# An Experiment on How Past Experience of Uncertainty Affects Risk Preferences *

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**Abstract**

We conduct an experiment to study how past experience of uncertainty affects risk preferences in subsequent decisions. 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 lasting effects on individuals' risk-taking behavior.

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# 1 Introduction

## 1.1 Motivation and Outline

Exposure to low probability or unexpected events can influence economic decision making and future perception of risk. Malmendier and Nagel (2011), for example, show that experiencing macroeconomic shocks—like the Great Depression—decreases people's willingness to take financial risks in the long run. And 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. An additional question that is difficult to address with field studies is whether it is the fact that agents observe unexpected events or whether it is exposure to extreme realizations (i.e. good vs. bad outcomes) that shape future risk aversion. Conducting a laboratory experiment can help to circumvent all these problems. In this paper we study experimentally how unexpected or unlikely events influence future risk attitudes and how strong and 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 risk attitudes in 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 own 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 any existing 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

[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.

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 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 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. Additional treatments help us to distinguish between different explanations of our main result. One question that arises is whether it is exposure to extreme realizations (i.e. negative vs. positive surprises) or the fact of being surprised (becoming aware of unawareness) *per se* that drives our result. We address this question in an additional treatment where we replace "negative surprises" with "positive surprises" and find that it is the mere presence of surprises and not their valence that triggers the results. Another possible hypothesis is that risk attitudes are affected by *perceived risk* in the first phase of the Ambiguity and Unawareness treatments rather than imperfect knowledge of the state space. To address this possibility we conduct an additional treatment, which coincides with the Risk treatment, but where the lottery has higher variance. We find that a 300% increase in risk (measured by the variance of the lottery) produces the same effect as the Risk treatment. Hence, if there is an equivalent increase in risk that produces the same effect as the Ambiguity and Unawareness treatments, this increase has to be (much) more than 300%. We also show that there are no reasonable priors in the Ambiguity and Unawareness treatments that could possibly produce such an increase in perceived risk. All this suggests that it is information about the state space per se that matters, rather than inferred perceptions of risk.

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. 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.

## 1.2 Related Literature

Previous research has used field data to demonstrate that risk-taking behavior is affected by macroeconomic shocks (Malmendier and Nagel, 2011) 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 boom. Osili and Paulson (2009) show that macroeconomic shocks affect investor confidence.[4] Furthermore, if one could identify an effect on risk aversion it is difficult to pin down what exactly drives this effect. For example, one could ask whether it is imperfect knowledge of the state space or exposure to good vs. bad outcomes that drives such effects. 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 domains are "very different." Nevertheless, Dohmen et al. (2011) detect some stability of risk preferences. Other studies of the stability of risk preferences across different domains include Andersen et al. (2008) or Barsky et al. (1997) among others. 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

[4]Similarly, Malmendier and Nagel (2011) 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.

in risk attitudes across domains might be due to different amounts of knowledge the decision maker had 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). Other authors have tried to establish correlations between risk aversion and ambiguity aversion. 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. While we are not primarily interested in how people make decisions being aware of unawareness, our design can help to inspire experiments studying such questions. Unawareness has recently attracted quite a lot of attention among game theorists as a special case of reasoning in the absence of introspective capacities.[5] The first major contributions in this literature 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, 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

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

we estimate. In sections 4 and 5.5 we present the main results. Section 5 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 the same 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.[6]

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

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.[7] 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

[6]See Supplementary Material (http://www.vostroknutov.com/pdfs/awarexp04supp.pdf) for more details.

[7]If the reader wants to think in terms of a state space and subjective probabilities, here is one example of such a state space. Think of an urn with 1000 balls. Some of these balls have written –20 on them, some Twix, some 10 etc. The decision maker does not know the number of balls of each kind. However, s/he knows all the possible numbers (labels of balls) that are allowed.

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. The reason that participants were initially only informed about positive outcomes is that negative outcomes are unusual in experiments and hence would generate more surprise (becoming aware of unawareness). The order of revelation –1, Twix, –20 was chosen to maximize "surprise." 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.[8] Figures 1.abc illustrate how the choices were presented to the participants.


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 all treatments the choices in periods 17 to 32 are between different lotteries 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 periods (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

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

are chosen such that the expected values of all lotteries are close to 8 Euro (in the interval between 7.94 and 8.05 Euro). The sure outcomes vary between 6 and 8 Euro with a 0.5 Euro interval.[9] 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 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 we do not know which priors participants have about the lottery in periods 1 to 16. We will return to this question in Section 5.[10]

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 5.2, 5.3 and 5.4. We did not run any other treatments than the 6 treatments described, nor did we run any pilot sessions.[11]

At the end of the experiment the participants were paid for one randomly chosen period in addition to a 4 Euro show-up fee.[12] 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. The minimum earnings in the experiment were 3 Euros and the maximum 23 Euros.

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[9]See the Supplementary Material (http://www.vostroknutov.com/pdfs/awarexp04supp.pdf) for the details.

[10]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.

[11]We disregard the data from one session of the Unawareness treatment where there was a substantial programming error.

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

The experiment lasted between 30-50 minutes. 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.[13] 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).[14] 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 $\ell$ 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. Table 2 summarizes the variables we use in the main regressions.

Alternatively to the mean-variance utility we could have estimated risk aversion coefficients from e.g. CRRA or similar utility models. Several authors have shown

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

[14] 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.

| Variable | Definition |
|---|---|
| *per* | period. Ranges from 1 to 16 for the first 16 periods and normalized to 1 to 16 for the last 16 periods (first and last 16 periods are always analyzed separately) |
| *choice* | 0/1 variable. takes value 1 if the lottery was chosen |
| *resptime* | response time in seconds |
| *unawar* | dummy Unawareness treatment |
| *amb* | dummy Ambiguity treatment |
| *unawarpos* | dummy Unawareness-POS treatment |
| *riskhigh* | dummy Risk-high treatment |
| *control* | dummy Control treatment |
| *sure* | value of sure outcome in first 16 periods. Range $[5.4, 8.4]$, mean 6.9 |
| *dexp* | $\mu_\ell - x$. Range $[-0.06, 2.04]$, mean 0.99, periods 17 to 32 |
| *stdv* | $\sigma_\ell$. Range $[1.73, 8.46]$, mean 4.54, periods 17 to 32 |

Table 2: Variables used in regressions.

that mean variance and expected utility maximization are equivalent for many utility functions and earnings or returns distributions (Levy and Markowitz, 1979; Kroll, Levy, and Markowitz, 1984). We chose to use mean-variance model because it can be estimated directly using different regression models and because we do not have to rely on maximum likelihood methods that involve additional assumptions.[15] In Section D of the Supplementary Material, however, we also estimate individual CRRA coefficients and show that (a) our qualitative results in terms of treatment rankings are robust and (b) that the estimated CRRA coefficients and the estimated $\beta$'s from the mean variance model are significantly correlated.

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).

[15] It is also well known that maximum likelihood methods are problematic exactly in those instances where mean variance and expected utility maximization are not equivalent, e.g. for non-quadratic utility functions with many local maxima.

# 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 risk associated with the different lotteries in periods 17 to 32.

| | Pr(Lottery) Risk, Ambiguity, Unawareness | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| dexp | 1.266*** | 1.265*** | 1.252*** | 1.212*** | 1.218*** | 1.180*** |
| | (0.107) | (0.107) | (0.106) | (0.063) | (0.105) | (0.062) |
| stdv | –0.347*** | –0.325*** | –0.322*** | –0.320*** | –0.312*** | –0.311*** |
| | (0.061) | (0.038) | (0.038) | (0.037) | (0.037) | (0.037) |
| per | –0.069** | –0.056*** | –0.043*** | –0.043*** | | |
| | (0.032) | (0.014) | (0.008) | (0.008) | | |
| stdv·per | 0.003 | | | | | |
| | (0.007) | | | | | |
| unawar | 0.861** | 0.859** | 1.093*** | 1.079*** | 1.073*** | 1.061*** |
| | (0.385) | (0.384) | (0.342) | (0.328) | (0.339) | (0.324) |
| amb | 0.513 | 0.513 | 0.629* | 0.555* | 0.621* | 0.549* |
| | (0.387) | (0.387) | (0.344) | (0.328) | (0.341) | (0.325) |
| unawar·stdv | –0.260*** | –0.260*** | –0.267*** | –0.267*** | –0.264*** | –0.263*** |
| | (0.056) | (0.056) | (0.056) | (0.055) | (0.055) | (0.054) |
| amb·stdv | –0.149*** | –0.149*** | –0.152*** | –0.158*** | –0.151*** | –0.156*** |
| | (0.056) | (0.056) | (0.055) | (0.055) | (0.055) | (0.054) |
| unawar·dexp | –0.038 | –0.038 | –0.015 | | –0.012 | |
| | (0.151) | (0.151) | (0.149) | | (0.149) | |
| amb·dexp | –0.120 | –0.120 | –0.107 | | –0.105 | |
| | (0.151) | (0.151) | (0.150) | | (0.149) | |
| unawar·per | 0.025 | 0.025 | | | | |
| | (0.019) | (0.019) | | | | |
| amb·per | 0.013 | 0.013 | | | | |
| | (0.019) | (0.019) | | | | |
| const | 1.385*** | 1.294*** | 1.178*** | 1.207*** | 0.795*** | 0.822*** |
| | (0.337) | (0.269) | (0.248) | (0.241) | (0.236) | (0.228) |
| *N* | 310 | 310 | 310 | 310 | 310 | 310 |

Table 3: 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 six different columns contain different specifications of our main regression. The first 4 columns contain a period term and/or its interactions. 4960 observations, 310 independent.

Table 3 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);[17] `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); `unawar` and `amb` – the dummies corresponding to treatments Unawareness (`unawar`) and Ambiguity (`amb`) as well as interactions. As can be seen from columns (1-3) and (5) of Table 3 in all three treatments participants respond in the same way to `dexp` (the difference between the expected values of lotteries and sure outcomes). In particular, the interaction terms `unawar·dexp` and `amb·dexp` are insignificant. Participants also tend to choose lotteries less often over time (`per` is significant and negative), but again there are no treatment differences (`unawar·per` and `amb·per` are insignificant). We included the variable `per` as well as interaction effects in regressions (1-4) to ensure that our variables `dexp` and `stdv` do not pick up time effects.[18] Regressions (5) and (6) 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 treatment (`stdv`), higher in the Ambiguity treatment (`stdv + amb·stdv`), and highest in the Unawareness treatment (`stdv + unawar·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 4). The difference of coefficients between Unawareness and Ambiguity treatments is $-0.109$ with standard error 0.057 and $p = 0.054$ (`unawar·stdv - amb·stdv`). The dummy variables `unawar` and `amb` have positive coefficients 1.079 and 0.555 respectively.

To check for robustness we also estimated the model using individual fixed effects and a random effects OLS (see Section B of the Supplementary Material). Under the fixed effects model the coefficients and significance levels in all five specifications in Table 3 are almost exactly the same. The OLS model has the same significance

[16]See Table 2 for definitions of the independent variables and the Supplementary Material (http://www.vostroknutov.com/pdfs/awarexp04supp.pdf) for a description of all lotteries.

[17]Note that only very few values of dexp are negative since the sure outcome typically is lower than the expected value of the lottery.

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

levels of all coefficients in all specifications and very similar marginal effects. Thus we conclude that all results are fully robust to these alternative estimations. One may wonder why we didn't control for the number of "bad" or "good" outcomes a participant experienced in these regressions. The reason is that this is endogenous to the degree of risk aversion of participants. We do address the question of whether "good" or "bad" realizations affect the results in detail in Section 5.

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. Interestingly, the critical level of $\sigma$ for which the ranking of treatments reverses coincides with the standard deviation of the lottery from periods 1 to 16. 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.

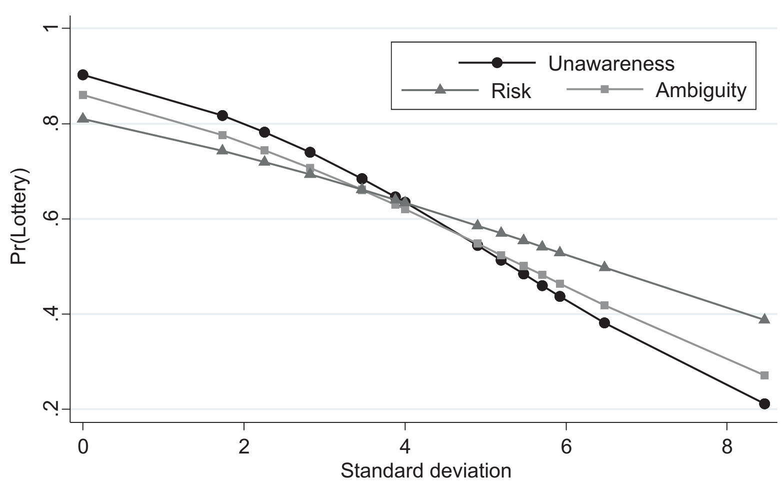


Figure 2: Predicted probabilities of choosing a lottery as a function of its standard deviation in the three treatments.

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 3) imply the following ranking of our treatments:

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

In addition Table 3 shows as well that

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

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. The effect is sizeable. The increase in $\beta$ is 50% when moving from Risk to Ambiguity and it is even 90% when moving from Risk to Unawareness. 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 Section 5 we show that the effect obtains also when we consider only periods 25-32. In fact the qualitative results are the same as described above and, interestingly, are even more pronounced. This shows that the effect is 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 $\beta_i$.[19] Figure 3 shows the cumulative distributions of $\beta_i$ for the three treatments.

Notice that the cdf of risk attitudes in Unawareness treatment first-order stochas-

[19]We dropped participants who always chose either lottery or sure outcome. This left us with 96 participants in the Unawareness treatment, 87 in ambiguity and 97 in the risk treatment.

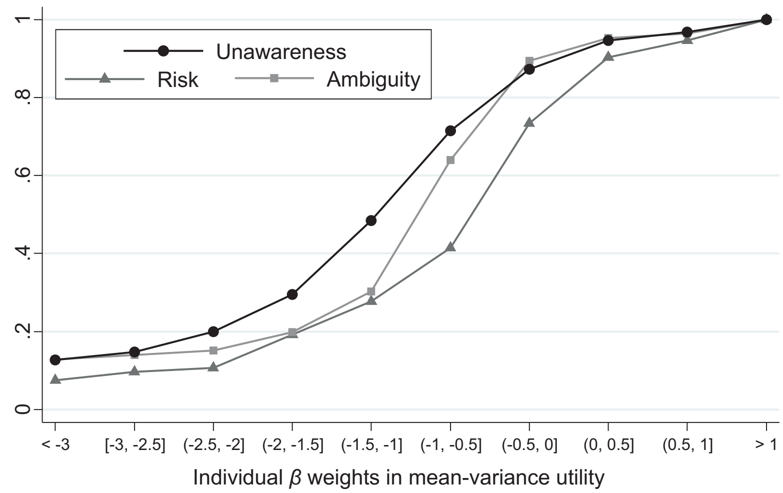


Figure 3: Cumulative distributions of (the negative of) individual $\beta$ weights (risk attitudes) in Risk, Ambiguity and Unawareness treatments.

tically dominates cdf in Risk treatment.[20] 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 Kolmogorov-Smirnov test rejects the hypothesis that the distribution of individual $\beta$'s comes from the same distribution pairwise for any two treatments ($p < 0.0001$).[21]

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 5 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.

**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*

[20]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.

[21]These observations provide further evidence for the lasting effects of exposure to environments with varying types of uncertainty on participants' risk attitudes. To make sure that individual $\beta$ coefficients indeed measure risk attitudes we estimate CRRA expected utility model for each participant. Section D in the Supplemental Material reports the results: 1) the cdfs for the three treatments are still ranked according to stochastic dominance; 2) the individual CRRA coefficients and $\beta$ coefficients have significantly positive correlation.

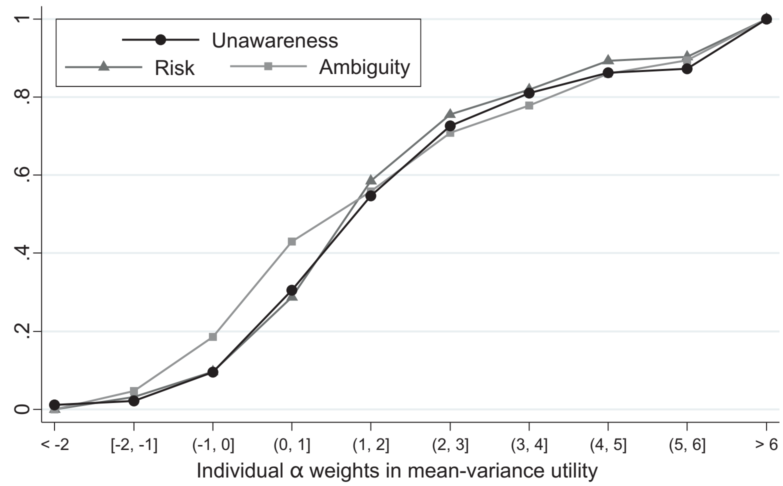


Figure 4: Cumulative distributions of individual $\alpha$ weights in Risk, Ambiguity and Unawareness treatments.

*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 Discussion and Explanation

In this section we first show that the treatment effect on risk aversion is lasting. Then we present evidence from an additional treatment designed to control for the effect of positive vs. negative surprises. Next, we discuss evidence from an additional Risk treatment, where we increased the variance of the lottery in periods 1 to 16 by 300%. Comparing this treatment with our main treatments allows us to clarify to which extent the main result is driven by priors in the Ambiguity and Unawareness treatment that might lead to higher perceived risk in periods 1 to 16. This treatment also shows how important the effect of imperfect knowledge of the state space is in comparison with a pure increase in risk. We then discuss our Control treatment, consisting only of the second task (periods 17 to 32). And finally we analyze behavior differences across treatment in periods 1 to 16.

## 5.1 Is the Effect Lasting?

We rerun our main regression (Table 3), but this time we select data only from periods 25 to 32 to see whether the effect is lasting or whether it vanishes after a few periods.

Of course "lasting" here is within the time scale of typical experiments. In the field (in studies such as e.g. by Malmendier and Nagel (2011)) much larger time scales can be observed. Table 4 reports the results.

| | 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) | | |
| unawar | 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) |
| unawar·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) |
| unawar·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) | |
| unawar·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 4: 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 3 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 + unawar·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 $p < 0.017$ (`unawar·stdv - amb·stdv`). Again there are no treatment differences with respect to the variable `dexp` nor with respect to period. This is remarkably similar to our earlier results and shows that the effect is lasting and—if at all—even becomes stronger.

**Result 2** *Treatment differences in estimated risk aversion found in Result 1 are lasting. In periods 25 to 32 treatment differences are even stronger than in periods 17 to 32.*

## 5.2 Surprise vs. Exposure to Positive or Negative Events

One may conjecture that it is the *negativity* of surprise rather than surprise per se that triggers our results. 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. The reason is that—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 collect additional evidence against this explanation we conducted an additional treatment. Unawareness-POS 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 3. Figures 5.a and 5.b illustrate the model predictions and individual $\beta_i$ coefficients for Unawareness-POS treatment in comparison with three main treatments.

**Result 3** *Whether surprises are "positive" or "negative" does not affect the ranking of our treatments. In particular* $\beta_{Unawareness-POS} > \beta_{Ambiguity} > \beta_{Risk}$.

## 5.3 Increase in Risk

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

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

Table 5: Random effects 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.

this idea 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 the first 16 periods.

Our analysis refutes this ranking of risk aversion 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 as the expectation of the lottery with high probabilities on negative outcomes is lower than the original expectation. Again, our data refute this: subjects choose the lottery in the Ambiguity treatment no less often than in other treatments.

In order to collect even more evidence on this issue 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

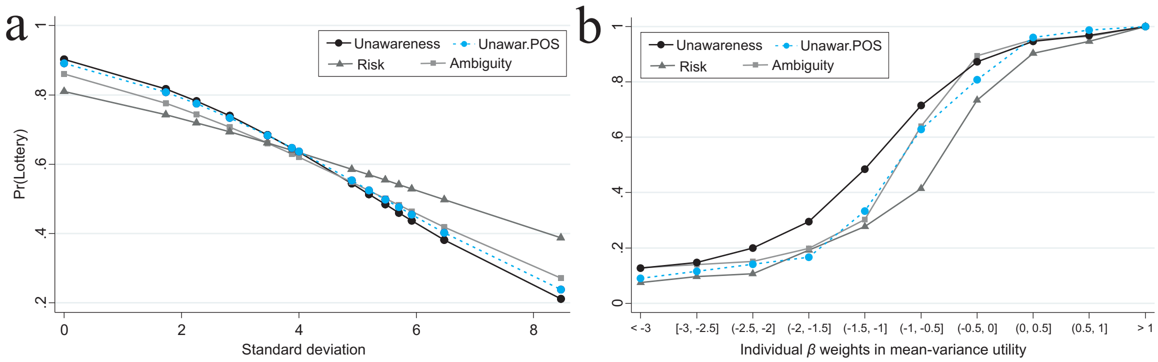


Figure 5: a) Estimated probability to choose a lottery as a function of its standard deviation. Treatments: Risk, Ambiguity, Unawareness and Unawareness-POS; b) Cumulative distributions of individual risk aversion coefficients $\beta_i$. Treatments: Risk, Ambiguity, Unawareness, Unawareness-POS.

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.

Comparing the Risk-high treatment with our main treatments can also help to assess how high an increase in risk should be to match the effect of the ambiguous environment or the environment with unawareness. 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 6 shows the results graphically. This analysis 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.

**Result 4** *A 300% increase in variance produces no change in periods 17 to 32 compared to the Risk treatment. In particular* $\beta_{Unawar} > \beta_{Ambiguity} > \beta_{Risk} = \beta_{Risk-High}$.

| Pr(Lottery) | |
|---|---|
| **All Treatments** | |
| dexp | 1.205*** (0.104) |
| stdv | –0.309*** (0.037) |
| unawar | 1.060*** (0.331) |
| unawarpos | 0.910*** (0.347) |
| amb | 0.614* (0.333) |
| riskhigh | 0.407 (0.349) |
| unawar·stdv | –0.260*** (0.055) |
| unawarpos·stdv | –0.190*** (0.056) |
| amb·stdv | –0.148*** (0.054) |
| riskhigh·stdv | –0.016 (0.055) |
| unawar·dexp | –0.132 (0.147) |
| unawarpos·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.

## 5.4 Control Treatment

In this subsection we discuss our control treatment. In the control treatment participants only made the choices from periods 17 to 32.

The regression in Table 8 shows that participants in the 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 learning at all. This explanation can be ruled out, since the Risk and Control treatments are not significantly different. Figure 7 shows the distributions

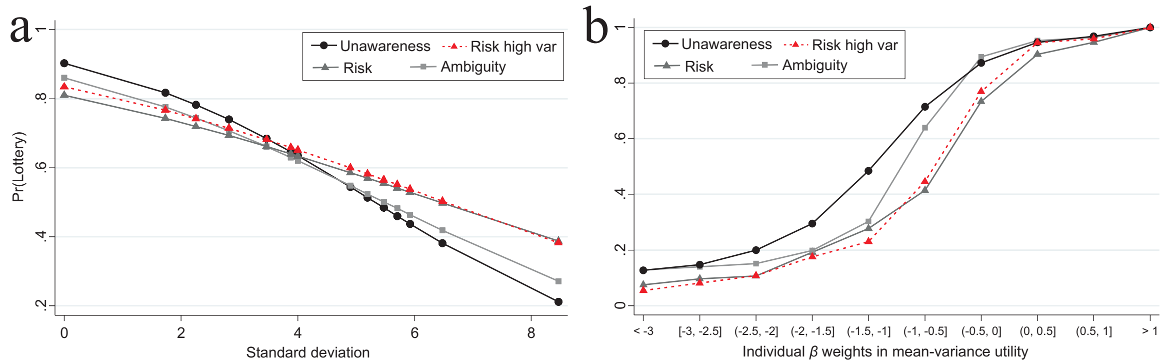


Figure 6: a) Estimated probability of choosing a lottery as a function of its standard deviation. Treatments: Risk, Risk-high, Ambiguity and Unawareness; b) Cumulative distributions of individual risk aversion coefficients $\beta_i$. Treatments: Risk, Risk-high, Ambiguity and Unawareness.

| | **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.

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.

**Result 5** *Behavior in the Control treatment is the same as in the Risk treatment in periods 17 to 32. In particular* $\beta_{Unawareness} > \beta_{Ambiguity} > \beta_{Risk} = \beta_{Control}$.

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

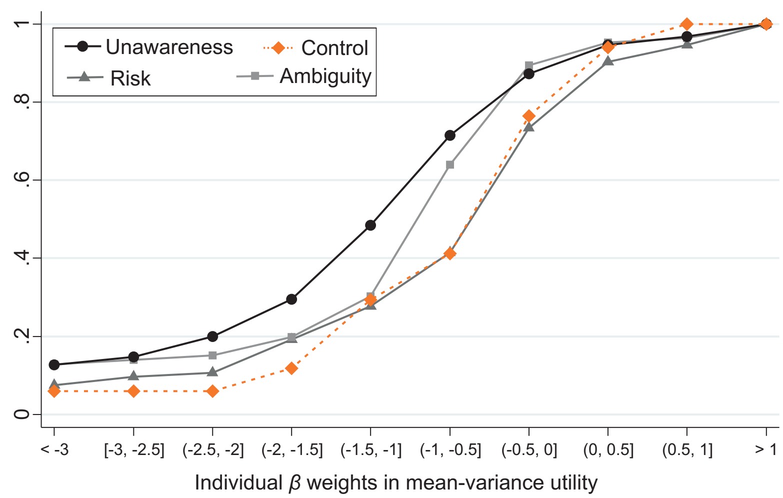


Figure 7: Cumulative distributions of individual risk aversion coefficients $\beta_i$. Treatments: Risk, Ambiguity, Unawareness and Control.

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 Section C in the Supplementary Material).[22] 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 periods 1 to 16 (see below). 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.

## 5.5 Treatment Comparison in Periods 1 to 16

Let us also look at treatment comparisons in periods 1 to 16. We analyze choices of participants in the first 16 periods across all three treatments. Table 9 reports the results of a logit regression of choices on the value of the sure outcome, treatment

[22] Supplementary Material can be found at http://www.vostroknutov.com/pdfs/awarexp04supp.pdf.

dummies 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`.

| | Pr(lottery) | |
|---|---|---|
| | Risk, Ambiguity, Unawareness | |
| | β/(se) | β/(se) |
| sure | –2.025*** | –2.104*** |
| | (0.113) | (0.088) |
| unawar | –6.294*** | –5.748*** |
| | (0.996) | (0.840) |
| amb | –0.761 | |
| | (1.161) | |
| unawar·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 9: Random effects logit regression of choices in the first 16 periods of Risk, Ambiguity and Unawareness treatments.

An important observation is that there are no apparent differences between the Risk and Ambiguity treatments (`amb` and `amb·sure` are insignificant). Hence, priors in the Ambiguity treatment do not seem to have been too far from actual probabilities, which are observed in the Risk treatment. At least they seem to have been close enough to produce (statistically) the same behavior. Choices in the Unawareness treatment are different, however. Here participants seem to be less sensitive to the value of the sure outcome than in the Risk treatment (`sure + unawar·sure`). Moreover, participants tend to choose the sure outcome more often overall (`unawar`). This is at least consistent with the fact that participants were "unaware" of the hidden outcome in this treatment.

As an additional consistency test we compare a measure of individual risk attitudes in the first 16 periods of the Risk treatment with the individual $\beta_i$ coefficients for the last 16 periods discussed in Section 4. Since the lottery in the first 16 periods is always the same it is not obvious how to measure risk attitudes. Therefore, we use a simple crude measure of risk attitude: the number of times $t_i$ each participant chose the lottery. We find that Spearman's rank correlation between $t_i$ and $\beta_i$ is $\rho = 0.18$ with $p < 0.09$. In addition, simple OLS regression of $\beta_i$ on $t_i$ gives significantly positive coefficient ($p < 0.046$). This tells us that the risk attitudes of participants in Risk treatment are consistent between the first and the second parts of the experiment.[23]

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 10 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 + unawar·sure` is insignificant). Moreover, in the Unawareness treatment there is an overall drop in the response time comparing to the Risk and Ambiguity treatments (`unawar`).

| | **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) |
| unawar | –8.875*** | –9.110*** |
| | (1.434) | (1.244) |
| amb | 0.478 | |
| | (1.455) | |
| unawar·sure | 0.446** | 0.476*** |
| | (0.189) | (0.167) |
| amb·sure | –0.655*** | –0.596*** |
| | (0.192) | (0.061) |
| unawar·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 10: Random effects regression of response times in the first 16 periods of the Risk, Ambiguity and Unawareness treatments.

**Result 6** 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.*

[23]The tests reported here were extremely sensitive to outliers in $\beta_i$'s. Hence, observations with $|\beta_i| > 6$ were omitted.

# 6 Conclusions

We studied decision-making under imperfect knowledge of the state space in an experiment and found that it can have lasting effects on future risk aversion. In particular, we conducted three treatments with lottery choice tasks. All treatments were identical in later periods, but differed in early periods. In the early periods of the Risk treatment there was perfect information about the lottery; in the Ambiguity treatment participants perfectly knew the outcome space but not the associated probabilities; in the Unawareness treatment participants had imperfect knowledge about both outcomes and probabilities. We found 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 first order stochastic dominance. We also found that the effect is lasting and that even a 300% increase in risk (measured by the variance of the lottery) in the first phase cannot produce the same effect as the Ambiguity or Unawareness treatments.

These results are of interest for any social scientist concerned with understanding how life experiences under different informational environments shape personality and attitudes towards risk in particular. Different political systems, media and education systems all create different informational environments.[24] Our results show how such environments can affect risk attitudes and hence entrepreneurship, saving decisions and other decisions involving risk. Our results, hence, matter also for policy makers. It has been argued, for example, that the fact that investors have very imperfect information about financial interconnections between banks (and, therefore, 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. They also matter for business leaders who want their employees to dare and make risky decisions. More generally speaking, our results are relevant for any situation where decisions are made under uncertainty and where there are possibilities to affect the amount of information available to decision makers.

Future research should explore the reasons behind this effect, create and test alternative theories that could explain this phenomenon. In the Supplementary Material accompanying this paper we outline one theoretical model that is consistent with our

[24] Alesina and Fuchs-Schuendeln (2007) have shown how experiencing different political systems can affect preferences for redistribution.

results.[25] However, other explanations are possible as well and future research could be aimed at discriminating between competing explanations.

[25]Supplementary Material can be found at http://www.vostroknutov.com/pdfs/awarexp04supp.pdf.

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