used to generate the bag B and the bag C will be publicly displayed. You will be free to check the content of all bags.

Besides, you will get a list describing the contents of all envelopes. This list describes the content of each envelope: number of the envelope, type of the envelope, option 1, option 2. You will then check that our description of the numbered envelopes was truthful. You will also be able to check that the list does contain the 13 mentioned tasks.

Your answers will be kept strictly confidential and anonymous, henceforth, feel free to answer as you like. Moreover, there is no time limit, so take all the time you need to read the instructions and answer the questions.

Do you have any questions?

If everything is clear, you can now start the experiment!

— End of Instructions —