# 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 behavior 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 behavior.

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# 1 Introduction

Exposure to low probability or unexpected events can influence economic decision making and future perception of risk. Malmendier and Nagel (2010), for example, 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 field studies is to isolate the effect of such events on risk aversion. Since in the contexts mentioned probabilities are often hard to assess, what looks like an increase in risk aversion may simply be (Bayesian) updating of consumers', banks' (or other market participants') 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 unlikely 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 occurs. It could also be that 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" of the event at all. In the literature on decision making under uncertainty these three notions correspond to standard "types" of uncertainty. 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 necessarily 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). Finally, in addition to not knowing the objective probabilities associated with each outcome the decision maker might be *unaware* of some possibilities entirely.

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 are informed about all outcomes of the lottery as well as their probabilities. In the Ambiguity treatment the participants are informed only about the possible outcomes, but not about the associated probabilities. In the Unawareness treatment participants are only informed about *some* possible outcomes and no information is given about probabilities. Upon choosing the lottery they can become aware of additional outcomes if they are realized. In each treatment it is clearly 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".[1] 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).

Note that it is possible that a decision-maker in our ambiguity treatment acts as an SEU maximizer. Equally it is possible that a decision maker in the Unawareness treatment deems "all" outcomes possible and then chooses as if the environment was one of ambiguity.[2] Since the cardinality of the set of "all possible outcomes" is very large, it is hardly conceivable that the decision maker would actually do this. But it is a theoretical possibility. Hence it is important to notice that in this experiment we are interested in how experiencing environments with different degrees of information about the state space shapes *future* decisions under risk. Unlike much of the existing literature, we are *not* primarily interested in how individuals make decisions in these three environments or whether they are ambiguity averse.[3] Therefore, in what follows, we will distinguish the environments (Risk, Ambiguity, Unawareness) by the information we provide without any claim as to whether behavior in the three treatments corresponds to models of decision-making in these environments.

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 choose high variance lotteries significantly less often on average than participants in the Ambiguity treatment who, in turn, choose the same lotteries significantly less often than participants in the Risk treatment. We estimate individual risk attitudes from choices

[1]See the literature surveyed below.

[2]Distinguishing zero probability events from unawareness is a topic which has attracted attention in theoretical research. See, for example, Feinberg (2009) for discussion.

[3]See for example Ellsberg (1961), Halevy (2007), Gollier (2011) among many others.

in the second task and find that the distribution of risk attitude parameters across our 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 the sense of FOSD. We also conduct this analysis separately for early and late periods within the second task to see if the effect dies out over time. We find that, if at all, the effect is stronger in later periods. 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 behavior.

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. We provide a theoretical explanation of how exposure to larger uncertainty in the first task makes participants react more to the uncertainty of the lotteries in the second task. Additional treatments allow us to rule out the possibility that unrelated emotional states as well as some other explanations are responsible for the result.

Our results matter for a vast array of policy issues. It has been argued, for example, that the fact that investors have very imperfect information about financial interconnections between banks (and hence about the state space) was a key contributing factor to the recent financial crisis. Results like those presented in this paper can help to suggest regulatory interventions (e.g. regarding disclosure of ownership structures or detail in the balance sheets) that might mitigate this problem in the future.[4] More generally speaking, our results are relevant for any situation where decisions are made under uncertainty and where policy makers have the possibility to affect the amount of information available to decision makers.

Previous research has used field data to demonstrate that risk-taking behavior is affected by macroeconomic shocks (Malmendier and Nagel, 2010) or financial crises (Nishiyama, 2006). However, it is difficult to establish in field studies whether such effects are due to an increase in risk aversion or to updated priors or other reasons. For example, Giuliano and Spilimbergo (2009) show that people growing up in a recession have different socio-economic beliefs than people growing up during a

[4]Understanding the impact of imperfect knowledge of the state space on risk aversion can also help to understand exchange rate movements. In fact, Fama (1984) has shown that current asset pricing models can only explain the pattern of exchange rate movements if risk aversion parameters change over time.

boom. Osili and Paulson (2009) show that macroeconomic shocks affect investor confidence.[5] Furthermore, if one could identify an effect on risk aversion it is difficult to pin down what exactly drives this effect. Our study avoids many of these problems and allows us to establish a clear link between imperfect knowledge of the state space and risk aversion.

Other related literature includes Barseghyan et al. (2011) who use insurance data to show that estimated risk aversion parameters are not constant across different contexts (types of insurance). In a similar study Einav et al. (2011) find that there is a domain-general component of risk preferences, but that the common element is weak if domain are "very different". Also, Dohmen et al. (2011) detect some stability of risk preferences.[6] We go one step beyond this literature by asking not only whether risk preferences are stable, but also by identifying one possible source of variation in risk attitudes over time. Our study also suggests (though does not demonstrate) that differences in risk attitudes across domains might be due to different amounts of knowledge the decision maker has experienced in these domains in the past.

In a different strand of literature it has been demonstrated that individuals' decisions are affected by whether a choice situation displays only risk or whether it is ambiguous (Ellsberg, 1961; Halevy, 2007; Gollier, 2011, among many others). These results are quite different from our experiment in that we do not compare behavior in risky/ambigous environments but rather investigate how having been *exposed* to such an environment affects risk attitudes in subsequent unrelated choices. To our knowledge this is the first paper to generate a clean laboratory environment which enables us to study the implications of the imperfect knowledge of the state space for future decision making under risk.

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 as a special case of reasoning in the absence of introspective capacities.[7] The first major contributions in this literature show that accommodating a notion of unawareness which satisfies some reasonable axioms is im-

[5]Similarly, Malmendier and Nagel (2010) show that subjective expectations about future inflation are shaped by people's lifetime experience of inflation. Bloom (2009) simulates a structural model of uncertainty shocks and studies the short and long term effects of such shocks on macroeconomic variables such as employment, output and productivity. Brandt and Wang (2003) show that aggregate risk aversion varies in response to news about inflation.

[6]Other studies of the stability of risk preferences across different domains include Andersen et al. (2008) or Barsky et al. (1997) among others.

[7]See for instance Feinberg (2009), Halpern and Rêgo (2008), Gossner and Tsakas (2010, 2011).

possible 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, 2008; 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). Halpern and Rêgo (2009) have recently extended this framework to capture states of mind such that agents are aware of the possibility that they may be unaware of some fact . 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. An appendix 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 provided to the participants about the lottery during the first 16 choices. Choices 17 to 32 are exactly identical across all 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.[8]

[8]See Appendix A for more details.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 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 to 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 this realization 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.[9] Figures 1.abc illustrate 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 all treatments and participants observe both outcomes and associated probabilities in all treatments (see Figure 1.d). Hence, all treatments are exactly identical in periods 17 to 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.[10] All participants are explicitly 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.

At this point it is important to remember that we are interested mainly in behavior

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

[10]See Appendix A 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) one typical choice from periods 17 to 32 (identical in all treatments).

in periods 17 to 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, for example, we do not know which priors participants have about the lottery in periods 1 to 16. We will return to this question in Section 6.[11]

In addition to the Risk, Ambiguity and Unawareness treatments we ran three more treatments: 1) A control treatment in which subjects faced only the lotteries from periods 17 to 32 (Control); 2) A treatment which is identical to the Unawareness treatment except that the payoff –20 was replaced by +20 (Unawareness-POS); 3) A treatment which coincided with the Risk treatment except that the outcomes of the lottery in periods 1 to 16 were associated with different probabilities such that variance was increased (Risk-high). We discuss these additional treatments in Sections 6.1, 6.2 and 6.3. We did not run any other treatments than the 6 treatments described, nor did we run any pilot sessions.[12]

[11]One may also wonder why we didn't choose a design where subjects first play the lotteries from periods 17 to 32, then have treatment variation, and then play period 17 to 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 behavior depending on their experience. We decided therefore to do a full between subjects analysis and use a large number of participants.

[12]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.[13] 508 participants took part in our experiment. 104 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. Each participant is one independent observation. All experiments were run with z-Tree (Fischbacher, 2007) at Maastricht University in June-September 2010 (Unawareness, Ambiguity, Risk and Control treatments) and May 2011 (Unawareness-POS and Risk-high).

# 3 Methods

In order to estimate risk attitudes we use a mean-variance utility model (Markowitz, 1952). The utility derived from 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 aversion. The mean-variance model is widely used to model decisions in finance and economics.[14] 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

$$u(\ell) = K_\theta + \alpha_\theta \mu_\ell - \beta_\theta \sigma_\ell$$

where $\alpha_\theta, \beta_\theta > 0$, $K_\theta$ is a constant, $\mu_\ell$ is expected value, $\sigma_\ell$ is standard deviation and the subindex $\theta$ denotes the treatment (Risk, Ambiguity, Unawareness).[15] For the degenerate lottery $(x)$ we have $u(x) = K_\theta + \alpha_\theta x$. We use a random utility model (see e.g. McFadden, 1976) which assumes that the probability of choosing the lottery

tial program error.

[13]Starmer and Sugden (1991) study the validity of the random lottery incentive system and find that participants treat every choice situation as isolated.

[14]See Markowitz (1952), Levy and Markowitz (1979) or the textbook by Sharpe (2008) among many others.

[15]We use standard deviation instead of variance, because standard deviation is measured in the same units as expected value, which makes it easier to compare coefficients. Non-surprisingly our results are robust to using either standard deviation or variance.

$\ell$ over sure outcome $x$ is monotonic with respect to the difference of the utilities

$$u(\ell) - u(x) = \alpha_\theta(\mu_\ell - x) - \beta_\theta \sigma_\ell.$$

To estimate $K_\theta$, $\alpha_\theta$ and $\beta_\theta$ we use random effects logit regressions. In what follows the independent variable $(\mu_{\ell t} - x_t)$ will be called `dexp` and $\sigma_{\ell t}$ will be called `stdv`, where $t$ indexes period.

Apart from the choices themselves we also analyze response times, or the time it takes a participant to choose between lottery and sure outcome to uncover more behavioral patterns. Longer response times may 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 periods 17 to 32. As was mentioned above the choices that participants face in these periods are exactly identical in all three treatments. Therefore, any behavioral differences between treatments should be attributed to the experiences participants had in periods 1 to 16. We conjecture 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 results of a random effects logit regression for choices in periods 17 to 32.[16] 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 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. As can be seen from columns

[16]See Appendix B for the definitions of the independent variables and Appendix A for a description of all lotteries.

| | Pr(Lottery) | | | | |
|---|---|---|---|---|---|
| | Risk, Ambiguity, Unawareness | | | | |
| | (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.

(1) and (2) of Table 2 in all three treatments participants respond in the same way to `dexp` (the difference between the expected values of lotteries and sure outcomes) there are no treatment effects. Participants also tend to choose lotteries less often over time, 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.[17] Regressions (4) and (5) show that our results are robust and quantitatively unchanged if we omit all period terms.

The most interesting effect is the sensitivity to the standard deviation of the lotteries across treatments. The sensitivity to standard deviation is lowest in the Risk

[17] In fact the correlation between period and dexp (stdv) is 0.1733*** (0.0044) respectively (Spearman correlation test).

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 $p = 0.054$ (`awar·stdv - amb·stdv`). The dummy variables `awar` and `amb` have positive coefficients 1.079 and 0.555 respectively.

Taken together, these results imply that for 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. Participants choose high standard deviation lotteries with the lowest probability in the Unawareness treatment, higher probability in the Ambiguity treatment and the highest probability in the Risk treatment. This lends support to our conjecture that participants become more sensitive to the standard deviations of the lotteries in periods 17 to 32 if they have been previously exposed to an environment characterized by very imperfect knowledge of the state space.

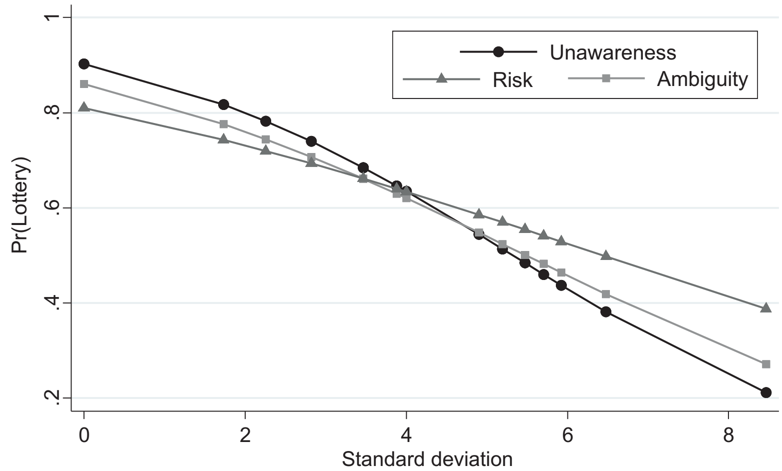


Figure 2: Predicted probabilities of choosing a lottery as a function of its standard deviation in the three treatments.

Figure 2 plots the estimated 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 $\alpha_\theta(\mu_\ell - x) - \beta_\theta \sigma_\ell$ 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.

Table 10 in Appendix C shows the regressions from Table 2 but only for the periods 25-32. The qualitative results are the same as described above and, interestingly, are even more pronounced. This shows that the effect is long-lasting and does not wash out after only a few periods.

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 $\beta$ 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, with which we explain their choices in periods 17 to 32 by the variables `dexp` and `stdv` to estimate individual coefficients $\alpha_i$ and $\beta_i$.[18] Figure 3 shows the cumulative distribu-

[18]We dropped participants who always chose either lottery or sure outcome. This left us with 96

tions of $\beta_i$ for the three treatments.

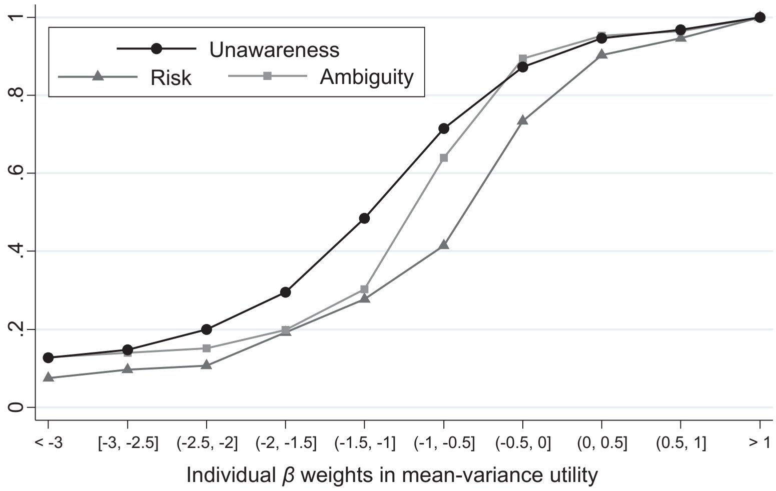


Figure 3: Cumulative distributions of (the negative of) individual $\beta$ weights (risk attitudes) in Risk, Ambiguity and Unawareness treatments.

Notice that the cdf of risk attitudes in Unawareness treatment first-order stochastically dominates cdf in Risk treatment.[19] 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 $\beta$'s comes from the same distribution pairwise for any two treatments ($p < 0.0001$). 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 $\alpha_i$ coefficients. Distributions look very similar across the three treatments (and are not significantly different, $p > 0.2$) which supports the previous claim that uncertainty of the environments does not affect our participants' attitude towards expectation of the lotteries.

In Section 6 we will discuss our three additional treatments: 1) Unawareness-POS; 2) Risk-high and 3) the Control treatment to rule out different explanations for our main result. We will also provide a theoretical explanation which is consistent with our evidence from all the treatments.

participants in the Unawareness treatment, 87 in ambiguity and 97 in the risk treatment.

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

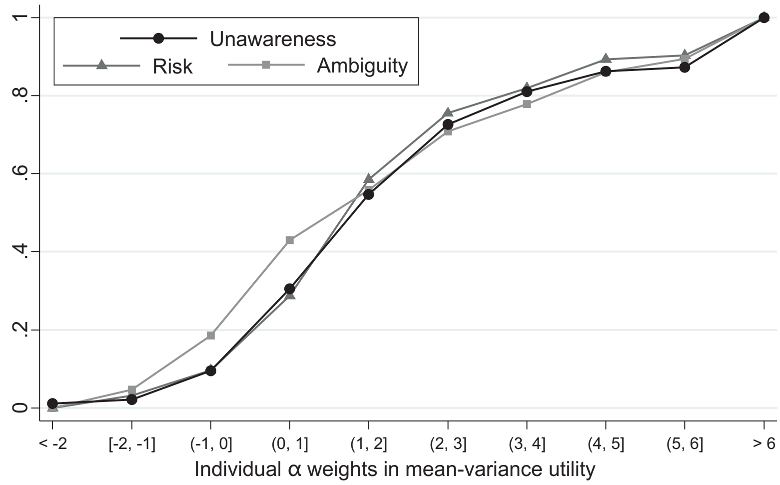


Figure 4: Cumulative distributions of individual $\alpha$ weights in Risk, Ambiguity and Unawareness treatments.

**Result 1**

1. *Participants in the Unawareness treatment are more (less) likely on average 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 $\beta$ 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 to 16

Before we start discussing several possible explanations for our main result let us briefly look at treatment comparisons in Periods 1 to 16. This will help us to address competing explanations of our main result.

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. Note that, since the lottery is the same in periods 1 to 16, there is no point in including variables `dexp` and `stdv`.

An important observation is that there are no apparent differences between the Risk and Ambiguity treatments (`amb` and `amb·sure` are insignificant). Choices in the Unawareness treatment are different. Here participants seem to be less sensitive to

| | 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.

the value of the sure outcome than in the Risk treatment (`sure + awar·sure`). Moreover, participants tend to choose the sure outcome more often overall (`awar`).

To gain more insight into the nature of the decision process in the first 16 periods we look at the response times across treatments. Table 4 shows that in the Risk and Ambiguity treatments the response time is shorter the higher the sure outcome is. However, in the Unawareness treatment the response time does not react to the value of the sure outcome (`sure + awar·sure` is insignificant). Moreover, in the Unawareness treatment there is an overall drop in the response time comparing to the Risk and Ambiguity treatments (`awar`).

To understand whether these results reflect different choice heuristics or are simply due to the fact that more participants refrain from choosing the lottery at all, we analyze patterns in average behavior as follows: 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.

Figure 5 shows the distributions of `absc` for the three treatments in periods 1 to 16.

| **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.

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.

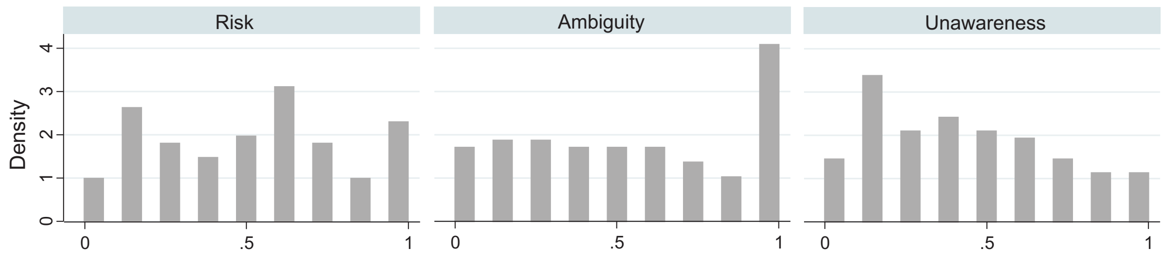


Figure 5: Histograms of absc by treatment in periods 1 to 16.

Mann-Whitney tests reveal 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 ($p > 0.542$). The difference between distributions is only observed in the first 16 periods but not in periods 17 to 32, as can be seen in Figure 6 (Mann-Whitney tests: $p > 0.0677$, $p > 0.1447$ and $p > 0.6464$ respectively). Overall, the evidence gathered in this sec-

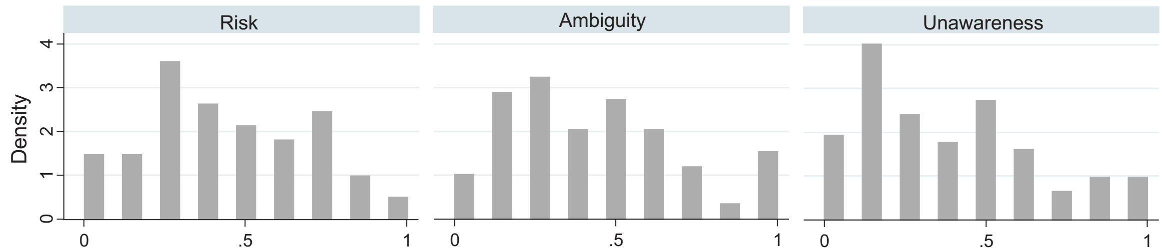


Figure 6: Histograms of absc by treatment in periods 17 to 32.

tion suggests that participants may employ different choice heuristics in periods 1 to 16 in the Unawareness treatment compared to the Risk and Ambiguity treatments between which we detect little differences in how choices are made. Keep in mind though that these differences arise *only* in periods 1 to 16.

**Result 2**

1. *In the 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 the Unawareness treatment compared to the Risk and Ambiguity treatments. Response times are shorter the higher the value of the sure outcome in both the 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 (see Section 6.4) 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 the –20 outcome. Table 5 shows the results of a regression comparing the Risk, the Ambiguity and the Unawareness-POS treatments. Participants in the Unawareness-POS treatment tend to choose lotteries with low variance 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.[20]

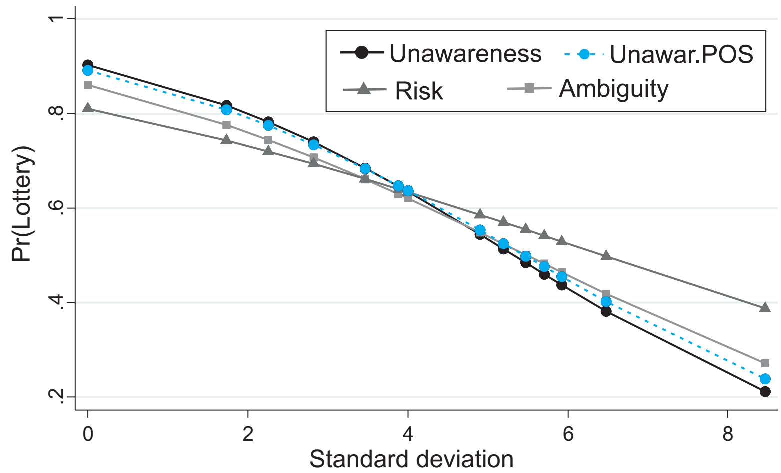


Figure 7: Estimated Probability to choose a lottery as a function of its standard deviation. Treatments: Risk, Ambiguity, Unawareness and Unawareness-POS.

[20]Appendix D shows the distributions of individual $\beta$ coefficients for Unawareness-POS treatment in comparison with Risk, Ambiguity and Unawareness.

| 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.

These results suggest that the effect we observe is not primarily driven by unrelated emotional states such as fear or anxiety, but instead is directly due to the informational environment. Finally, note that negative surprises are those that are more relevant in terms of the motivation brought forward in the introduction, which inspired our design choice.

## 6.2 Perceived Risk in Periods 1 to 16

Another possible explanation of the effect of exposure to different levels of uncertainty on the future choices is that subjects *perceive* a lottery in the Ambiguity and Unawareness treatments as exhibiting higher variance than the same lottery with observed probabilities. One hypothesis is, hence, that it is only the perceived amount of risk that matters and not the type of uncertainty that participants face. 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 a reasonable implication would be that we should have observed the smallest risk aversion in Risk treatment, more risk aversion in the Unawareness treatment and even more risk aversion in the Ambiguity treatment. The perceived variance in the Ambiguity treatment should be highest because subjects observe all possible outcomes and therefore might assign high probabilities to negative outcomes, whereas in the 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 4). In addition, if participants did indeed perceive more risk in the Ambiguity treatment then we should have observed subjects choosing the sure outcome in the Ambiguity treatment substantially more often than in other treatments. Again, our data refute this: subjects choose the lottery in the Ambiguity treatment no less often than in other treatments.

In order to completely rule out the above hypothesis we ran a Risk treatment with high variance (Risk-high). This treatment is the same as the Risk treatment (all information in first 16 periods is observed), except for the probabilities assigned to the outcomes. Table 6 shows the lottery that participants observe in the Risk-high 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 estimates of coefficients in the random effects logit model of choices for all treatments (except the Control treatment). None of the independent variables associated with the Risk-high treatment are significant (`riskhigh`, `riskhigh·dexp`, `riskhigh·stdv`). Choices in the Risk-high treatment are not significantly different from the original Risk treatment.

Figure 8 shows the result graphically.[21] Those results make us confident that the effect we observe is not primarily driven by the perceived risk of the lottery, but instead is directly due to the informational environment.

[21] Appendix D shows the distributions of individual $\beta$ coefficients for the Risk-high treatment in comparison with the Risk, Ambiguity and Unawareness treatments.

| | 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 logit regression of choices between lotteries and sure outcomes in periods 17 to 32 including all treatments except for the Control treatment (* – 10% significance; ** – 5%; *** – 1%). The numbers in parentheses are standard errors. 7616 observations, 476 independent.

## 6.3 Control Treatment and Heuristics

In this subsection we discuss evidence on whether participants use different heuristics in the three treatments in periods 17 to 32 and ask to which extent learning affects the results. Our control treatment can help to address these questions.

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 is relevant because one may conjecture that some of the observed differences are due to the fact that in the Risk treatment participants, being given more information, have better opportunities to learn to make good choices. Under this explanation we should observe the following treatment ranking: $\beta_{Control} > \beta_{Unawareness} > \beta_{Ambiguity} > \beta_{Risk}$, since in the Control treatment there are no opportunities for learn-

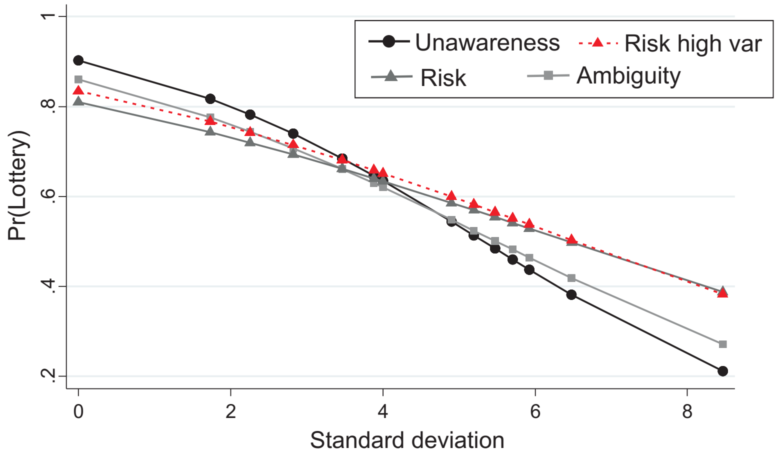


Figure 8: Estimated Probability of choosing a lottery as a function of its standard deviation. Treatments: Risk, Risk-high, Ambiguity and Unawareness.

ing at all. This explanation can be ruled out, since the Risk and Control treatments are not significantly different. Figure 9 shows the distributions of individual $\beta_i$ coefficients for the main treatments and the Control treatment. The Control treatment distribution is not very different from that of the Risk treatment. One should be careful to note that we are *not* claiming that differential learning across the three treatments cannot affect behavior. However, we can rule out that the result is primarily due to the fact that participants have less opportunities for learning in the Ambiguity and Unawareness treatments, because they have have less information about the lottery.

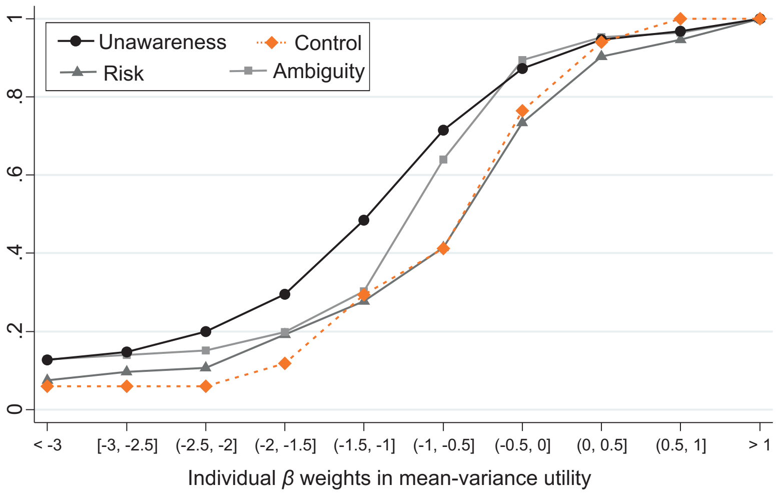


Figure 9: Cumulative distributions of individual risk aversion coefficients $\beta_i$. Treatments: Risk, Ambiguity, Unawareness and Control.

One may also ask whether participants carry over different heuristics from peri-

| 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 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.

ods 1 to 16 to periods 17 to 32 in the three treatments. This is related to a literature on behavioral spillovers (see e.g. Gneezy, Rustichini, and Vostroknutov, 2010) concerned with extrapolation of cognitive skills (such as applying backward induction) 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, since behavior in the control treatment is not significantly different from behavior in the risk treatment. There is also no evidence in our study that participants would use different heuristics in periods 17 to 32 across the different treatments (see, for example, Figure 6). We also ran regressions on response times in periods 17 to 32 including variables `dexp`, `standev` as well as treatment dummies and interactions and we find that all treatment dummies and interactions are jointly insignificant ($Pr > \chi^2 = 0.6688$). This is in stark contrast to Result 2.2 concerning periods 1 to 16. Hence nothing in our evidence suggests that participants would use different heuristics in periods 17 to 32. 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). We will provide a more precise explanation in the following subsection.

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

In this section we propose a theoretical explanation of the spillover effects observed in the experiments. Our explanation is based on Prospect theory (Tversky and Kahneman, 1992) and includes three key steps which we discuss informally here and formalize in Appendix E.

1. In periods 1 to 16 participants estimate possible probability distribution over lotteries.

2. The uncertainty from periods 1 to 16 is carried over to periods 17 to 32. Upon observing lottery $\ell$ with mean and standard deviation $(\mu_\ell, \sigma_\ell)$, participants attach small probabilities to lotteries with mean/standard deviation pairs $(\mu, \sigma)$ which are one (estimated) standard deviation away from the actual mean and standard deviation $(\mu_\ell, \sigma_\ell)$

3. In accordance with Prospect theory participants overweigh probabilities far away from the reference point, where the reference point is given by $(\mu, \sigma) = (8, 3.8)$, the mean and standard deviation of the lottery in periods 1 to 16

All of our experimental findings can be explained by a model that builds on these assumptions. The intuition 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 the Unawareness treatment compared to the Ambiguity treatment and will have zero variance under the Risk treatment (this is formalized in Appendix E). Let us elaborate on it. 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. Any estimation procedure that will create a higher standard deviation of $\mu$ and $\sigma$ in the Unawareness treatment compared to the Ambiguity treatment will be consistent with our explanation.[22] An example of estimation procedures which have this property are bootstrapping techniques; another example are

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

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). It is important to note that we do not believe that participants actually do estimate probability distributions. Rather we maintain that making choices in these environments creates a feeling of uncertainty that can be captured by a model where decision makers act *as if* they reasoned in this manner.

Now, if participants carry over this uncertainty, they will—for each lottery $\ell$ with $(\mu_\ell, \sigma_\ell)$ they face in periods 17 to 32—attach small probability also to pairs $(\mu, \sigma)$ one estimated standard deviation away from $(\mu_\ell, \sigma_\ell)$. Remember that this estimated standard deviation is 0 in the Risk treatment, positive in the Ambiguity treatment and largest in the Unawareness treatment. Overweighing of probabilities far away from the reference point $(8, 3.8)$ then implies that for lotteries with variance below the reference point participants will attach overweighed probability to variances, which are even lower. This effect will be strongest in the Unawareness treatment. On the other hand, for lotteries with high variance participants attach overweighed probability to variances which are even higher. And again this effect will be strongest in the Unawareness treatment. This makes lotteries with variances below (above) the reference point more (less) attractive in the Unawareness and Ambiguity treatments compared to the Risk treatment.[23] Note also that, as predicted by this theory, the intersection of the three curves in Figure 2 occurs approximately at a standard deviation of 3.8, i.e. at the reference point.

Note that a simpler model built on Prospect theory, which does not include Step 1 above, cannot explain our results. In particular, a theory which assumes simply that the mean and standard deviation of the lottery in periods 1 to 16 are reference points in periods 17 to 32 will fail to accommodate most of 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, since the lottery in periods 1 to 16 has the same standard deviation in all three treatments (Risk, Ambiguity, Unawareness), 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 them.[24] Again this is clearly against empirical observation. Hence

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

[24] One way out of this would be to assume that the mean and variance of the lottery in periods 1 to 16 are estimated in a *biased* way, which seems ad hoc. In addition, even if we did assume this such a theory would still predict a difference between the Risk and Risk-high treatments, which is not what

it is not the estimated standard deviation but the standard deviation of the estimated $(\mu, \sigma)$ that matters, i.e. the fundamental uncertainty by which the environment is characterized.

we observe.

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# Appendix

# A 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 period 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.

# B 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) |

# C Choices in periods 25 to 32

| | Pr(Lottery) | | | | |
|---|---|---|---|---|---|
| | Risk, Ambiguity, Unawareness | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| dexp | 1.255*** | 1.218*** | 1.223*** | 1.114*** | 1.121*** |
| | (0.163) | (0.154) | (0.096) | (0.149) | (0.089) |
| stdv | –0.246*** | –0.231*** | –0.231*** | –0.188** | –0.188** |
| | (0.091) | (0.089) | (0.089) | (0.087) | (0.087) |
| per | –0.097** | –0.072*** | –0.073*** | | |
| | (0.045) | (0.025) | (0.025) | | |
| awar | 1.372 | 2.456*** | 2.551*** | 2.435*** | 2.538*** |
| | (1.051) | (0.639) | (0.611) | (0.638) | (0.610) |
| amb | 1.383 | 1.298** | 1.194* | 1.287** | 1.181* |
| | (1.067) | (0.641) | (0.611) | (0.641) | (0.610) |
| awar·stdv | –0.564*** | –0.613*** | –0.605*** | –0.609*** | –0.601*** |
| | (0.133) | (0.127) | (0.127) | (0.127) | (0.126) |
| amb·stdv | –0.300** | –0.295** | –0.297** | –0.292** | –0.294** |
| | (0.132) | (0.126) | (0.126) | (0.126) | (0.126) |
| awar·dexp | 0.028 | 0.135 | | 0.143 | |
| | (0.230) | (0.214) | | (0.214) | |
| amb·dexp | –0.110 | –0.118 | | –0.118 | |
| | (0.230) | (0.210) | | (0.210) | |
| awar·per | 0.078 | | | | |
| | (0.060) | | | | |
| amb·per | -0.005 | | | | |
| | (0.061) | | | | |
| const | 1.500** | 1.161** | 1.162** | 0.168 | 0.161 |
| | (0.740) | (0.564) | (0.551) | (0.448) | (0.431) |
| *N* | 310 | 310 | 310 | 310 | 310 |

Table 10: Random effects logit regression of choices between lotteries and sure outcomes in periods 25 to 32 in Risk, Ambiguity and Unawareness treatments (* – 10% significance; ** – 5%; *** – 1%). 2480 observations, 310 independent.

As in Table 2 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 $-0.528$ with standard error 0.093 and $p < 0.0001$. In the Unawareness treatment it is $-0.836$ with standard error 0.093 and $p < 0.0001$ (column 3). The difference of coefficients between Unawareness and Ambiguity treatments is $-0.308$ with standard error 0.128 and $p < 0.017$ (`awar·stdv - amb·stdv`).

# D Individual $\beta$ cdfs for Additional Treatments

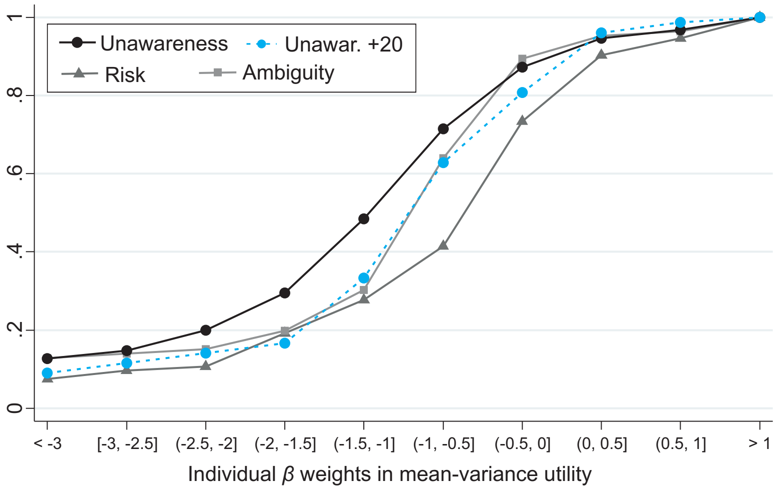


Figure 10: Cumulative distributions of individual risk aversion coefficients $\beta_i$. Treatments: Risk, Ambiguity, Unawareness, Unawareness-POS.

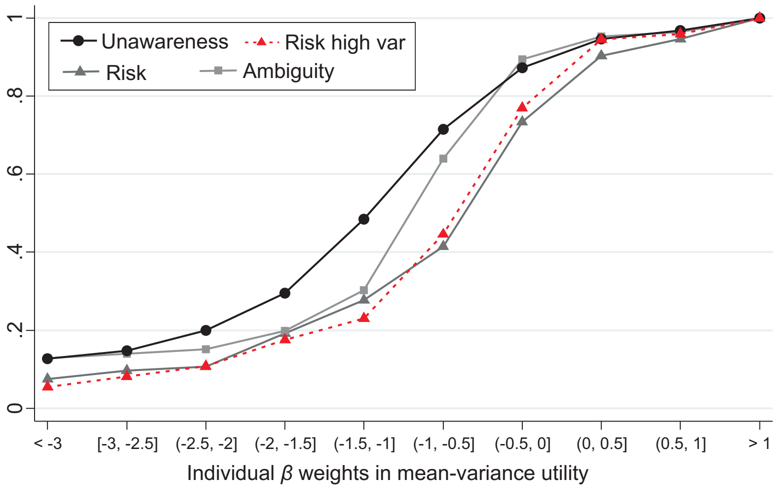


Figure 11: Cumulative distributions of individual risk aversion coefficients $\beta_i$. Treatments: Risk, Risk-high, Ambiguity and Unawareness.

# E Theoretical Explanation Corresponding to Section 6.4

In this subsection we provide a formal theoretical model that can explain the effects we observe. As mentioned above, our theoretical explanation is built on three key ingredients which we present in turn: 1) estimation of (distributions over) lotteries in periods 1 to 16; and 2) carrying over the uncertainty to periods 17 to 32.

## E.1 Estimation in Periods 1 to 16

First we illustrate one possible manner of estimating a distribution over lotteries that the agent deems possible in periods 1 to 16 which works for our theoretical explanation. This method is built on the framework of DeGroot (1970). Other methods, such as variants of bootstrapping, will be consistent with our explanation 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 $q_x \in \mathbb{N}$ 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

$$p_x = \frac{\alpha_x + q_x}{\sum_{y \in X}(\alpha_y + q_y)}. \tag{E.1}$$

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* are possible (even if $q_x = 0$). This is the case for instance, when the participant in our experiment has been informed (e.g. in the Ambiguity treatment) that $-20$ is possible, even if it was never drawn. Notice that, $X_s \subseteq X_a$.

$X_u$ : 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.

To reduce the number of degrees of freedom and make our analysis less arbitrary, we impose some assumptions that restrict the agent's *ex ante* probabilistic assessments.

**Assumption 1.** Elements of $X$ that cannot be distinguished *a priori* share the same $\alpha$:

- $\alpha_x = \alpha_a$ 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 $\alpha_x = \alpha_y$. ◁

**Assumption 2.** $\alpha_a \gg \alpha_u$. ◁

Assumption 2 says that the agent deems the outcomes in $X_a$ (much) more likely than the ones in $X_u$.

In our experiment, we consider $X_a = \{-20, -1, 1, 6, 8, 10, 14\}$.[25] In the Ambiguity treatment $X_u = \emptyset$, whereas in the Unawareness treatment we assume that $X_a \cup X_u$ is sufficiently rich containing all outcomes between $-50$ and 50. In the Risk treatment participants don't need to estimate distributions over lotteries since the lottery is known (i.e. they have a degenerate estimate over the lottery which places probability one on the objective lottery.)

**Distribution over the Lotteries**

We assume that the agent believes that $\alpha_u$ is distributed uniformly in $[0, \alpha_0]$, and $\alpha_a$ is uniformly distributed in $[\alpha_1, \alpha_2]$, where $\alpha_0 \ll \alpha_1$. This is consistent with Assumption 2 in that the probability that the agent attaches to $\alpha_a$ being much larger than $\alpha_u$ is equal to 1. Clearly, if $\alpha_0 = 0$, which implies that the agent is certain that $X_u$ is empty, the unawareness case degenerates 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 the expected value $E_p(X)$ and standard deviation $SD_p(X)$.

**Expected Value**

The agent estimates from the sample the probability of each outcome she deems possible through equation (E.1). Throughout this section we assume that the sample size is equal to 10.[26]

In the Ambiguity treatment this yields an expected value as follows:

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

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

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

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 $(\alpha_a, \alpha_u)$ in the Unaware-

[25]Here we assume Twix has value 1.

[26]If an agent chooses the lottery each time the sample size would be 16. A sample size of 10 corresponds roughly to what we observe.

ness treatment:

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

Observe that for every $(\alpha_a, \alpha_u)$, $E_u X < E_a X$. However, since $\alpha_u$ is assumed to be very small (sufficiently close to 0), they will typically lie very close together as we will see below.

**Standard Deviation**

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

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

implying that the estimated standard deviation given $\alpha_a$ is equal to

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

On the other hand, the estimated variance in the Unawareness treatment for some $(\alpha_a, \alpha_u)$ is equal to

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

implying that the estimated SD given $(\alpha_a, \alpha_u)$ is equal to

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

**Uncertainty over Means and Standard Deviations**
Using $\alpha_a \in [0.1, 0.2]$ and $\alpha_u \in [0, 0.01]$ 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 $SD(SD_u X) = 1.79$. Therefore, there is much more uncertainty in periods 1 to 16 regarding the standard deviation of the lottery than regarding its expected value. Hence, even if agents carried over the uncertainty regarding both expected value and standard deviation, the latter would have a much stronger impact on choices. This may be a reason why we do not see a treatment effect on expected value in our main regression.

## E.2 Carrying over Uncertainty

We assume that the agent uses reference points estimated in periods 1 to 16. These are 8 and 3.8 corresponding to the mean and standard deviation of the lottery in periods 1 to 16. Denote by $p(\mu_\mu, \sigma_\mu)$ the marginal distribution of means and by $r(\mu_\sigma, \sigma_\sigma)$ the marginal distribution of standard deviations resulting from the estimation procedure described above. Since these estimations are unbiased their means correspond to $\mu_\mu = 8$ and $\mu_\sigma = 3.8$, i.e. to the reference points.[27] The two standard deviations $\sigma_\mu$ and $\sigma_\sigma$ represent the fundamental uncertainty of the environment for a decision maker who cares about mean and variance. Note that in the case of the Risk treatment $\sigma_\mu = \sigma_\sigma = 0$ since the estimated distribution is degenerate.

When participants make decisions in periods 17 to 32, they evaluate the mean and variance of the lottery faced $(\mu_\ell, \sigma_\ell)_{\ell=17..32}$ by attaching weight $\lambda$ to $\mu_\ell$ (and $\sigma_\ell$) and weight $1 - \lambda$ to the (normalized) restriction of the estimated distribution to $[\mu_\ell - \sigma_\mu, \mu_\ell + \sigma_\mu]$ ($[\sigma_\ell - \sigma_\sigma, \sigma_\ell + \sigma_\sigma]$), where $\lambda \in [0, 1]$. This is the second crucial assumption of this theoretical explanation. Denote the resulting distributions by $\pi$ and $\rho$ respectively. Participants then evaluate lotteries, as in Prospect theory (Tversky and Kahneman, 1992), as follows:

$$\begin{aligned} U_\ell = \alpha & \left( \int_{\mu>8} d\pi^+ \left(\pi^+ v_\mu(\mu)\right) + \int_{\mu<8} d\pi^- \left(\pi^- v_\mu(\mu)\right) \right) \\ & + \beta \left( \int_{\sigma<3.8} d\rho^+ \left(\rho^+ v_\sigma(\sigma)\right) + \int_{\sigma>3.8} d\rho^- \left(\rho^- v_\sigma(\sigma)\right) \right). \end{aligned}$$

Prospect theory makes the following assumptions on the probability weighting

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

functions $\pi^+, \pi^-$ and $\rho^+, \rho^-$ and the value functions $v_\mu$ and $v_\sigma$.[28] (i) $v$ is concave above the reference point and convex below, (ii) v is steeper for gains than for losses and (iii) the weighting functions are concave near the reference point and convex away from the reference point. Now assuming that $v$ is linear, overweighing of probabilities away from the reference point and underweighing of probabilities near the reference point can explain our results. The reason is that if $\sigma_\ell < 3.8$ in the Unawareness treatment, then participants attach some probability to good outcomes $\sigma < \sigma_\ell$ which are far from the reference point and are, hence, overweighed and some probability to bad outcomes $\sigma > \sigma_\ell$, which are underweighed. This effect is strongest in the Unawareness treatment. Hence participants are more likely to choose a lottery if $\sigma_\ell < 3.8$ in the Unawareness treatment and less likely if $\sigma_\ell > 3.8$ compared to other treatments. The shape of the value function (as assumed by prospect theory) however works in the opposite direction. Concavity for $\sigma_\ell < 3.8$ will mean that a degenerate lottery is preferred to a mean preserving spread and hence would imply that lotteries with $\sigma_\ell < 3.8$ are least likely to be chosen in the Unawareness treatment. Hence for prospect theory to work here the value function should be "close enough" to linear.

[28]Note that there is no unique way in prospect theory to rank prospects $(\mu_i, \sigma_i)$ and $(\mu_j, \sigma_j)$ where $\mu_i > \mu_j$ and $\sigma_i > \sigma_j$. Hence we assume additive separability.

# F Instructions

## F.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).

## F.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.**

## F.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.**