Decision Making with Imperfect Knowledge of the State Space*

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Abstract

We conduct an experiment to study how *imperfect* knowledge of the state space affects subsequent choices under uncertainty with *perfect* knowledge of the state space. Participants in our experiment choose between a sure outcome and a lottery in 32 periods. All treatments are exactly identical in periods 17 to 32 but differ in periods 1 to 16. In the early periods of the "Risk Treatment" there is perfect information about the lottery; in the "Ambiguity Treatment" participants perfectly know the outcome space but not the associated probabilities; in the "Unawareness Treatment" participants have imperfect knowledge about both outcomes and probabilities. We observe strong treatment effects on behaviour in periods 17 to 32. In particular, participants who have been exposed to an environment with very imperfect knowledge of the state space subsequently choose lotteries with high (low) variance less (more) often compared to other participants. Estimating individual risk attitudes from choices in periods 17 to 32 we find that the distribution of risk attitude parameters across our treatments can be ranked in terms of first order stochastic dominance. Our results show how exposure to different degrees of uncertainty can have long-lasting effects on individuals' risk-taking behaviour.
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1 Introduction

Exposure to low probability or unexpected events can influence economic decision making and perception of risk in future seemingly unrelated domains. For example, Malmendier and Nagel (2010) show that experiencing macroeconomic shocks—like the Great Depression—decreases people's willingness to take financial risks in the long run, whereas experiencing an economic boom in the past increases future participation in the stock market. Nishiyama (2006) demonstrates that the Asian crisis of 1997 has resulted in a persistent increase in US banks' risk aversion.

One difficulty with empirical studies is to isolate the effect of such events on risk aversion. Since in the contexts mentioned there are few objective probabilities, what looks like an increase in risk aversion may be just (Bayesian) updating of the banks' or consumers' priors. There are many other possible confounding factors and hence it is extremely difficult to isolate the effect of such unexpected events on future risk aversion in field studies. Conducting a laboratory experiment can help to circumvent this problem. In this paper we study experimentally how unexpected or rare events influence future risk attitudes and how strong and long lasting these effects are.

Events can be unexpected in a number of different ways. It is possible that an event with low objective (or subjective) probability realizes, or the probability of an event is unknown and the decision-maker realizes she was attaching a wrong (maybe zero) probability to it. Or it may be the case that the decision-maker was not even "aware" that the event can realize at all. In the literature on decision making under uncertainty these three notions correspond to standard "types" of uncertainty, which, in their turn, correspond to different amounts of information the decision maker holds about objective parameters of the lotteries. In a *risky* environment a decision maker knows all possible outcomes, as well as the associated probabilities. In an *ambiguous* environment the decision maker is typically assumed to know all possible outcomes but not the corresponding probabilities with which they occur (Ellsberg, 1961; Maccheroni, Marinacci, and Rustichini, 2006). Such "immeasurable" risk is also often referred to as Knightian uncertainty (Knight, 1921). In addition to not knowing the objective probabilities associated with each outcome the decision maker might be *unaware* of some possibilities, but, at the same time, be conscious about being not aware of the entire state space.

In this paper we study how such *imperfect* knowledge of the state space affects subsequent (unrelated) choices under uncertainty with *perfect* knowledge of the state space. In particular, participants in the computer lab experiment are first given a sequence of choices between a fixed lottery and varying sure monetary outcomes (first task). There are three treatments that differ in the amount of information available about the lottery. In the Risk treatment participants see all outcomes of the lottery as well as their probabilities. In the Ambiguity treatment only outcomes are observed. In the Unawareness treatment participants see only some possible outcomes and no probabilities. Upon choosing the lottery they can become aware of additional outcomes. In each treatment it is explained to participants which amount of information they do or do not have. This also means that in the Unawareness treatment they are "aware of their unawareness". After the first task participants in all three treatments are given another sequence of choices between different lotteries and sure outcomes with all information available (second task).

Since in our experiment participants in the Unawareness treatment are *aware* of the fact that they do not know all outcomes, this treatment, in principle, is the same as Ambiguity treatment, if one assumes that the decision maker deems "all" outcomes possible.[1] However, the cardinality of the set of "all possible outcomes" is rather large, and it is hardly conceivable that the decision maker would think of all outcomes at once. Therefore, in what follows, we will differentiate the environments with unknown outcomes (Unawareness) from the environments with unknown probabilities (Ambiguity).

Our main finding is that participants who have been exposed to an environment with *imperfect* knowledge of the state space subsequently become more risk averse in standard decision making under risk than participants who had full information about the state space. In particular, participants in the Unawareness treatment chose high variance lotteries significantly less often than participants in the Ambiguity treatment who, in turn, chose the same lotteries significantly less often than participants in the Risk treatment. We also find that, as expected, lotteries with high expected value are chosen more often than those with low expected value and that lotteries with high variance are chosen less often than those with low variance irrespective of the treatment. We estimate individual risk attitudes from choices in the second task and find that the distribution of risk attitude parameters across our

[1]Decision maker might attach probability zero to some events. Distinguishing this situation from unawareness is a topic which has attracted attention in theoretical research. See, for example, Feinberg (2009) for discussion.

treatments can be ranked in terms of first order stochastic dominance (FOSD). Consistently with our first result we find that the distribution of risk parameters in the Unawareness treatment dominates that of the Ambiguity treatment which dominates that of the Risk treatment in terms of FOSD. These results demonstrate how exposure to different types of uncertainty—even in such a clinical environment as a laboratory experiment—can have long-lasting effects on individuals' risk-taking behaviour.

We conjecture that these spillovers are due to the fact that participants in the treatments with less information about the state space become more sensitive to the variance or risk associated with a lottery. Exposure to larger uncertainty in the first task makes participants react more to the uncertainty of the lotteries in the second task. We give an example of how such increase in sensitivity to uncertainty can be derived from a theory with the following properties: 1) agents carry over estimated uncertainty from periods 1-16 to later periods; 2) they use early periods as reference points. Additional treatments allow us to rule out the possibility that unrelated emotional states as well as some other explanations are responsible for the result.

Previous research has demonstrated that individuals' decisions are affected by whether a choice situation displays only risk or whether it is ambiguous (Ellsberg, 1961; Halevy, 2007, among many others). In particular, it was found that people are ambiguity averse in a way which is inconsistent with subjective probability theories (Savage, 1954; Anscombe and Aumann, 1963). However, Ahn et al. (2010) estimate parametric models of ambiguity aversion and risk aversion in portfolio-choice problems and find that—despite considerable heterogeneity—the majority of subjects are well described by subjective expected utility. Gollier (2009) also studies the relation between risk aversion and ambiguity aversion. These results are quite different from our experiment in that we do not compare behaviour in risky/ambigous environments but rather investigate how having been *exposed* to such an environment affects risk attitudes in subsequent unrelated choices. Effects similar to ours have been documented more or less explicitly in several empirical and field studies (Malmendier and Nagel, 2010; Nishiyama, 2006; Giuliano and Spilimbergo, 2009; Osili and Paulson, 2009). However, to our knowledge this is the first paper to generate clean laboratory environment which enables us to compare behaviour in risky/ambiguous situations and situations characterized by (awareness of) unawareness and isolate the persistent behavioural differences generated by each of these environments.

An additional novelty of our approach is to propose an experimental design to study (awareness of) unawareness. Unawareness has recently attracted quite a lot of attention among game theorists. It belongs to the broader literature on bounded rationality, and more specifically it is a special case of reasoning in the presence of unforeseen contingencies. One of the main reasons for the great focus Unawareness has received recently, besides the obvious need to clarify its behavioral implications, is the fact that the first major contributions in this literature were two negative results that show that accommodating a notion of unawareness which satisfies some reasonable axioms is impossible both in a standard state space model (Dekel, Lipman, and Rustichini, 1998) and in a syntactic model (Modica and Rustichini, 1994). The solution that was proposed in order to overcome the technical difficulties emerging from these results was to make reasoning an awareness-dependent process (Fagin and Halpern, 1988; Modica and Rustichini, 1999; Heifetz, Meier, and Schipper, 2006; Li, 2009), i.e., to restrict agents' language to facts they are aware of and to only allow them to reason within the bounds of their language. All the early models share the common feature that agents are unaware of their own unawareness (AU-introspection). More recently, there have been attempts to extend this framework in a way that captures states of mind such that agents are aware of the possibility that they may be unaware of some fact (Halpern and Rêgo, 2008). This is the case that corresponds to our experiment, since—as mentioned before—participants in our experiment are aware of the fact that they may be unaware of some outcomes.

The paper is organized as follows. Section 2 gives the details of the experimental design. Section 3 describes the statistical tools and the mean variance utility model we estimate. In sections 4 and 5 we present the main results. Section 6 discusses the results. Appendix 7 contains instructions and further details of the experiment.

2 Experimental Design

In our experiment, participants are presented with 32 consecutive choices between lotteries and sure outcomes. There are 6 treatments in total. The three main treatments are called "Unawareness", "Ambiguity", and "Risk". These treatments differ only in the amount of information about the lotteries provided to the participants during the first 16 choices. The choices 17 to 32 are exactly identical across treatments.

In periods 1 to 16 participants choose between a fixed lottery and varying sure outcomes. The lottery is presented in Table 1. Notice that apart from the monetary outcomes the lottery also has an outcome called "Twix". A participant who chose the lottery and received the Twix outcome was given a real Twix chocolate bar at the end of the experiment. The idea behind the introduction of non-monetary outcome is to enlarge the space of outcomes that participants might consider. The sure outcomes in the first 16 choices varied from 5.4 Euro to 8.4 Euro with a 0.2 Euro interval and occurred in the same random order in all treatments.[2]

Outcomes (Euro)							
	-20	-1	Twix	6	8	10	14
	0.001	0.05	0.05	0.2	0.25	0.379	0.07
Probabilities							

Table 1: The lottery participants faced in periods 1-16.

The treatments differ in the amount of information participants have about the lottery in Table 1. In the Risk treatment participants observe all outcomes and all probabilities as shown in Table 1. In the Ambiguity treatment participants are shown all outcomes but not the associated probabilities. In the Unawareness treatment participants see no probabilities and only some outcomes. In particular, from the first period on participants observe the possible outcomes 6, 8, 10 and 14; starting from period 6 they are also shown the possible outcome –1; starting from period 11 they are shown Twix; and in period 16 they see outcome –20. If a participant chooses the lottery and an outcome is realized that she was previously unaware of (that she was not shown previously) she is informed about it and the outcome is displayed in all subsequent periods. In all treatments participants are informed about these details in the Instructions, i.e. they know in the Ambiguity and Risk treatments that they know all outcomes and in the Unawareness treatment they are aware of the fact that they do *not* know all outcomes.[3] Figures 1.abc show how the choices were presented to the participants.

In all treatments the choices in periods 17 to 32 are between a lottery with 2 outcomes and different sure amounts. These choices are the same across treatments. Participants observe both outcomes and associated probabilities in all treatments (see Figure 1.d). Hence, all treatments are exactly identical in periods 17-32. The outcomes of the lotteries vary between 2 Euro and 20 Euro. The probabilities are chosen such that the expected values of all lotteries are in the interval between 7.94 Euro and 8.05 Euro. The sure outcomes vary between 6 and 8 Euro with a 0.5 Euro interval.[4] All participants are informed that there are no other outcomes than those shown on the screen. They could also infer this from the fact that probabilities add up to one.

[2]See Section 7 for more details of the design.

[3]We ran the treatments in the order Unawareness, Ambiguity, Risk to avoid communication among participants regarding the information provided in different treatments.

[4]See Section 7.1 for the details.

Figure 1: Screen shots of a typical choice in periods 1 to 16 in a) Risk treatment; b) Ambiguity treatment; c) Unawareness treatment: Screen of a participant who received a Twix some time before Period 6. d) a choice in periods 17 to 32 in all treatments.

At this point it is important to remember that we are interested mainly in behavior in periods 17-32 which are identical across treatments. We are not interested for example in eliciting ambiguity attitudes, which would clearly not be possible with our design, since we do not know which priors participants have about the lottery. We will return to this question in Section 6.[5]

In addition to the Risk, Ambiguity and Unawareness treatments we ran three more treatments: 1) Control treatment in which subjects faced only the lotteries from periods 17 to 32; 2) Unawareness-POS treatment which is identical to Unawareness treatment except the payoff –20 which was replaced by +20; 3) Risk with high variance treatment which is similar to Risk treatment except the changes in probabilities of the outcomes in the first 16 periods. The discussion of additional treatments can be found in Section 6 and Appendix 6.3. We did not run any other treatments than the 6 treatments described, nor did we run any pilot sessions.[6]

[5]One may also wonder why we didn't choose a design where subjects first play the lotteries from periods 17-32, then have treatment variation, and then play period 17-32 lotteries again. This would allow to see whether any participants change their behavior. The big disadvantage of such a design is that it allows for possible confounds. Participants may change their behaviour depending on their experience. Many studies have shown that such period effects may play a role even if only one period is paid at random. We decided therefore to do a full between subjects analysis and use a large number of participants.

[6]We disregard the data from one session of the Unawareness treatment where there was a substan-

At the end of the experiment the participants were paid for one randomly chosen period in addition to a 4 Euro show-up fee. Overall, 104 participants have participated in the Risk treatment; 100 participants in the Ambiguity treatment; 106 participants in the Unawareness treatment; 32 participants in the Control treatment; 85 participants in Unawareness-POS treatment; and 81 participants in Risk with high variance treatment. All experiments were run with z-Tree (Fischbacher, 2007) at Maastricht University in June 2010 - May 2011.

3 Methods

In order to estimate risk attitudes we use a mean-variance utility model (Markowitz, 1952). Utility of a lottery is assumed to be a weighted sum of its expected value and standard deviation. The positive coefficient on the expected value reflects the desire for higher monetary outcome and the negative coefficient on standard deviation reflects risk attitude. The mean-variance model is consistent with expected utility theory if and only if the utility function is quadratic.[7] Some neuroeconomic evidence (e.g. Preuschoff, Bossaerts, and Quartz, 2006) even claims that mean-variance utility is encoded in the striatal regions of the brain.

Consider a lottery $\ell = (x_1 \circ p_1, x_2 \circ p_2, ..., x_n \circ p_n)$. We model utility as

$$u(\ell) = K_\theta + \alpha_\theta E[\ell] - \beta_\theta SD[\ell]$$

where $\alpha_\theta, \beta_\theta > 0$, K_θ is a constant, $E[\ell]$ is expected value, $SD[\ell]$ is standard deviation and θ denotes the treatment (Risk, Ambiguity, Unawareness).[8] For the degenerate lottery (x) we have $u(x) = K_\theta + \alpha_\theta x$. We estimate random utility logit model (see e.g. McFadden, 1976) which assumes that the probability of choosing the lottery ℓ over

tial program error.

[7]Tobin (1958) shows that the mean-variance model is consistent with the axioms of expected utility if the utility function is quadratic. Markowitz (1959) shows the converse, i.e., decisions based on MV can be reconciled with the axioms of EU only when the utility function is quadratic. For an overview, see Johnstone and Lindley (2011).

[8]We use standard deviation instead of usual variance, because standard deviation is measured in the same units as expected value, which makes it easier to compare coefficients. There is also ample evidence in neuroeconomics literature in favor of the Temporal Difference (TD) learning model. In particular, many studies have found the encoding of the TD prediction error in the brain (e.g. O'Doherty et al., 2003). In case of a choice between two lotteries prediction error naturally translates into standard deviation (whereas variance corresponds to the squared prediction error). Finally (and non-surprisingly), our results are robust to using either standard deviation or variance.

sure outcome x is monotonic with respect to the difference of the utilities

$$\alpha_\theta E[\ell] - \beta_\theta SD[\ell] - \alpha_\theta x = \alpha_\theta (E[\ell] - x) - \beta_\theta SD[\ell].$$

Thus, for the choices between lotteries ℓ_{ti} and sure outcomes x_{ti} in period t for participant i we can use the random effects logit regression

$$\text{Prob}[\ell_{ti} \text{ chosen}] = \Phi(E[\ell_{ti}] - x_{ti}, SD[\ell_{ti}], ...)$$

to estimate K_θ, α_θ and β_θ. In what follows the independent variable $(E[\ell_{ti}] - x_{ti})$ will be called `dexp` and $SD[\ell_{ti}]$ will be called `stdv`.

Apart from the choices themselves we analyze response times, or the time it takes a participant to choose between lottery and sure outcome to uncover more behavioral patterns. In general, longer response times reflect more information processing before the choice is made (e.g. Gneezy, Rustichini, and Vostroknutov, 2010) which is typically connected to the complexity of a decision problem. Thus, response times can shed some light on the process by which participants make choices under the different informational regimes (Risk, Ambiguity and Unawareness).

4 Main Result

In this section we analyze treatment differences in the behavior in periods 17 to 32. As was mentioned above the choices that participants face in these periods are exactly the same in all three treatments. Therefore, any behavioral differences between treatments should be attributed to the experiences participants had in periods 1 to 16. We hypothesize that experiencing different levels of knowledge about the state space in the first 16 periods differentially affects which aspects of the decision problem participants become more sensitive to. In particular, participants that have been exposed to a higher degree of uncertainty in periods 1 to 16 might be more sensitive to the uncertainty associated with the lottery in periods 17 to 32.

Table 2 shows the random effects logit regression of choices in periods 17 to 32.[9] Independent variables of interest are `dexp` – the difference between the expected value of the lottery and the sure outcome (ranging from –0.06 to 2.04 with an average of 0.99); `stdv` – the standard deviation of the lottery (ranging from 1.73 to 8.46 with an

[9] See Section 7.2 for the definitions of the independent variables and Section 7.1 for the exact payoffs used in each of the choices.

	Pr(Lottery)				
	(1)	(2)	(3)	(4)	(5)
dexp	1.265***	1.252***	1.212***	1.218***	1.180***
	(0.107)	(0.106)	(0.063)	(0.105)	(0.062)
stdv	–0.325***	–0.322***	–0.320***	–0.312***	–0.311***
	(0.038)	(0.038)	(0.037)	(0.037)	(0.037)
per	–0.056***	–0.043***	–0.043***		
	(0.014)	(0.008)	(0.008)		
awar	0.859**	1.093***	1.079***	1.073***	1.061***
	(0.384)	(0.342)	(0.328)	(0.339)	(0.324)
amb	0.513	0.629*	0.555*	0.621*	0.549*
	(0.387)	(0.344)	(0.328)	(0.341)	(0.325)
awar·stdv	–0.260***	–0.267***	–0.267***	–0.264***	–0.263***
	(0.056)	(0.056)	(0.055)	(0.055)	(0.054)
amb·stdv	–0.149***	–0.152***	–0.158***	–0.151***	–0.156***
	(0.056)	(0.055)	(0.055)	(0.055)	(0.054)
awar·dexp	–0.038	–0.015		–0.012	
	(0.151)	(0.149)		(0.149)	
amb·dexp	–0.120	–0.107		–0.105	
	(0.151)	(0.150)		(0.149)	
awar·per	0.025				
	(0.019)				
amb·per	0.013				
	(0.019)				
const	1.294***	1.178***	1.207***	0.795***	0.822***
	(0.269)	(0.248)	(0.241)	(0.236)	(0.228)
N	310	310	310	310	310

Table 2: Random effects logit regression of choices between lotteries and sure outcomes in periods 17 to 32 (* – 10% significance; ** – 5%; *** – 1%). The numbers in parentheses are standard errors. The first 3 columns contain a period term and/or its interactions. 4960 observations, 310 independent.

average of 4.54); `per` – the number of the period (normalized to range from 1 to 16); `awar` and `amb` – the dummies corresponding to treatments Unawareness (`awar`) and Ambiguity (`amb`) ; as well as interactions.[10] As can be seen from columns (1) and (2) of Table 2 in all three treatments participants respond in the same way to the expected values of lotteries and sure outcomes: there are no treatment effects. Participants also show a slight tendency towards choosing the sure outcome as periods increase, but again there are no treatment differences (all coefficients `awar·dexp`, `amb·dexp`, `awar·per` and `amb·per` are insignificant). We included the variable `per` as well as interaction effects in regressions (1)-(3) to ensure that our variables `dexp` and `stdv` do not pick up time effects. In fact the correlation between `per` and `dexp` (`stdv`) is $\rho = 0.1733^{***}$ ($p = 0.0044$) respectively (Spearman correlation test). Regressions (4) and (5) show that our results are robust and quantitatively unchanged if we omit all period terms.

[10]See Section 3 for the explanations why these variables are used.

The most interesting effect though is the sensitivity to the standard deviation of the lotteries across treatments. We observe that the sensitivity to standard deviation is lowest in the Risk treatment (`stdv`), higher in the Ambiguity treatment (`stdv + amb·stdv`), and highest in the Unawareness treatment (`stdv + awar·stdv`). In the Ambiguity treatment the regression coefficient for the standard deviation of the lottery is -0.478 with standard error 0.041 and $p < 0.0001$. In the Unawareness treatment it is -0.587 with standard error 0.041 and $p < 0.0001$ (column 3). The difference of coefficients between Unawareness and Ambiguity treatments is -0.109 with standard error 0.057 and $p < 0.055$ (`awar·stdv - amb·stdv`). The dummy variables `awar` and `amb` have positive coefficients 1.079 and 0.555 respectively.

Taken together these results mean that for the lotteries with standard deviations close to zero participants choose the lottery with the highest probability in the Unawareness treatment, lower probability in the Ambiguity treatment and the lowest probability in the Risk treatment. However, for the lotteries with high standard deviation (`stdv` > 3.8 approximately) the situation is reversed. The model predicts that participants choose high standard deviation lotteries with the lowest probability in Unawareness treatment, higher probability in Ambiguity treatment and the highest probability in Risk treatment. This lends support to our conjecture that participants become more sensitive to the standard deviations of the lotteries in periods 17-32 if they have been previously exposed to an environment characterized by very imperfect knowledge of the state space.

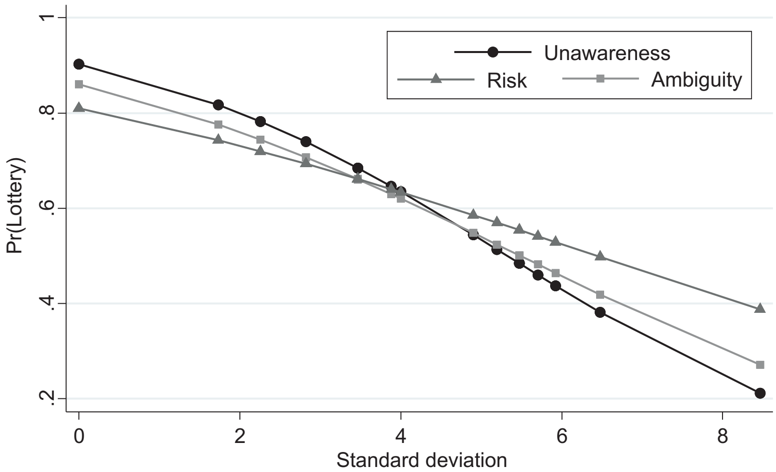

Figure 2: Predicted probabilities of choosing lottery as a function of its standard deviation in three treatments.

Figure 2 plots the probability with which a lottery was chosen in periods 17 to 32 as a function of the standard deviation of that lottery. As expected, lotteries with higher standard deviation are chosen less often reflecting risk aversion. Most interestingly, though, the order of treatments reverses as standard deviation increases. Lotteries with low standard deviation are chosen most often in the Unawareness treatment and least often in the Risk treatment. For lotteries with high standard deviation this effect is exactly opposite – they are chosen most often in the risk treatment and least often in the Unawareness treatment. Interestingly all three treatments intersect at about the same point.

In terms of the mean-variance criterion $\alpha_\theta(E[\ell] - x) - \beta_\theta SD[\ell]$ our results (from Table 2) imply the following ranking of our treatments:

$$\begin{aligned} \alpha_{Unawareness} &= \alpha_{Ambiguity} = \alpha_{Risk} \\ \beta_{Unawareness} &> \beta_{Ambiguity} > \beta_{Risk}. \end{aligned}$$

Hence, while the participants' reaction to expected value in all treatments is the same, they react more strongly to variance in the Unawareness treatment than in the Ambiguity treatment than in the Risk treatment. Keep in mind that here we are talking about choices in periods 17 to 32, i.e. about the *spillover effect* from having experienced choices in a risky/ambiguous environment or an environment characterized by "unawareness" on standard decision making under risk. In addition the last column of Table 2 shows that

$$K_{Unawareness} > K_{Ambiguity} > K_{Risk}.$$

Taken together this evidence suggests that participants exposed to an environment characterized by "unawareness" start to focus much more on variance than other participants. They are less likely to choose lotteries characterized by high variance and more likely to choose lotteries characterized by very small variance.

Finally, we compare the distributions of individual risk attitudes in periods 17 to 32 in all three treatments. As was mentioned in Section 3 the weight β on standard deviation in the mean-variance utility model can be thought of as an estimator of risk attitude. For each participant i in our experiment we ran a logit regression

$$\text{Prob}[\ell_{ti} \text{ chosen}] = \Phi(E[\ell_{ti}] - x_{ti}, SD[\ell_{ti}])$$

on 16 choices in periods 17 to 32 to estimate individual coefficient β_i.[11] Figure 3 shows

[11] We dropped participants who always chose either lottery or sure outcome. In total there were 96 participants in the Unawareness treatment, 87 in ambiguity and 97 in the risk treatment.

the cumulative distributions of β_i for the three treatments.

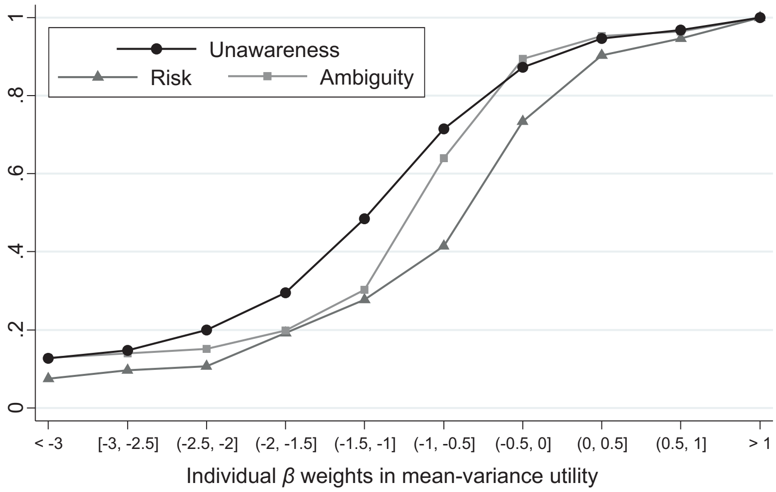

Figure 3: Cumulative distributions of (the negative of) individual β weights (risk attitudes) in Risk, Ambiguity and Unawareness treatments.

Notice that cdf of risk attitudes in Unawareness treatment first-order stochastically dominates cdf in Risk treatment.[12] This implies that exposure to an environment with awareness of unawareness uniformly increases risk aversion (as measured by β_i) of all participants with any risk attitude. The cdf for Ambiguity treatment is in between the cdfs for the Unawareness and Risk treatments in terms of first order stochastic dominance in the steep part of the graph where most observations are. A Mann-Whitney test rejects the hypothesis that the distribution of individual β's comes from the same distribution pairwise for any two treatments ($p < 0.0001$). The test returns a probability that $\beta_{Unawareness} > \beta_{Ambiguity}$ of 0.58 and if we restrict to the risk-averse part of the distribution of 0.61. For the event that $\beta_{Unawareness} > \beta_{Risk}$ the test returns a probability of 0.66 and for $\beta_{Ambiguity} > \beta_{Risk}$ a probability of 0.61. This provides further evidence for the lasting effects of exposure to environments with varying types of uncertainty on participants' risk attitudes. Figure 4 reports the distribution of individual α_i coefficients. Distributions look very similar across the three treatments which supports previous claim that uncertainty of the environments does not affect attitude towards expectation of the lotteries.

In Section 6 three additional treatments are considered in detail: 1) Unawareness treatment with +20; 2) Risk with high variance treatment and 3) Control treatment. These treatments provide further evidence that it is the nature of the uncertainty

[12]The graph plots the negative of the risk aversion parameter. Hence indeed the distribution of β's in the Unawareness treatment first-order stochastically dominates that of the Risk treatment.

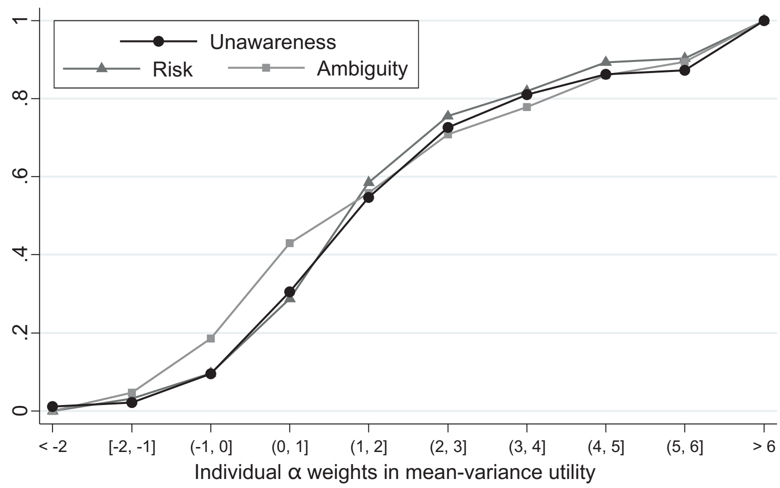

Figure 4: Cumulative distributions of individual α weights in Risk, Ambiguity and Unawareness treatments.

(Risk, Ambiguity, Unawareness) that affects the change in risk attitudes rather than the quantitative aspects of the uncertainty.

Result 1

1. *Participants in the Unawareness treatment are more (less) likely to choose low (high) variance lotteries than participants in the Ambiguity treatment than participants in the Risk treatment, implying the following ranking of risk parameters β on the population level:* $\beta_{Unawareness} > \beta_{Ambiguity} > \beta_{Risk}$.

2. *The distributions of individual risk attitude parameters across the three treatments are ranked as follows in terms of first-order stochastic dominance:* $\beta_{Unawareness} \succ_{FOSD} \beta_{Ambiguity} \succ_{FOSD} \beta_{Risk}$.

5 Treatment Comparison in Periods 1-16

Before we start discussing several possible explanations for our main result let us briefly look at treatment comparisons in Periods 1-16. This will be relevant to understanding our hypotheses.

We analyze the choices of participants in first 16 periods across all three treatments. Table 3 reports the logit regression of choices depending on sure outcome; dummies that indicate the treatment as well as interaction terms.

	Pr(lottery)	
	Risk, Ambiguity, Unawareness	
	β/(se)	*β/(se)*
sure	–2.025***	–2.104***
	(0.113)	(0.088)
awar	–6.294***	–5.748***
	(0.996)	(0.840)
amb	–0.761	
	(1.161)	
awar·sure	0.979***	1.051***
	(0.134)	(0.114)
amb·sure	–0.203	
	(0.164)	
const	14.312***	13.821***
	(0.826)	(0.621)
N	310	310

Table 3: Random effects logit regression of choices in the first 16 periods of Risk, Ambiguity and Unawareness treatments.

Important observation is that there are no apparent differences between Risk and Ambiguity treatment (`amb` and `amb·sure` are insignificant). This suggests that participants in these treatments make choices in similar fashion. However, choices in Unawareness treatment are very different. Here participants seem to be less sensitive to sure outcomes than in the Risk treatment (`sure + awar·sure`). Moreover, participants tend to choose sure outcome more often overall (`awar`). This suggests that participants may employ different decision heuristics in the Unawareness and Ambiguity/Risk treatments. One conjecture could be that in the Unawareness treatment the first occurrence of "surprise" triggers some simple decision heuristic that biases choices towards sure outcomes (compared to EU maximization).

To gain more insight into the nature of the decision process in the first 16 periods we now look at the response times across treatments. Table 4 shows that response time depends on the sure outcome in Risk and Ambiguity treatments in the right direction: the higher the sure outcome the faster is the decision.[13] However, in Unawareness treatment response time does not react to the value of the sure outcome (`sure + awar·sure` is insignificant). Moreover, in Unawareness treatment there is an overall drop in the response time comparing to Risk and Ambiguity treatments (`awar`). This is consistent with the conjecture made above that choice heuristic is different between Unawareness and Risk/Ambiguity treatments: in Unawareness treatment the decisions are faster and less dependent on the sure outcomes.

	Response time	
	Risk, Ambiguity, Unawareness	
	β/(se)	*β/(se)*
sure	–0.421***	–0.450***
	(0.135)	(0.101)
per	–0.807***	–0.810***
	(0.027)	(0.026)
awar	–8.875***	–9.110***
	(1.434)	(1.244)
amb	0.478	
	(1.455)	
awar·sure	0.446**	0.476***
	(0.189)	(0.167)
amb·sure	–0.655***	–0.596***
	(0.192)	(0.061)
awar·per	0.487***	0.489***
	(0.038)	(0.037)
amb·per	0.243***	0.248***
	(0.038)	(0.036)
const	18.216***	18.450***
	(1.019)	(0.727)
N	310	310

Table 4: Random effects regression of response times in the first 16 periods of the Risk, Ambiguity and Unawareness treatments.

We finally analyze the patterns in average behavior across treatments. We construct the variable `absc`. For each participant i for periods 1 to 16

$$\text{absc}_i = |\text{average choice}_i - 0.5| \times 2.$$

`absc` ranges from 0 to 1. Participants with `absc=0` choose the sure outcome and the lottery an equal number of times. Participants with `absc=1` choose only the sure outcome *or* only the lottery. Thus, `absc` shows how often participants switch between the alternatives.

[13]See Section 3 for possible theoretical explanation of this effect.

Figure 5 shows the distributions of `absc` for the three treatments in periods 1 to 16. One can see that on average in Unawareness treatment participants tend to switch a lot between the lottery and sure outcome whereas in the Ambiguity treatment participants stick more often to the same alternative.

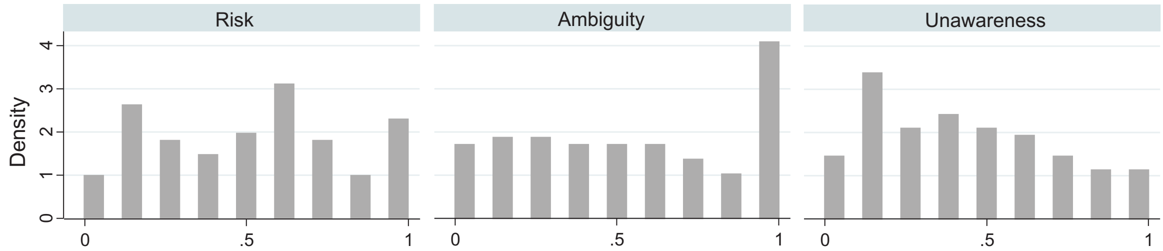

Figure 5: Histograms of absc by treatment in periods 1 to 16.

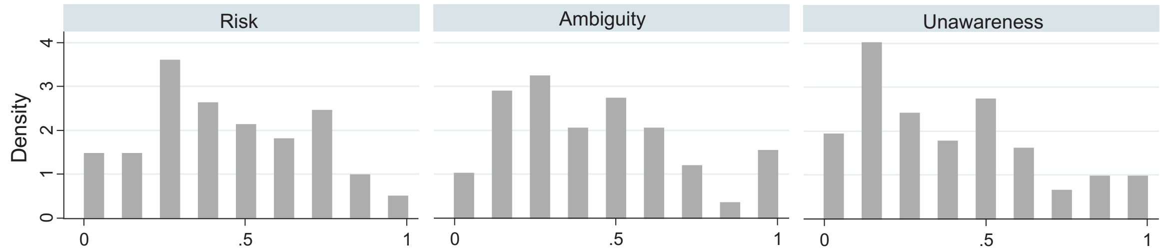

Figure 6: Histograms of absc by treatment in periods 17 to 32.

Mann Whitney tests show significant difference in the distributions of `absc` between Risk and Unawareness ($p < 0.041$) and between Ambiguity and Unawareness ($p < 0.017$) but no significant difference between Risk and Ambiguity ($p > 0.542$). This again confirms our hypothesis that choice process in Ambiguity and Risk treatments is different from Unawareness treatment.

The difference between distributions is only observed in the first 16 periods but not in the periods 17 to 32. All distributions on Figure 6 look the same with the peak in the middle and no significance in the Mann-Whitney tests ($p > 0.0677$, $p > 0.1447$ and $p > 0.6464$ respectively). This shows that in periods 17 to 32 participants do react to the choices in a similar way since they observe full information about the lotteries. The only difference is a shift in the risk attitudes.

Result 2

1. *In Unawareness treatment participants are less likely to choose the lottery in periods 1 to 16 and react less to the value of the sure outcome compared to either Risk or Ambiguity treatment which are not significantly different.*

2. *Response times are overall faster in Unawareness treatment compared to Risk and Ambiguity treatments. Participants are faster the higher the value of the*

sure outcome in both Risk and Ambiguity treatments, but do not vary with the value of the sure outcome in the Unawareness treatment.

6 Discussion and Explanation

In this section we discuss some possible explanations for the lasting effects of past exposure to Risk, Ambiguity and Unawareness.

6.1 Unrelated Emotional States

Several studies in psychology suggest that *emotional states* influence the perception of risk. For example, it was found that affect (Johnson and Tversky, 1983), fear (Lerner and Keltner, 2001) and anxiety (Raghunathan and Pham, 1999) make people more risk averse in the future. Functional Magnetic Resonance Imaging studies point at specific regions in the human brain, for example amygdala, that are activated in these emotional states (see e.g. the meta-study by Phan et al., 2002).

Our theory allows for the fact that emotional states which are directly connected to the informational environment (risk, ambiguity, unawareness) may be triggered. However, we want to rule out the possibility that our results are due to *unrelated* emotional states. In particular, one may conjecture that *negative* surprises trigger emotional states which "increase" risk aversion and that *positive* surprises do not.

Such an explanation based on negative surprise could at least explain the ranking between the Risk and the Unawareness treatment. It cannot explain, though, the difference between the Ambiguity and the Risk treatment. If at all it seems that surprises should be "positive" in the Ambiguity treatment (when participants realize that negative outcomes occur with very low probability).

To fully rule out this explanation we conducted an additional treatment, Unawareness - POS, which is the same as the Unawareness treatment but with +20 instead of –20 outcome. Table 5 shows the results of a regression comparing the Risk, the Ambiguity and the Unawareness-POS treatments. For lotteries with low variance there is only a marginally significant difference between Risk and Ambiguity. However, participants in the Unawareness-POS treatment tend to choose lotteries significantly more often than participants in the Risk treatment. For lotteries with high standard deviation this effect reverses. They are chosen most often by participants in the Risk treatment, followed by the Ambiguity treatment and least often by participants in the Unawareness-POS treatment. Qualitatively these results and the implied treatment rankings are exactly the same as those obtained with the original Unawareness treatment with negative surprises in Table 2. Figure 7 illustrates the result.[14]

[14]Appendix 7.3 shows the distributions of individual β coefficients for Unawareness-POS treatment

Pr(Lottery)	
	Risk, Ambiguity, Unawareness-POS
dexp	1.204***
	(0.104)
stdv	–0.308***
	(0.037)
awarpos	0.909***
	(0.346)
amb	0.613*
	(0.333)
awarpos·stdv	–0.190***
	(0.056)
amb·stdv	–0.148***
	(0.054)
awarpos·dexp	–0.165
	(0.152)
amb·dexp	–0.105
	(0.148)
const	1.294***
	(0.269)
N	289

Table 5: Random effects panel data logit regression of choices between lotteries and sure outcomes in periods 17 to 32 if surprise in the Unawareness treatment is positive (* – 10% significance; ** – 5%; *** – 1%). The numbers in parentheses are standard errors. 4624 observations, 289 independent.

Finally, note that negative surprises are those that are more relevant in terms of the motivation brought forward in the introduction.

6.2 Perceived Risk in Periods 1-16

Another possible explanation of the effect of exposure to different levels of uncertainty on the future choices is that subjects *perceive* ambiguous lottery and lottery with unawareness as exhibiting higher variance than analogous lottery with observed probabilities. According to this hypothesis the higher is the perceived variance in first 16 periods the more risk averse subjects should become in last 16 periods. If this hypothesis were true we should have observed the smallest risk aversion in Risk treatment, more risk aversion in Unawareness treatment and even more risk aversion in Ambiguity treatment. The perceived variance in Ambiguity treatment should be highest because subjects observe all possible outcomes and therefore might assign high probabilities to negative outcomes, whereas in Unawareness treatment subjects learn about the existence of negative outcomes only closer to the end of first 16 periods.

Our analysis refutes this ranking of risk aversions among treatments (see Section

in comparison with Risk, Ambiguity and Unawareness.

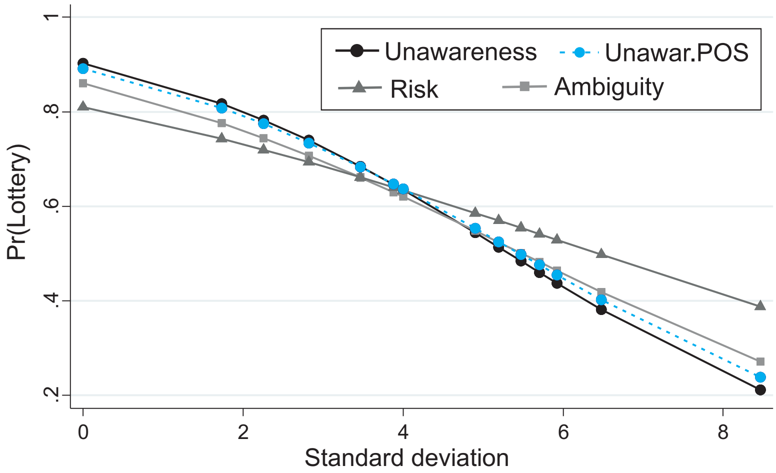

Figure 7: Estimated Probability to choose a lottery as a function of its standard deviation. Treatments: Risk, Ambiguity, Unawareness and Unawareness-POS.

4). In addition, the hypothesis stated above implies that subjects should have more or less uniform prior over the outcomes in Ambiguity treatment. However, this means that the expectation of the lottery should be much lower than 8. Therefore, we should observe subjects to choose sure outcomes in Ambiguity treatment substantially more often than in other treatments. Again, our data refute this: subjects choose lottery in Ambiguity treatment no less often than in other treatments.

In order to completely rule out the above hypothesis we ran Risk with high variance treatment. This treatment is the same as Risk treatment (all information in first 16 periods is observed), except the probabilities assigned to the outcomes. Table 6 shows the lottery that participants observe in Risk with high variance treatment. The variance of this new lottery is three times higher than that of the original lottery.

Outcomes (Euro)	-20	-1	Twix	6	8	10	14
Probabilities	0.03	0.05	0.05	0.12	0.2	0.37	0.18

Table 6: The lottery from the first 16 choices in Risk with high variance treatment.

The regression in Table 7 shows the estimates of the coefficients in the logit model of choices in periods 17 - 32 for all treatments. None of the independent variables associated with Risk with high variance treatment are significant (`riskhigh`, `riskhigh·dexp`, `riskhigh·stdv`). This demonstrates that the choices in Risk with high variance treatment are not significantly different from original Risk treatment, thus rejecting the hypothesis that variance of the lottery influences future risk aversion.

	Pr(Lottery)
	All Treatments
dexp	1.205***
	(0.104)
stdv	–0.309***
	(0.037)
awar	1.060***
	(0.331)
awarpos	0.910***
	(0.347)
amb	0.614*
	(0.333)
riskhigh	0.407
	(0.349)
awar·stdv	–0.260***
	(0.055)
awarpos·stdv	–0.190***
	(0.056)
amb·stdv	–0.148***
	(0.054)
riskhigh·stdv	–0.016
	(0.055)
awar·dexp	–0.132
	(0.147)
awarpos·dexp	–0.165
	(0.152)
amb·dexp	–0.105
	(0.148)
riskhigh·dexp	–0.249
	(0.154)
const	0.786***
	(0.231)
N	476

Table 7: Random effects panel data logit regression of choices between lotteries and sure outcomes in periods 17 to 32 including all treatments (* – 10% significance; ** – 5%; *** – 1%). The numbers in parentheses are standard errors. 7616 observations, 476 independent.

Figure 8 shows the result graphically.[15]

[15] Appendix 7.3 shows the distributions of individual β coefficients for Risk with high variance treatment in comparison with Risk, Ambiguity and Unawareness.

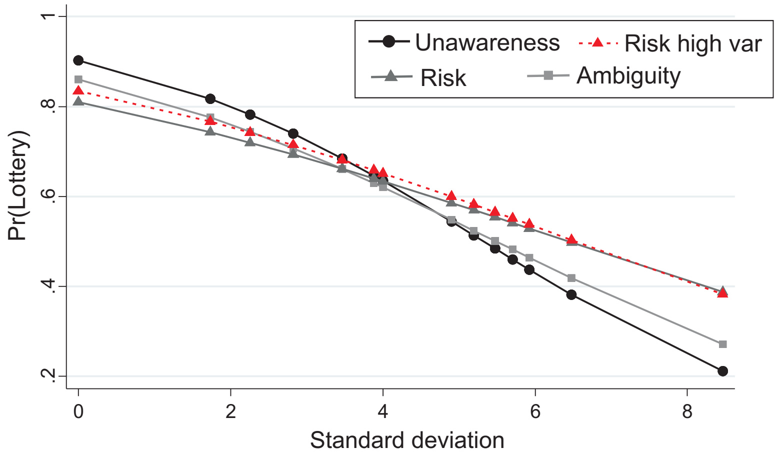

Figure 8: Estimated Probability of choosing a lottery as a function of its standard deviation. Treatments: Risk, Risk-high, Ambiguity and Unawareness.

6.3 Control Treatment

In order to check the consistency of our results we ran Control treatment in which subjects faced only last 16 choices. Table 8 shows the regression with Control and Risk treatments.

	Pr(Lottery)
	Risk, Control
dexp	1.185*** (0.104)
stdv	–0.304*** (0.037)
control	0.108 (0.571)
control·dexp	–0.406 (0.249)
control·stdv	–0.048 (0.094)
const	0.772*** (0.224)
N	121

Table 8: Random effects panel data logit regression of choices between lotteries and sure outcomes in periods 17 to 32 in Risk and Control treatments (* – 10% significance; ** – 5%; *** – 1%). The numbers in parentheses are standard errors. 3600 observations, 121 independent.

The regression shows that participants in Control treatment behave in the same way as in Risk treatment. There are no significant differences between the two treatments. This supports our hypothesis that ambiguous environments and environments with unawareness increase future risk aversion comparing to the "normality" which is characterized by known outcomes and probabilities. Figure 9 shows the distributions of individual β_i coefficients for main treatments and Control treatment. It can be noticed that Control treatment distribution is not very different from Risk treatment.

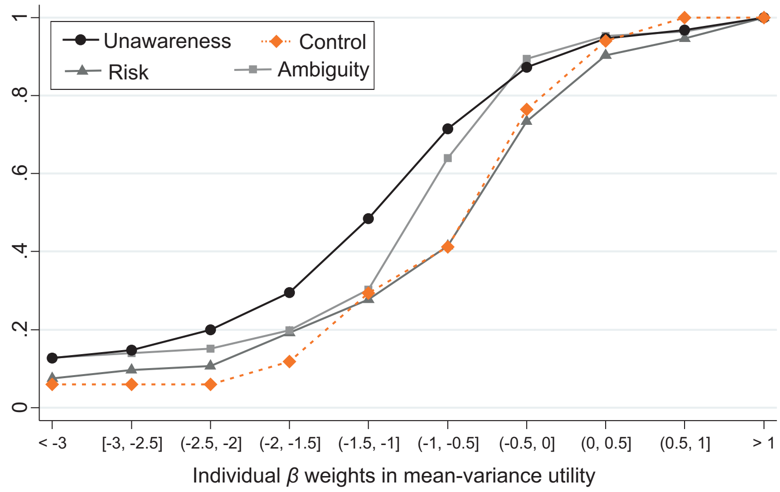

Figure 9: Cumulative distributions of individual risk aversion coefficients β_i. Treatments: Risk, Ambiguity, Unawareness and Control.

6.4 The Effect of Imperfect Knowledge of the State Space on Risk Aversion

In this section we propose a theoretical model of the spillover effects observed in the experiments. Our explanation is based on two steps which we discuss here and formalize in Appendix 7.4.

1. In the first task participants estimate possible probability distribution over outcomes for the lottery (periods 1-16).

2. In the second task the uncertainty from the first task is carried over. Participants attach small probabilities to mean/standard deviation pairs (μ, σ) which are one (estimated) standard deviation away from the actual (observed) mean and standard deviation (μ_ℓ, σ_ℓ) of the lottery ℓ.

Our results can be explained by a value function which associates utility with standard deviation. The function is steeper around the reference point (which is given by the estimated standard deviation from the first task), concave below the reference point (small standard deviations) and convex above.[16] In Appendix 7.4 we show that

[16]Note that risk averse participants will prefer *lower* standard deviation.

estimated value functions do indeed have this shape. The intuition then is as follows. The estimated probability distributions in Step 1 induce a joint probability distribution over means and variances. This distribution (as well as the marginals) will have the highest variance in Unawareness treatment compared to Ambiguity treatment and will have zero variance under Risk (see Appendix). If participants carry over this uncertainty to the second task, they will—for lotteries with low variance—attach positive probability to many lotteries with a variance below the reference point. The concavity of the value function below the reference point then ensures that those are chosen most often in the Unawareness treatment. On the other hand, for lotteries with high variance participants attach positive probability to many lotteries with a variance above the reference point. The convexity of the value function above the reference point then ensures that those are chosen least often in the Unawareness treatment.[17]

Let us elaborate on the first point. Clearly in the Risk treatment probability distributions are trivially estimated since there is perfect knowledge of the state space, i.e. both outcomes and associated probabilities are given. Now, any estimation procedure for probability distributions in the Ambiguity and Unawareness treatments will induce a distribution over estimated means and standard deviations (possibly degenerate). Any estimation procedure that will create a higher standard deviation of $\widehat{\mu}$ and $\widehat{\sigma}$ in Unawareness compared to Ambiguity will be consistent with our explanation.[18] An example of estimation procedures which have this property are bootstrapping techniques; another example are procedures estimating parameters of a Dirichlet function which provides a foundation for learning procedures such as fictitious play (see e.g. Fudenberg and Levine, 1998). We formalize this in the Appendix.

Our explanation is not unrelated to prospect theory. However, there are some elements in our theory which need to be accommodated. In particular, the first step is crucial. If we assumed simply that the (estimated) mean and standard deviation of the lottery in Periods 1-16 are reference points in periods 17-32, this will not explain our results. Such a theory would, for example, predict differences between the treatments Risk and Risk High (which have different standard deviations). But this is not what we observe. In addition, as long as we assume that mean and variance are

[17]Of course participants also estimate distributions over means. However those have a much lower variance (see Appendix), which makes it intuitive that we do not observe an effect with respect to the sensitivity to the mean.

[18]Since in the Risk treatment the lottery is known, the estimated standard deviation of $\widehat{\mu}$ and $\widehat{\sigma}$ will be zero.

estimated in an *unbiased* way in the Ambiguity and Unawareness treatments, such a theory would lead to the same reference points in our three main treatments and hence as such would *not* predict a difference between our three main treatments.[19] Again this is clearly against empirical observation. Hence it is not the estimated standard deviation but the standard deviation of the estimated $(\widehat{\mu},\widehat{\sigma})$ that matters, i.e. the fundamental uncertainty by which the environment is characterized.

It is worth mentioning a literature on behavioural spillovers (see e.g. Gneezy, Rustichini, and Vostroknutov, 2010; Haruvy and Stahl, 2009; Mengel and Sciubba, 2010). These authors show that cognitive skills (such as applying backward induction or iterated elimination of dominates strategies) can be extrapolated across games. It is hard to argue that the spillover effects in our experiment have much to do with transfer of cognitive skills or learning. In fact we conducted a control treatment, where participants only faced the lotteries from periods 17 to 32. Behaviour in this treatment is not significantly different from behaviour in the risk treatment.[20] There is also no evidence in our study that participants would use different heuristics in periods 17 to 32 across the different treatments.[21] Instead it seems that their attention is shifted towards giving greater weight to the uncertainty of a choice option. This supports the view that preferences can be endogenous to the decision situation and can be shaped by previous experiences and/or a process of cultural transmission of norms and ideas. It is also consistent with the "risk-as-feelings" hypothesis outlined above and supported e.g. by Loewenstein et al. (2001).

[19] Assuming that the mean and variance of the lottery in task 1 are estimated in a *biased* way seems ad hoc. In addition, even if we did assume this such a theory would still predict a difference between Risk and Risk-High, which is not what we observe.

[20] See Section 6.3.

[21] See the end of Section 5.

7 Appendix

7.1 Details of the Design

Table 9 shows the sequence of lotteries and sure outcomes observed by the participants in periods 17 to 32.

Choice	Lottery				Sure Outcomes Cohort			
	x_1	x_2	p_1	p_2	1	2	3	4
17	4	14	0.6	0.4	7.0	7.5	6.0	6.5
18	4	10	0.33	0.67	6.5	7.5	7.0	6.0
19	5	17	0.75	0.25	7.5	6.5	8.0	7.0
20	2	15	0.54	0.46	6.0	7.0	7.5	6.5
21	5	9	0.25	0.75	7.5	8.0	6.5	7.0
22	3	9	0.17	0.83	8.0	7.0	6.5	7.5
23	2	20	0.67	0.33	6.5	7.5	7.0	8.0
24	5	19	0.79	0.21	7.0	6.0	6.5	7.5
25	3	14	0.55	0.45	6.5	8.0	7.5	7.0
26	4	11	0.43	0.57	6.5	7.0	8.0	7.5
27	4	12	0.5	0.5	7.0	6.5	7.5	8.0
28	2	13	0.45	0.55	8.0	6.5	7.0	7.5
29	3	11	0.38	0.62	6.0	7.0	7.5	6.5
30	3	15	0.58	0.42	7.5	6.0	6.5	7.0
31	2	10	0.25	0.75	7.0	7.5	6.0	6.5
32	5	12	0.57	0.43	7.5	6.5	7.0	6.0

Table 9: Choices 17 to 32.

Participants were divided into 4 cohorts. In each choice each cohort faced the same lottery but different sure outcome. The participants were divided into 4 cohorts in order to create more variability in the data.

7.2 Definitions of Variables

Variable	Definition
per	Choice period. Ranges from 1 to 16 for the first 16 periods and 1 to 16 for the last 16 periods (first and last 16 periods are always analyzed separately)
choice	0/1 variable. Is 1 if the lottery was chosen
resptime	Time in seconds it took participant to choose
awar	0/1 variable. Is 1 if the choice is made in the Unawareness treatment
amb	0/1 variable. Is 1 if the choice is made in the Ambiguity treatment
awarpos	0/1 variable. Is 1 if the choice is made in the Unawareness-POS treatment
riskhigh	0/1 variable. Is 1 if the choice is made in the Risk with high variance treatment
control	0/1 variable. Is 1 if the choice is made in the Control treatment
x_1, x_2	For the last 16 periods: outcomes of the lottery
p_1, p_2	For the last 16 periods: probabilities of the outcomes of the lottery
sure	The sure outcome. For the first 16 periods ranges in $[5.4, 8.4]$, mean 6.9
dexp	For the last 16 periods: expected value of the lottery minus sure outcome $= (p_1 x_1 + p_2 x_2) - sure$. Ranges in $[-0.06, 2.04]$, mean 0.99
stdv	For the last 16 periods: square root of the variance of the lottery. Ranges in $[1.73, 8.46]$, mean 4.54
firstsp	0/1 variable. For periods 1 to 16 in Unawareness treatment: is equal to 1 in all periods including and after the one in which participant saw first previously unknown outcome (–1, Twix, or –20)

7.3 Individual β cdfs for Additional Treatments

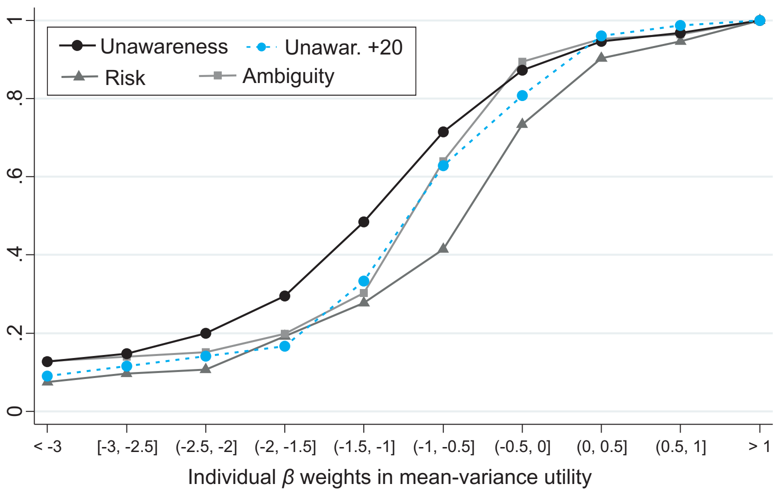

Figure 10: Cumulative distributions of individual risk aversion coefficients β_i. Treatments: Risk, Ambiguity, Unawareness, Unawareness-POS.

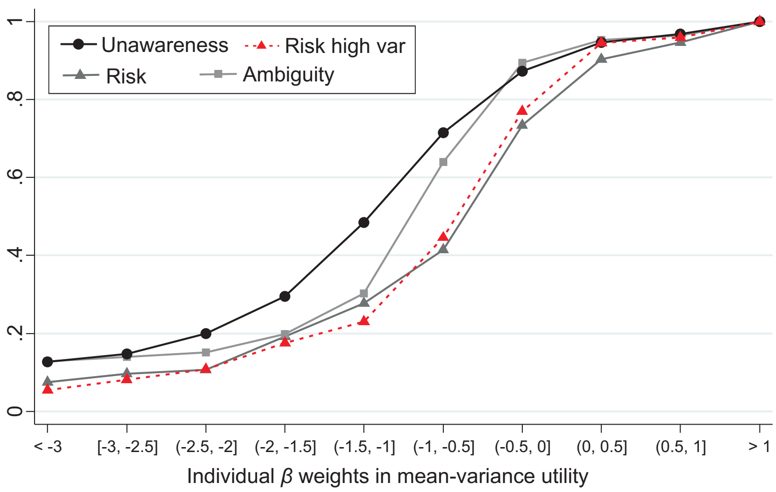

Figure 11: Cumulative distributions of individual risk aversion coefficients β_i. Treatments: Risk, Risk-high, Ambiguity and Unawareness.

7.4 Theoretical Explanation Corresponding to Section 6.4

In this subsection we provide a formal theoretical model that can explain the effects we observe. We also show supporting regression tables and graphs. Let us start by outlining the formal theory.

7.4.1 Estimation

First we illustrate one possible manner of estimating a distribution over lotteries that the agent deems possible in periods 1-16 which works for our theoretical explanation. This method is built on the framework of DeGroot (1970). Other methods, such as many variants of bootstrapping, are possible as well.

Types of possible outcomes

Let us start with some notation. There is a set of possible outcomes X with typical elements x and y. Suppose that the agent observes a random sample $q = (q_x\,;\, x \in X)$, where q_x stands for the frequency of x in the sample. Let $\alpha_x > 0$ denote the prior weight that the agent assigns to $x \in X$. Then, the posterior expected probability assigned to x by the agent, given the sample q is equal to

$$p_x = \frac{\alpha_x + q_x}{\sum_{y \in X}(\alpha_y + q_y)}. \tag{7.1}$$

We distinguish three types of outcomes:

X_s : The outcomes that are realized in the sample, i.e., $x \in X_s$ if and only if $q_x > 0$.

X_a : The outcomes that the agent knows that are possible, i.e., if the agent knows that $x \in X$, even if $q_x = 0$, then $x \in X_a$. This is the case for instance, when the participant in our experiment has been informed (in the Ambiguity treatment) that -20 is possible, but has never been drawn. Notice that, $X_s \subseteq X_a$. Moreover, it follows directly from equation (7.1) that if $x \in X_s$ and $y \in X_a \setminus X_s$, then $p_x > p_y$.

X_u : The outcomes that the agent deems possible, without having been explicitly informed that they belong to X. Obviously, if $x \in X_u$ then $q_x = 0$. This is for instance the case when the subject (in the Unawareness treatment) deems -10 possible, without having ever observed it.

We impose some assumptions that restrict the agent's *ex ante* probabilistic assessments.

Assumption 1. Elements that cannot be distinguished *a priori* share the same α:

- $\alpha_x = \alpha_a$ for all $x \in X_a$,
- $\alpha_x = \alpha_u$ for all $x \in X_u$.

Observe that if $x \in X_s$ and $y \in X_a$ then $\alpha_x = \alpha_y$. $\triangleleft$

Assumption 2. $\alpha_a \gg \alpha_u$. $\triangleleft$

The previous assumption says that the agent deems the outcomes in X_a much more likely than the ones in X_u.

In our experiment, we consider $X_a = \{-20, -1, 1, 6, 8, 10, 14\}$.[22] In the ambiguity treatment $X_u = \emptyset$, whereas in the unawareness treatment we assume that X is sufficiently rich containing all outcomes between -50 and 50.

Distribution over the lotteries

Suppose now that the agent is *ex ante* uncertain about the relative likelihood between an outcome in X_a and one in X_u. We capture this by assuming that the agent believes that α_u is distributed uniformly in $[0, \alpha_0]$, and α_a is uniformly distributed in $[\alpha_1, \alpha_2]$, where $\alpha_0 \ll \alpha_1$. Clearly, if $\alpha_0 = 0$, which implies that the agent is certain that X_u is empty, the unawareness case is degenerated to the ambiguity case.

For every $(\alpha_u, \alpha_a) \in [0, \alpha_0] \times [\alpha_1, \alpha_2]$, the agent estimates a p_x for every $x \in X$, and therefore estimates $E_p(X)$ and $SD_p(X)$.

Expected value

The agent estimates from the sample the probability of each outcome she deems possible through equation (7.1). Throughout this section we assume that the sample size is equal to 10.

The latter yields an expected value of X in the Ambiguity treatment for each $\alpha_a \in [0, \alpha_0]$. More specifically,

$$\begin{aligned} E_a X &= \sum_{x \in X_a} \frac{\alpha_x + q_x}{\sum_{y \in X_a} (\alpha_y + q_y)} x \\ &= \frac{\alpha_a}{10 + \alpha_a |X_a|} \sum_{x \in X_a} x + \frac{10}{10 + \alpha_a |X_a|} \sum_{x \in X_s} \frac{q_x}{10} x. \end{aligned}$$

Since the sample mean is an unbiased estimator of EX, it follows that

$$E_a X = \frac{80 + 18\alpha_a}{10 + 7\alpha_a}.$$

[22] Here we assume Twix has value 1.

Recall that this is a random variable, yielding one value for each $\alpha_a \in [0, \alpha_0]$.

Likewise, the agent estimates the expected value of X for (α_a, α_u) in the Unawareness treatment:

$$\begin{aligned} E_u X &= \sum_{x \in X_a \cup X_u} \frac{\alpha_x + q_x}{\sum_{y \in X_a \cup X_u} (\alpha_y + q_y)} x \\ &= \frac{1}{10 + \alpha_a |X_a| + \alpha_u |X_u|} \left(\alpha_a \sum_{x \in X_a} x + \alpha_u \sum_{x \in X_u} x \right) + \\ & \quad \frac{10}{10 + \alpha_a |X_a| + \alpha_u |X_u|} \sum_{x \in X_s} \frac{q_x}{10} x \\ &= \frac{80 + 18(\alpha_a - \alpha_u)}{10 + 7\alpha_a + 94\alpha_u} \end{aligned}$$

Observe that for every (α_a, α_u), $E_u X < E_a X$. However, since α_u is assumed to be very small (sufficiently close to 0), the two expectations can be considered to be approximately the same.

Standard deviation

Likewise, for every α_a the agent estimates the variance of X in the Ambiguity treatment as follows:

$$\begin{aligned} V_a X &= E_a X^2 - (E_a X)^2 \\ &= \sum_{x \in X_a} \frac{\alpha_x + q_x}{\sum_{y \in X_a} (\alpha_y + q_y)} x^2 - \left(\frac{80 + 18\alpha_a}{10 + 7\alpha_a} \right)^2 \\ &= \frac{\alpha_a}{10 + 7\alpha_a} \sum_{x \in X_a} x^2 + \frac{10}{10 + 7\alpha_a} \sum_{x \in X_a} \frac{q_x}{10} x^2 - \left(\frac{80 + 18\alpha_a}{10 + 7\alpha_a} \right)^2 \\ &= \frac{750 + 798\alpha_a}{10 + 7\alpha_a} - \left(\frac{80 + 18\alpha_a}{10 + 7\alpha_a} \right)^2, \end{aligned}$$

implying that the estimated standard deviation given α_a is equal to

$$SD_a X = \sqrt{\frac{750 + 798\alpha_a}{10 + 7\alpha_a} - \left(\frac{80 + 18\alpha_a}{10 + 7\alpha_a} \right)^2}.$$

On the other hand, the estimated variance in the Unawareness treatment for some

(α_a, α_u) is equal to

$$\begin{aligned}
V_u X &= E_u X^2 - (E_u X)^2 \\
&= \sum_{x \in X_A \cup X_u} \frac{\alpha_x + q_x}{\sum_{y \in X_a \cup X_u} (\alpha_y + q_y)} x^2 - \left(\frac{80 + 18(\alpha_a - \alpha_u)}{10 + 7\alpha_a + 94\alpha_u} \right)^2 \\
&= \frac{10 + 7\alpha_a}{10 + 7\alpha_a + 94\alpha_u} \sum_{x \in X_a} \frac{\alpha_a + q_x}{10 + 7\alpha_a} x^2 + \frac{\alpha_u}{10 + 7\alpha_a + 94\alpha_u} \sum_{x \in X_u} x^2 - \\
&\quad \left(\frac{80 + 18(\alpha_a - \alpha_u)}{10 + 7\alpha_a + 94\alpha_u} \right)^2 \\
&= \frac{750 + 798\alpha_a}{10 + 7\alpha_a + 94\alpha_u} + \frac{85,850\alpha_u}{10 + 7\alpha_a + 94\alpha_u} - \left(\frac{80 + 18(\alpha_a - \alpha_u)}{10 + 7\alpha_a + 94\alpha_u} \right)^2 \\
&= \frac{750 + 798\alpha_a + 85,850\alpha_u}{10 + 7\alpha_a + 94\alpha_u} - \left(\frac{80 + 18(\alpha_a - \alpha_u)}{10 + 7\alpha_a + 94\alpha_u} \right)^2,
\end{aligned}$$

implying that the estimated SD given (α_a, α_u) is equal to

$$SD_u X = \sqrt{\frac{750 + 798\alpha_a + 85,850\alpha_u}{10 + 7\alpha_a + 94\alpha_u} - \left(\frac{80 + 18(\alpha_a - \alpha_u)}{10 + 7\alpha_a + 94\alpha_u} \right)^2}.$$

Using $\alpha_u \in [0.1, 0.2]$ and $\alpha_a \in [0, 0.01]$ we obtain numerically that $SD(E_a X) = 0.09$ and $SD(E_u X) = 0.19$ for the expected values and $SD(SD_a X) = 0.21$ and $SD(SD_u X) = 1.79$.

Decision Rule

We assume that the agent uses reference points estimated in task 1. These are $\mu = 8$ and $\sigma = 3.8$ corresponding to the mean and standard deviation of the lottery in Periods 1-16. Denote by $(\mu_i, p_i)_\theta$ the marginal distribution of means and by $(\sigma_i, r_i)_\theta$ the marginal distribution of standard deviations resulting from the Estimation procedure described above. Since these estimations are unbiased their means correspond to $\mu = 8$ and $\sigma = 3.8$, i.e. to the reference points.[23] These distributions have a standard deviation themselves which we denote by σ_μ and σ_σ. Those two standard deviations result from the estimations described above. They represent the fundamental uncertainty of the environment for a decision maker who cares about mean and variance. Note that in the case of Risk $\sigma_\mu = \sigma_\sigma = 0$ since the estimated distribution is

[23] We treat $\mu = 8$ and $\sigma = 3.8$ as two reference points and assume additive separability. Alternatively one could have one reference point (μ, σ). This complicates matters since this does not induce a complete order on the (μ, σ) space. In other words it is unclear how to define gains and losses with respect to such a reference point.

degenerate.

When participants make decisions in periods 17-32, they evaluate the mean and variance of the lottery faced $(\mu_l, \sigma_l)_{l=17,..32}$ by attaching weight λ to μ_l (σ_l) and weight $1-\lambda$ to the (normalized) restriction of the estimated distribution to $[\mu_l \pm \sigma_\mu]$ ($[\sigma_l \pm \sigma_\sigma]$), where $\lambda \in [0,1]$. Denote the resulting distributions by $(\mu_i, \pi_i)_\theta$ and $(\sigma_i, \rho_i)_\theta$ respectively. Participants then evaluate lotteries as follows:

$$U_l = \alpha \left(\int_{\mu_i} d\pi_i \left(\pi_i v(\mu_i) \right) \right) + \beta \left(\int_{\sigma_i} d\rho_i \left(\rho_i v(\sigma_i) \right) \right).$$

Note that we have not assumed any probability weighting here (as in cumulative prospect theory), since we do not need to make such an assumption to explain our results. Several shapes for the function $v(\sigma_i)$ are sufficient to explain our results. Below we estimate the $v(\sigma_i)$ functions. The question remains why we do not see a treatment difference in estimated α's or an effect on the mean. The reason here is that—as we have seen above—the estimated standard deviation σ_μ is much smaller (by an order of magnitude of X) than σ_σ and does not vary much across treatments.

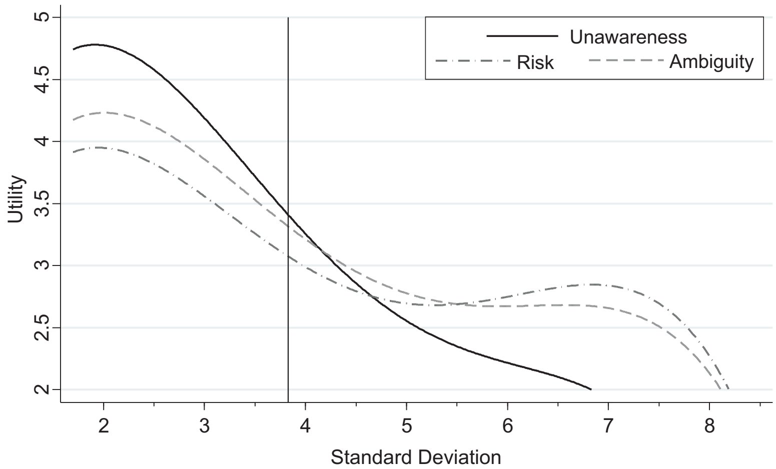

Figure 12: Utility estimated as a 4th-degree polynomial in σ. Vertical line is the reference point.

Figure 12 shows estimations of our $v(\sigma)$ functions. They display typical properties assumed in prospect theory, but also some differences. As in prospect theory our estimated $v(\sigma)$ functions are convex above the reference point (of $\sigma = 3.8$) and concave below.[24] They are also steeper around the reference point. On the other hand our estimated $v(\sigma)$ functions tend to be steeper for gains than for losses.

[24]Remember that risk averse participants dislike standard deviation.

The functions in Figure 12 are estimated from the regressions shown in Table 10. As can be seen from the Table the coefficient on σ^4 is significant in all three treatments.[25] However if we move to a 5-th degree polynomial all coefficients lose significance in both the Ambiguity and Risk treatment, which suggests to us that a four-degree polynomial is the best description of the underlying value functions. Also note that ρ barely increases when adding σ^5 to the regression.

	Unawareness	Ambiguity	Risk
constant	–2.405	–2.1276	–2.0485
σ	5.6237**	4.6897*	4.5029
σ^2	–2.3598**	–1.9272*	–1.9155**
σ^3	0.3577**	0.2888*	0.3006**
σ^4	–0.1842**	–0.0147**	–0.0159**
ρ	0.2900	0.3338	0.2663

Table 10: Random Effects Logit regression of Lottery Choice on 4-th degree polynomials in σ *** 1%,** 5%,* 10%.

	Unawareness	Ambiguity	Risk
constant	17.9875**	–7.3782	–9.8305
σ	–21.4049**	11.6941	14.8998
σ^2	10.8605**	–5.3694	–7.0331
σ^3	–2.6611**	1.0777	1.4754
σ^4	0.3061**	–0.0998	–0.1428
σ^5	–0.0132**	0.0034	0.0051
ρ	0.2923	0.3339	0.2666

Table 11: Random Effects Logit regression of Lottery Choice on 5-th degree polynomials in σ *** 1%,** 5%,* 10%.

[25]The results do not change qualitatively if we add the mean μ_l to the regression.

7.5 Instructions

7.5.1 Risk Treatment

General Explanations for Participants

You are participating in a choice experiment that is financed by the Marie Curie grant. You will receive 4 Euro for your participation. You can earn additional money with the decisions you make. Your earnings may also depend on random events. The exact way your earnings are calculated is explained in this document and during the experiment. It is, therefore, very important that you carefully read the following explanations. At the end of the experiment you will be instantly and confidentially paid in cash all the money you have earned.

During the experiment you are not allowed to communicate. If you have any questions please raise your hand. An experimenter will come to answer your questions.

Information on the Exact Procedure of the Experiment

The experiment consists of a main part and a questionnaire. The main part consists of a sequence of 32 periods. In the questionnaire we will ask you to provide some general information about yourself. In each period in the main part of the experiment you will have a chance to earn money. At the end of the experiment you will be paid for one period only that will be determined randomly.

Instructions for the Main Part of the Experiment

Typical Choice

The main part of the experiment consists of 32 different periods. In each period you can choose between a lottery and a sure outcome. Here is an example of one period:

Outcomes (Euro)				
	2	5	7	Sure Outcome (Euro)
	0.2	0.5	0.3	4.5
Probabilities				

In this example, if you choose sure outcome then in case this period is selected for your payment you will receive 4.5 Euro in addition to the 4 Euro you receive for your participation. If you choose the lottery then you might receive 2 Euro, 5 Euro, or 7 Euro (also in addition to the 4 Euro you receive for your participation). Each of these three possible outcomes can happen with the probabilities described below each number. For example here there is a 20% chance that you receive 2 Euro; a 50% chance that you receive 5 Euro; and a 30% chance that you receive 7 Euro. In case you choose the lottery you will be informed after your choice about which outcome of the lottery has occurred.

Also keep in mind that irrespective of whether you choose the sure outcome or the lottery you receive this amount of money only if this period is selected for your payment.

Non-Monetary Outcomes

The outcomes of the lottery might also be represented by the objects other than monetary outcomes. For example, you might have a Twix candy as one of the outcomes of the lottery. If this is the case, instead of the monetary amount you will see a picture like this:

In case you choose a lottery, Twix occurs as the outcome and the period in which you received Twix is randomly selected for your payment you will receive the candy from the experimenters in the end of the experiment (plus the show up payment).

7.5.2 Ambiguity Treatment

General Explanations for Participants

You are participating in a choice experiment that is financed by the Marie Curie grant. You will receive 4 Euro for your participation. You can earn additional money with the decisions you make. Your earnings may also depend on random events. The exact way your earnings are calculated is explained in this document and during the experiment. It is, therefore, very important that you carefully read the following explanations. At the end of the experiment you will be instantly and confidentially paid in cash all the money you have earned.

During the experiment you are not allowed to communicate. If you have any questions please raise your hand. An experimenter will come to answer your questions.

Information on the Exact Procedure of the Experiment

The experiment consists of a main part and a questionnaire. The main part consists of a sequence of 32 periods. In the questionnaire we will ask you to provide some general information about yourself. In each period in the main part of the experiment you will have a chance to earn money. At the end of the experiment you will be paid for one period only that will be determined randomly.

Instructions for the Main Part of the Experiment

Typical Choice

The main part of the experiment consists of 32 different periods. In each period you can choose between a lottery and a sure outcome. Here is an example of one period:

Outcomes (Euro)				
	2	5	7	Sure Outcome (Euro)
	0.2	0.5	0.3	4.5
Probabilities				

In this example, if you choose sure outcome then in case this period is selected for your payment you will receive 4.5 Euro in addition to the 4 Euro you receive for your participation. If you choose the lottery then you might receive 2 Euro, 5 Euro, or 7 Euro (also in addition to the 4 Euro you receive for your participation). Each of these three possible outcomes can happen with the probabilities described below each number. For example here there is a 20% chance that you receive 2 Euro; a 50% chance that you receive 5 Euro; and a 30% chance that you receive 7 Euro. In case you choose the lottery you will be informed after your choice about which outcome of the lottery has occurred.

Also keep in mind that irrespective of whether you choose the sure outcome or the lottery you receive this amount of money only if this period is selected for your payment.

Non-Monetary Outcomes

The outcomes of the lottery might also be represented by the objects other than monetary outcomes. For example, you might have a Twix candy as one of the outcomes of the lottery. If this is the case, instead of the monetary amount you will see a picture like this:

In case you choose a lottery, Twix occurs as the outcome and the period in which you received Twix is randomly selected for your payment you will receive the candy from the experimenters in the end of the experiment (plus the show up payment).

Hidden Information

It is also possible that you will not observe all the information about the lottery. For example you might see a choice represented like this:

Outcomes (Euro)				
	2	5	7	Sure Outcome (Euro)
				4.5
Probabilities				

Here you are still choosing between a sure outcome and some fixed lottery (for example, this could be the exact same lottery as in the previous example above). The only difference is that you do not know the probabilities with which the outcomes of the lottery occur. In case you choose the lottery you will observe the realized outcome immediately.

IMPORTANT NOTE: in ALL periods in which you do not observe the probabilities of the lottery outcomes, the actual lottery is EXACTLY THE SAME, both in terms of the outcomes and the unobserved probabilities.

7.5.3 Unawareness Treatment

General Explanations for Participants

You are participating in a choice experiment that is financed by the Marie Curie grant. You will receive 4 Euro for your participation. You can earn additional money with the decisions you make. Your earnings may also depend on random events. The exact way your earnings are calculated is explained in this document and during the experiment. It is, therefore, very important that you carefully read the following explanations. At the end of the experiment you will be instantly and confidentially paid in cash all the money you have earned.

During the experiment you are not allowed to communicate. If you have any questions please raise your hand. An experimenter will come to answer your questions.

Information on the Exact Procedure of the Experiment

The experiment consists of a main part and a questionnaire. The main part consists of a sequence of 32 periods. In the questionnaire we will ask you to provide some general information about yourself. In each period in the main part of the experiment you will have a chance to earn money. At the end of the experiment you will be paid for one period only that will be determined randomly.

Instructions for the Main Part of the Experiment

Typical Choice

The main part of the experiment consists of 32 different periods. In each period you can choose between a lottery and a sure outcome. Here is an example of one period:

Outcomes (Euro)				
	2	5	7	Sure Outcome (Euro)
	0.2	0.5	0.3	4.5
Probabilities				

In this example, if you choose sure outcome then in case this period is selected for your payment you will receive 4.5 Euro in addition to the 4 Euro you receive for your participation. If you choose the lottery then you might receive 2 Euro, 5 Euro, or 7 Euro (also in addition to the 4 Euro you receive for your participation). Each of these three possible outcomes can happen with the probabilities described below each number. For example here there is a 20% chance that you receive 2 Euro; a 50% chance that you receive 5 Euro; and a 30% chance that you receive 7 Euro. In case you choose the lottery you will be informed after your choice about which outcome of the lottery has occurred.

Also keep in mind that irrespective of whether you choose the sure outcome or the lottery you receive this amount of money only if this period is selected for your payment.

Hidden Information

It is also possible that you will not observe all the information about the lottery. For example you might see a choice represented like this:

Outcomes (Euro)			
	2	5	Sure Outcome (Euro)
			4.5
Probabilities			

Here you are still choosing between a sure outcome and some fixed lottery (for example, this could be the exact same lottery as in the previous example above). The only difference is that you do not know the probabilities with which the outcomes of the lottery occur. It may also be the case that you do not know some of the outcomes. For example, if the lottery here is the same as in the example on the previous page, you do not know that the outcome 7 Euro can occur. Note that outcomes can occur also if you don't observe them. If you choose the lottery and the previously unobserved outcome 7 Euro occurs, then you will observe it as a possibility afterwards:

Outcomes (Euro)				
	2	5	7	Sure Outcome (Euro)
				6.5
Probabilities				

Not all the lotteries you are about to see will have hidden information. For some lotteries you will observe the probabilities of the outcomes. To check that there are no hidden outcomes you may sum up the probabilities and verify that they add up to 1.

IMPORTANT NOTE: in ALL periods in which you do NOT observe the probabilities and/or the outcomes, the actual lottery is EXACTLY THE SAME, both in terms of the outcomes and the unobserved probabilities. In addition, some unobserved outcomes will be revealed to you over time. When this happens you will observe them on your screen.

References

AHN, D., S. CHOI, D. GALE, AND S. KARIV (2010): "Estimating Ambiguity Aversion in a Portfolio Choice Experiment," UC Berkeley, UCL, NYU and UC Berkeley.

ANSCOMBE, F., AND R. AUMANN (1963): "A Definition of Subjective Probability," *Annals of Mathematical Statistics*, 34(1), 199–205.

DEGROOT, M. H. (1970): *Optimal statistical decisions*. McGrow-Hill.

DEKEL, E., B. LIPMAN, AND A. RUSTICHINI (1998): "Standard State-Space Models Preclude Unawareness," *Econometrica*, 66(1), 159–173.

ELLSBERG, D. (1961): "Risk, Ambiguity, and the Savage Axioms," *Quarterly Journal of Economics*, 75(4), 643–669.

FAGIN, R., AND J. HALPERN (1988): "Belief, awareness, and limited reasoning," *Artificial Intelligence*, 34, 39–76.

FEINBERG, Y. (2009): "Games with Unawareness," Stanford University.

FISCHBACHER, U. (2007): "z-Tree: Zurich Toolbox for Ready-made Economic Experiments," *Experimental Economics*, 10(2), 171–178.

FUDENBERG, D., AND D. K. LEVINE (1998): *The theory of learning in games*. Cambridge, Mass.: MIT Press.

GIULIANO, P., AND A. SPILIMBERGO (2009): "Growing up in a recession: beliefs and the macroeconomy," UCLA, NBER, IZA, IMF, WDI and CEPR.

GNEEZY, U., A. RUSTICHINI, AND A. VOSTROKNUTOV (2010): "Experience and insight in the Race game," *Journal of Economic Behavior and Organization*, 75, 144–155.

GOLLIER, C. (2009): "Portfolio choices and asset prices: The comparative statics of ambiguity aversion," Toulouse School of Economics (LERNA and IDEI).

HALEVY, Y. (2007): "Ellsberg Revisited: An Experimental Study," *Econometrica*, 75, 503–536.

HALPERN, J. Y., AND L. C. RÊGO (2008): "Interactive unawareness revisited," *Games and Economic Behavior*, 62(1), 232–262.

HARUVY, E., AND D. O. STAHL (2009): "Learning Transference Between Dissimilar Symmetric Normal-Form Games," mimeo, University of Texas at Dallas and University of Texas at Austin.

HEIFETZ, A., M. MEIER, AND B. C. SCHIPPER (2006): "Interactive unawareness," *Journal of Economic Theory*, 130, 78–94.

JOHNSON, E. J., AND A. TVERSKY (1983): "Affect, Generalization, and the Perception of Risk," *Journal of Personality and Social Psychology*, 45(1), 20–31.

JOHNSTONE, D., AND D. LINDLEY (2011): "Elementary proof that meanvariance implies quadratic utility," *Theory and Decision*, 70, 149–155.

KNIGHT, F. (1921): *Risk, uncertainty and profit*. Boston: Houghton Mifflin.

LERNER, J. S., AND D. KELTNER (2001): "Fear, Anger, and Risk," *Journal of Personality and Social Psychology*, 81(1), 146–159.

LI, J. (2009): "Information structures with unawareness," *Journal of Economic Theory*, 144, 977–993.

LOEWENSTEIN, G. F., E. U. WEBER, C. K. HSEE, AND N. WELCH (2001): "Risk as Feelings," *Psychological Bulletin*, 127(2), 267–286.

MACCHERONI, F., M. MARINACCI, AND A. RUSTICHINI (2006): "Ambiguity Aversion, Robustness, and the Variational Representation of Preferences," *Econometrica*, 74(6), 1447–1498.

MALMENDIER, U., AND S. NAGEL (2010): "Depression babies: do macroeconomic experiences affect risk taking?," *Quarterly Journal of Economics*, forthcoming.

MARKOWITZ, H. (1952): "Portfolio Selection," *Journal of Finance*, 7(1), 77–91.

MARKOWITZ, H. M. (1959): *Portfolio selection: Efficient diversification of investments*. NewYork: Wiley.

MCFADDEN, D. (1976): "Quantal Choice Analysis: A Survey," *Annals of Economics and Social Measurement*, 5, 363–390.

MENGEL, F., AND E. SCIUBBA (2010): "Extrapolation and structural learning in games," Maastricht University and Birkbeck College London.

MODICA, S., AND A. RUSTICHINI (1994): "Awareness and partitional information structures," *Theory and Decision*, 37(1), 107–124.

——— (1999): "Unawareness and Partitional Information Structures," *Games and Economic Behavior*, 27, 265–298.

NISHIYAMA, Y. (2006): "The Asian Financial Crisis and Investors' Risk Aversion," *Asia-Pacific Financial Markets*, 13, 181–205.

O'DOHERTY, J. P., P. DAYAN, K. FRISTON, H. CRITCHLEY, AND R. J. DOLAN (2003): "Temporal Difference Models and Reward-Related Learning in the Human Brain," *Neuron*, 28, 329337.

OSILI, U. O., AND A. PAULSON (2009): "Banking crises and Investor Confidence: An Empirical Investigation," Indiana University-Purdue University at Indianapolis and Federal Reserve Bank of Chicago.

PHAN, K. L., T. WAGER, S. F. TAYLOR, AND I. LIBERZON (2002): "Functional Neuroanatomy of Emotion: A Meta-Analysis of Emotion Activation Studies in PET and fMRI," *Neuroimage*, 16(2), 331348.

PREUSCHOFF, K., P. BOSSAERTS, AND S. R. QUARTZ (2006): "Neural Differentiation of Expected Reward and Risk in Human Subcortical Structures," *Neuron*, 51(3), 381–390.

RAGHUNATHAN, R., AND M. T. PHAM (1999): "All Negative Moods Are Not Equal: Motivational Influences of Anxiety and Sadness on Decision Making," *Organizational Behavior and Human Decision Processes*, 79(1), 5677.

SAVAGE, L. (1954): *The foundations of Statistics*. New York: Wiley.

TOBIN, J. (1958): "Liquidity preference as behavior towards risk," *Review of Economic Studies*, 25, 65–86.