Running head: Background Uncertainty and Decision Making

Word count: 9301

Background Uncertainty Can Increase Risk Aversion in Decision Making

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Parts of this research has been pre-registered. The pre-registration documents, data and materials are available at: https://osf.io/5qtez/?view_only=4d58e08e4bce4b1f8561795d5352d2bc

Declarations of interest: none

Abstract

Some theories based on economics and psychology propose that *background uncertainty*, that is uncertainty which is independent of the actual decision, can alter people's risk preferences. Previous empirical research testing this proposition, however, is inconclusive and relies on single studies. Here, we aim to investigate the effect of background uncertainty on decision making systematically. After reviewing the existing empirical studies, we argue that two types of uncertainty should be distinguished: a) *ambiguity*, i.e., uncertain outcomes without probability information and b) *risk*, i.e., uncertainties involving probabilities regarding a negative outcome. We test the hypothesis that the type of uncertainty moderates the effect of background uncertainty on risk preferences. In four studies (total $N = 405$), we induced background uncertainty (ambiguity and risk) with different methods, and measured risk preferences with multiple behavioral tasks. Study 2 was carried out using virtual reality to induce background uncertainty in a naturalistic way, all other studies were computer-based. Using a mini meta-analysis, we found a small but consistent positive effect of increased risk aversion with background uncertainty. As predicted, the type of background uncertainty moderated the observed effects: background ambiguity compared to background risk resulted in a higher increase of risk aversion.

Keywords: background uncertainty, risk preferences, risk, uncertainty, decision making, ambiguity

Background Uncertainty Increases Risk Aversion

Humans live in a fundamentally uncertain world. People face all kinds of uncertain situations, where they have to make decisions. In some situations, the perceived uncertainty is attributable to the decision, in others it is not. However, when examining decision making, researchers typically only focus on the uncertainty that is inherent in a given decision. Whereas uncertainty associated with a decision can be avoided by choosing the safe option, *background uncertainty* is characterized by the fact that the decision-maker cannot avoid or influence it. Background uncertainty is a context factor that is independent of the decision itself but likely to influence decisions, for example, becoming aware of the threat for oneself from a closeby volcano increases risk-aversion in an unrelated task (Willinger et al., 2013).

Understanding how and why background uncertainty alters choices could help to gain insights into how humans represent uncertainty and incorporate it in their decision-making. For example, if risk preferences are constructed on the fly as suggested by some authors (Pedroni et al., 2017; Slovic, 1995), understanding the effect of background uncertainty could help to better understand this process. But before one can embark on the endeavor of understanding the phenomenon, it is paramount to ensure that it exists – so far results were inconclusive — towards this goal this paper takes two steps.

As a first step, we review the extant literature in psychology and economics on background risk. The body of literature examining the effect of background uncertainty is heterogeneous in their methods; particularly for what type of background uncertainty was investigated – and that this fact may explain their heterogeneous results. We propose to distinguish two types of background uncertainty. If the probabilities and the properties of outcomes of the background event are *unknown*, we refer to *background ambiguity*. If

probabilities and properties of the background event were *known*, we refer to *background risk*.

Reviewing the literature we conclude that risk aversion is more strongly affected by background ambiguity than by background risk. As a second step, we test the robustness of the effect of background uncertainty on risk preferences with four experimental studies. We also test whether the type of background uncertainty (ambiguity vs. risk) determines the magnitude of the effect of background uncertainty as compared to a situation with no background uncertainty.

Related Psychological Literature

The effect of background uncertainty on risk preferences has not been tested explicitly in the psychological literature. However, the concept is related to theories of risk compensation (Hillman & Adams, 2001) and risk homeostasis (Wilde, 1998). Both frameworks predict that individuals aspire to a specific level of risk (threshold model). These theories are used to explain the changes in human behavior with and without protective measures. For example, when wearing a helmet, cyclists behaved more recklessly than when they did not wear a helmet (Fyhri & Phillips, 2013; Phillips et al., 2011), and reduced experience of risk was associated with faster driving in a simulation (Lewis-Evans & Rothengatter, 2009). Similar adaptations of safety behavior are also observed in vehicle operators (Sagberg et al., 1997), in children's behavior in obstacle courses (Morrongiello et al., 2013), or the utilization of protective measures in humanitarian aid workers (Leder, 2019). Importantly, the predictions based on these theories only focus on risk associated with the decision, but neglect background uncertainty even though the assumption, that increasing background uncertainty should increase risk aversion can directly be derived from the relevant theories.

The assumption inherent in risk homeostasis theory of risk compensation theory is that increasing background uncertainty should increase aversion. Hitherto, this assumption was

addressed directly only in one study showing that wearing a helmet decreased risk aversion in an unrelated task (Gamble & Walker, 2016). However, that result could also be explained by demand effects (Radun & Lajunen, 2018). To sum up, empirical evidence on the effects of background uncertainty is extremely scant in the psychological literature.

Related Economical Literature

In economics, the effect of background uncertainty on the decision has received some attention. Gollier and Pratt (1996) argue that risk preferences are affected by independent risks, and humans display higher risk-aversion when background risk is present. This proposition has been put to the test but the results are incoherent. Experiments either tested background risk, which was part of the argument by Gollier and Pratt (1996), or background ambiguity, a different type of uncertainty that has not been explicitly distinguished in that literature yet.

A first test of the theoretical prediction by Gollier and Pratt (1996) that background risk would increase risk aversion in an independent decision situation was done at a field experiment. At a coin collector fair, Harrison et al. (2007) recruited visitors and assigned them to one of three experimental groups. In one group, participants made decisions regarding lotteries with monetary payoffs, in the other two groups, subjects made decisions about lotteries with payoffs expressed in collectors coins of type A or of type B. The monetary value of the grade type A coin was certified, whereas for type B it was not. Group B showed greater risk aversion than both group A and the control group. Hence, monetary payoffs or similar payoffs in certified coins resulted in similar risk preferences, while the introduction of uncertainty about a coin's value by using uncertified coins increased risk aversion. In hindsight, that form of uncertainty should be termed ambiguity.

As a conceptual replication of the field study at the coin fair, Herberich and List (2012) asked participants to make decisions either in a standard multiple price list lottery decision making task (Holt & Laury, 2005) or one of three modified multiple price list lotteries similar to Harrison et al. (2007). In one of these modified lotteries, the monetary values were replaced with images of bags filled with quarters, i.e., coins worth 25 US cents (instead of valuable coins). In a second modified lottery, participants were informed about the weight of the coin bags (instead of the grade of the coins, which functions as a value certificate). In the third modified lottery, payoff ranges instead of coin bags were used. Participants were farmers and students who made decisions in all four conditions. While risk aversion was lower in the standard lottery as compared with the modified lotteries including background risk, this effect was not significant.

Results from other studies also support the hypothesis that background risk increases risk aversion. Individuals who recently experienced floods or earthquakes showed higher risk aversion than individuals in similar areas who had not been affected (Cameron & Shah, 2015). This result is consistent with the observation that individuals' risk preferences were more risk-averse after experiencing a volcanic eruption than before (Willinger et al., 2013). Finally, Bacon, Conte, and Moffatt (2019) used a set of socio-economic survey data from Germany, the Socio-Economic-Panel (SOEP). The SOEP assesses risk aversion using a hypothetical lottery decision, a self-reported risk attitude, and the VDAX index, capturing volatility in the German stock market. They show that risk aversion covaried with financial insecurity between 2004 and 2012. Particularly in 2008, risk aversion increased, which was regarded as evidence for the effect of background risk on risk preferences.

The empirical findings reported here seem to support Gollier and Pratt (1996). However, if one scrutinizes the way background risk was operationalized, differences become obvious. In

all studies referenced above, the probabilities and the properties of outcomes of the background event were unknown to the decision-maker, e.g., coin collectors only knew the coin was not certified, but not how likely it was valuable. Thus, what these studies found was the effect of a specific form of background uncertainty which should more precisely be referred to as *background ambiguity*, and not *background risk*.

If, however, experimenters introduce *background risk*, that is uncertainty about an independent event which is described in terms of probabilities and payoffs known to the decision-maker, findings are less consistent. In a laboratory experiment, Lusk and Coble (2008) compared a control group, an unfair background risk group, and a fair background risk group to explore the effect of background risk. All participants completed lottery decisions in a multiple price list design and participants in the background risk group were informed that there would be another lottery afterward. In the fair background risk group, the subsequent lottery had a mean of zero, and with a 50% chance, participants could win an additional \$10 or lose \$10. In the unfair background risk group, the subsequent lottery had a mean of -\$5, and with a 50% chance, participants lost \$10 or otherwise lost nothing from a previously received endowment. Background risk did *not* result in a change of risk preferences. However, due to the design of the experiment, the second lottery was only present in the background risk groups leading to different cumulated final payoffs. For this reason, two parameters reflecting risk aversion were compared which tested the effect of final wealth, i.e., income. The constant relative risk aversion without considering the additional wealth from the lottery and constant absolute risk aversion did not show an effect of background risk. But the constant relative risk aversion incorporating additional wealth from the lottery showed an effect of background risk. Thus, depending on the

modeling of the incorporation of the endowment from the background risk, the results differed.

To sum up, this study provides weak evidence for the effect of background risk in the lab.

When comparing individuals' risk preferences in an investment game, Beaud and Willinger (2015) found evidence for a background risk effect. Here, background risk was introduced by splitting a participant's initial endowment into two accounts. Participants played the investment game for two rounds, and in one of the two rounds, half of the endowment could be lost. Participants were informed that with the equal likelihood they either lost or kept half of their endowment for this round. The results show that participants showed higher risk aversion when their endowment was subject to background risk.

When individuals experience high risk in terms of variations in one lottery task which results in greater risk aversion, the higher degree of risk aversion is maintained in later lottery decisions that yield moderate variance (He & Hong, 2018). He and Hong (2018) used a multiple price list decision making task where participants faced 12 lotteries. Three groups were compared, and groups differed regarding the variance of six lotteries, which were high, medium, and low. Participants completed all multiple price lists, and one decision was randomly selected to rule out learning and portfolio effects. Participants who completed the high-risk lotteries first were more risk-averse in later medium-risk and low-risk lotteries.

To sum up, the literature survey in Table 1 shows that field studies provide support for the effect of background uncertainty, while results from laboratory studies are mixed. However, laboratory and field studies differ in their methods which might explain the observed heterogeneity. In laboratory studies, probabilities and outcomes were known; thus, these studies examined the effect of background risk (Beaud & Willinger, 2015; He & Hong, 2018; Lusk & Coble, 2008). In the field studies (Cameron & Shah, 2015; Willinger et al., 2013), the field

experiment by Harrison et al. (2007), and one experimental study (Herberich & List, 2012) information about the probabilities of payoffs was vague, thus, studies investigated background ambiguity.

Table 1

Previous Studies Testing the Effect of Background Uncertainty. Characteristics, Results, and Comments

Authors	Method	Location	Manipulation	Type of uncertainty	Seq. order of measure of risk aversion concerning the Exposure to background uncertainty	Design	Result	Comment
Harrison et al., 2007	Experiment	Field	Money vs. graded coin vs. ungraded coin	ambiguity	during	between	Higher risk aversion in ungraded coin group compared to money and graded coin	
Herberich and List (2012)	Experiment	Laboratory	Money vs. coin bag vs. weighted coin bag vs. a range of money	ambiguity	during	within	No significant effect	When comparing between subjects only round one, then higher risk aversion resulted in additional ambiguity
Cameron & Shah, 2015	Survey	Field	Natural disaster experienced (yes vs. no)	ambiguity	after	between	Higher risk aversion in the location that experienced nat. disaster	
Willinger et al., 2013	Survey	Field	Natural disaster experienced	ambiguity	before and after	within	Increase in risk aversion after nat. disaster	
Bacon, Conte, and Moffatt (2019)	Survey	Field	Financial crisis 2008	ambiguity	before and after	within	Increase in risk aversion comparing risk preference in 2004 and 2009	
Lusk & Coble, 2008	Experiment	Laboratory	No additional lottery vs. 50% probability to lose or gain \$10 (mean preserving) vs. 50% probability to lose \$10 or \$0 (unfair)	risk	before	between	No difference in aggregated data between treatments.	Final payoffs differ, the control group has no additional payoff. When modeling takes this

into account using
CRRA effect of
background risk is
observed

Beaud & Willinger, 2015	Experiment	Laboratory	50% probability to lose or keep 50% of endowment vs. certainty	risk	during	within	Increase in risk aversion in background risk condition	
He & Hong, 2018	Experiment	Laboratory	Variance in the previous lottery was high vs. medium vs. low	risk	after	between	Experience of high-risk environment results in an increase of risk aversion in later choices	Exhibition to background risk was not independent of the choice

Orthogonal to the problem of clarity regarding the type of uncertainty, not all studies involving background risk introduced its conception as (i) exogenous, (ii) present during the decision, and (iii) beyond the decision-maker's control. He and Hong (2018) examined the carry-over effect of decision about high variance outcomes to decisions regarding options yielding medium variance of payoffs. While they find an effect, it is not clear if this is due to background risk, since the risk of the first decision is not exogenous, and its outcome is dependent on the decision-maker. A similar point is apparent in the field study of Willinger et al. (2013), where risk preferences were measured before and after resolving the background uncertainty, while during the presence of background uncertainty they were not. Lusk and Cobble (2008) on the other hand, informed participants that an additional lottery would be played after the decisions were made, but this was a future event and possibly not salient during the decision. In line with the definition of background risk, that it has to be present and unresolved during choice, only the experiment of Beaud and Willinger (2015) observed an effect of background risk.

Overview of Studies

The current state of the literature calls for an experimental design that allows (i) the measurement of risk preferences while being exposed to background uncertainty, and (ii) the variation of the information provided to the participant to test whether the two types of uncertainty (ambiguity and risk) have different effects on risk preferences. The four studies presented here aim to answer this call (for an overview of methods see Table 2).

Table 2*Overview of Studies: Manipulations and Risk Preference Measures*

	Background uncertainty		Risk preference measure					
	manipulation		LDT	BART	BRET	CEM	MPL	SCL
	Background Lottery	Elevation in Virtual Reality						
Study 1	X		X					
Study 2		X		X				
Study 3	X			X				
Study 4	X				X	X	X	X

Note. LDT = binary lottery decision task, BART = Balloon analogue risk task, BRET = Bomb risk elicitation task, CEM = Certainty equivalent method, MPL = Multiple price list, SCL = Single choice list.

In four studies, we induced background uncertainty using different methodologies and measured risk preferences with different tasks. In Study 1, participants had to make lottery decisions and we varied background uncertainty (control vs. risk vs. ambiguity) using a wheel of fortune that was spinning while decisions were made whose outcome would determine payoffs.

In Study 2, subjects made decisions in the Balloon Analogue Risk Task (BART), and we manipulated background uncertainty (control vs. ambiguity) using elevation in a virtual environment. The manipulation of background uncertainty in the laboratory by using lotteries is far from the “real” background risk (such as uncertainty about product quality, political situations), which induces psychological and physiological responses that might differ from the effect of lotteries. By enabling the creation of an ecologically valid environment, virtual reality experiments offer a new way to overcome this problem (c.f. Harrison et al. 2011). We observed participants’ choices while they were “immersed” in the virtual reality environment and exposed

to (virtual) elevation. The participants in the control group were also immersed in virtual reality. They were not elevated but just standing on the floor. In both Study 1 and Study 2, background ambiguity resulted in greater risk aversion compared with a control group.

In Study 3, we used the wheel of fortune to manipulate background uncertainty (control vs. risk vs. ambiguity) and used the BART as a measure of risk preferences. We did not observe a significant effect of background risk or background ambiguity.

In Study 4, we compared a background ambiguity group to a control group and used four different measures of risk preferences, to test if the effect of background ambiguity differs depending on the risk elicitation task used to measure risk preferences. We found only an effect of background ambiguity in one task.

To estimate the effect of the two types of background uncertainty across all four experiments we carried out a mini-meta analysis. We used the packages {esc} (Lüdtke, 2019) to transform effect sizes to Cohen's d and {meta} (Balduzzi et al., 2019) for the meta-analysis. The results are shown in Figure 7. The random-effects model showed an overall negative effect of $d = -.19$, 95% CI[-0.3411, -0.0306] of background uncertainty on risk preferences, with background uncertainty resulting in higher risk aversion. The estimated heterogeneity of variance was $\tau^2 = 0.03$ (95%CI: 0.0000; 0.2369), with an I^2 value of 48% (95%CI: 0.0% - 75.8%) suggesting that 48% of variance is not explained by the randomness due to sampling. This suggests that the measure and the type of background uncertainty (ambiguity vs. risk) matters.

Figure 1

Forest Plot Showing the Results of Fixed Effect and Random Effects Meta-Analysis

Study 1 aimed to provide a first test of our proposition that the two types of uncertainty (risk and ambiguity) have different effects on risk preferences, by experimentally manipulating the type of background uncertainty. The study also put the moderating effects of framing the decision and the probability of winning to the test. We wanted to test both of these aspects since they have been largely ignored in previous studies.

Methods

Participants and Design

Students (N = 88, 73% women) were recruited at the local university campus and participated in a decision making experiment. Participants were randomly assigned to one of three experimental groups: a control group and two groups with a background lottery. One background lottery involved *risk* (known probabilities and payoffs) while the other one involved *ambiguity* (unknown probabilities and known payoffs). All participants made repeated decisions between a gamble and a fixed payout in a computerized lottery decision making task.

Participants viewed gambles that varied regarding the frame (gain and loss) and the probability of winning (9 different probabilities). Each gamble was presented twice so that the safe option was once presented on the left and once on the right side of the screen. All gambles had the same expected value of 5€. The order of gambles was random, and each lottery was presented once as gain, and once as loss, which resulted in 36 choices (see Table 3 for a list of all choices). In the end, one of the decisions was randomly selected and played out. The payoff of that decision constitutes part of the participants' compensation (payoffs). Additionally, participants were endowed with 5 € in the control group, whereas they could win 10 € in the background lotteries (*ambiguity* and *risk* group).

Measure of Risk-taking behavior

To measure participant's degree of risk aversion, we utilized the *lottery decision task* employed by de Martino, Kumaran, Seymour, and Dolan (2006). Here participants made decisions in multiple trials. In each trial, participants were informed about their endowment for this trial and faced two options, one safe option and an option with two probabilistic outcomes (gamble). The payoffs for the gambles varied whereas the safe option remained stable. The probabilities were depicted numerically and as pie charts. The dependent variable was whether the participant chose the gamble or the safe.

Experimental Groups

Background uncertainty varied between subjects and was carried out with a wheel of fortune, partitioned in green and red. The wheel of fortune was spinning while participants made their decisions. Participants in both background uncertainty groups won an additional 10 € if the wheel stopped at the green. If it stopped at red, they received no additional payoff. Importantly,

participants already received the 10 € at the beginning of the experiment and either lost that sum or were able to keep it. The control group received 5 € for sure and the outcome of wheel turn had no consequences.

In the background *ambiguity* group, participants could not see the distribution of the green and red areas on the wheel of fortune because they were covered and thus did not know the probability of winning. In the background *risk* group, participants could see that 50% of the area was green, thus, the probability of winning was 50%.

The framing of decisions varied within subjects, as a loss frame or a gain frame. In the gain frame, participants were informed that their initial endowment was 0 €. They faced the decision between 5 € for sure or a positive payoff with a given probability or otherwise 0 €. In the loss frame, participants received an endowment for each trial. They faced a decision between a sure loss of x so that $endowment - x = 5$ €, or a gamble with a loss of 0 € with a given probability or otherwise the (whole) endowment in this trial.

The probability of winning also varied within subjects. The probability of the two outcomes of each gamble added up to one. To cover the low, medium, and high range, the gambles' likelihood of resulting in a better outcome (winning) had nine different probabilities. All trial information presented to the participants is depicted in Table 3.

Table 3

Information Presented to the Participant for Each Trial Depicting Endowment and Payoffs for the Sure Option, and each Gamble for the Gain and Loss Frame

Frame	endowment	sure option	Gamble			
			outcome 1 (winning)		outcome 2 (loosing)	
			payoff	with p	payoff	with 1-p
loss	100	-95	0	0.05	-100	0.95
	50	-45	0	0.1	-50	0.9
	25	-20	0	0.2	-25	0.8
	15	-10	0	0.333	-15	0.667
	10	-5	0	0.5	-10	0.5
	7.5	-2.5	0	0.667	-7.5	0.333
	6.25	-1.25	0	0.8	-6.25	0.2
	5.55	-0.55	0	0.9	-5.55	0.1
	5.25	-0.25	0	0.95	-5.25	0.05
gain	0	5	100.0	0.05	0	0.95
	0	5	50.0	0.1	0	0.9
	0	5	25.0	0.2	0	0.8
	0	5	15.0	0.333	0	0.667
	0	5	10.0	0.5	0	0.5
	0	5	7.5	0.667	0	0.333
	0	5	6.3	0.8	0	0.2
	0	5	5.5	0.9	0	0.1
	0	5	5.3	0.95	0	0.05

Procedure

Participants were recruited via posts in university groups on social media, billboards, direct instant messaging, email, and direct face-to-face conversation. After signing up online for a testing session, all participants completed an online version of the Emotion Regulation Questionnaire (Abler & Kessler, 2009) at least 24 hours before the laboratory session took place. In the laboratory, participants were tested in groups of 1 or 2. Participants were seated in individual cubicles and received written instructions. In each session, we tested the participants of the same experimental group. The instructions were standardized and differed only in the group-specific parts, i.e., the instructions referring to the background lottery. In case of questions regarding the procedure, participants were allowed to ask the experimenter. Participants were

informed that their decisions would determine one part of their compensation. Furthermore, participants in the control group were informed that they would receive an additional payoff of 5 € which was placed in front of them. In the background lottery groups, 10 € was placed in front of the participants, and they were told that they could keep these 10€ or lose these 10€ depending on if the wheel of fortune showed a green or red area at the marker. When participants were ready, the wheel of fortune was started, and participants completed the computerized decision task. When participants signaled that they finished the decision task, the wheel of fortune was stopped by the experimenter and the position was recorded. Then one decision made in the decision making task was randomly selected and played out. Participants then were paid and left the laboratory.

Results and Discussion

We analyzed the choice behavior first by calculating the percent of trials in which the gamble was chosen for each group, frame, and probability expressed as log odds of winning (see Figure 2).

Figure 2

Percent of Trials in Which the Gamble was Chosen for Each Condition and Experimental Group

Note. The markers depict the percent of trials across all participants where the risky option was chosen. The Errorbars show the 95% CI.

To test our hypothesis, that background uncertainty results in higher risk aversion, we ran a multilevel logistical regression (to account for the within-subjects design) to predict the

probability of a risky choice in each trial. The dependent variable, i.e., whether the gamble was chosen in a given trial or not, is coded with 1 and 0. Predictors are entered step by step and deviance tests are used to compare the fit of models. The experimental groups are entered as dummy variables and the position of the gamble on the screen (left or right) is entered as control. Interaction effects between the experimental groups, framing and the log-odds of winning were entered step by step.

We compared a model's fit using a deviance test. Comparing the model containing the experimental group and the side (model 1) to the null model indicated better fit, $\chi^2(3) = 12.34$, $p = .006$. Adding the main effect of the frame (model 2) also increased the fit, $\chi^2(1) = 60.54$, $p < .001$. Adding the log odds of winning as a predictor (model 3) further increased fit, $\chi^2(1) = 60.60$, $p < .001$. Adding interaction terms in the other models (4-6) did not increase fit. Interactions are all not significant and odds ratios are close to 1.00.

Table 4 presents the regression results where the standard errors are clustered for each subject and all interaction effects were included. The control group was less risk-averse than the background lottery risk group, OR = 0.57, 95% CI = [0.31, 1.05], and the background lottery ambiguity group, OR = 0.38, 95% CI = [0.21, 0.70]. The difference between the ambiguity and risk group was not significant, OR = 0.63, 95% CI = [0.39, 1.03]. Participants were more risk-averse in the gain than in the loss frame, OR = 1.93, 95% CI = [1.47, 2.54], and the proportion of choices in favor of the gamble was affected by the probability of the payoffs, higher odds in favor of winning resulted in higher risk aversion, OR = 0.89, 95% CI = [0.80, 0.98].

Table 4*Effects of Experimental Group, Framing and Odds of Winning on Risky Choices*

Predictors	<i>Odds Ratios</i>	<i>95 % CI</i>	<i>p</i>
Int.	1.20	[0.77, 1.89]	0.419
Risk	0.57	[0.31, 1.05]	0.073
Ambiguity	0.38	[0.21, 0.70]	0.002
Frame	1.93	[1.47, 2.54]	<0.001
Log-odds win	0.89	[0.80, 0.98]	0.018
Side	0.95	[0.81, 1.11]	0.491
Risk X Frame	1.02	[0.70, 1.51]	0.907
Ambiguity X Frame	0.90	[0.61, 1.32]	0.598
Risk X Log_odd_win	0.94	[0.82, 1.09]	0.418
Ambiguity X Log_odd_win	0.91	[0.79, 1.05]	0.189
Frame X Log_odd_win	0.99	[0.85, 1.14]	0.877
Risk X Frame X Log_odd_win	0.98	[0.79, 1.20]	0.819
Ambiguity X Frame X Log_odd_win	1.07	[0.87, 1.31]	0.508
Random Effects			
σ^2		3.29	
τ_{00} VP_Code		1.16	
ICC		0.26	
N VP_Code		85	
Observations		3240	
Marginal R ² / Conditional R ²		0.080 / 0.319	

Note. σ^2 shows the within subjects standard deviation. τ_{00} shows the between subject standard deviation. ICC indicates the intra-class correlation, i.e. the proportion of variation between individuals (τ_{00}) explained by the overall variance ($\sigma^2 + \tau_{00}$). Marginal R² provides the variance explained only by fixed effects and conditional R² provides the variance explained by the entire model, i.e., both fixed effects and random effects.

Results show that risk aversion is on average higher when background uncertainty is present. Second, the type of background uncertainty (ambiguity or risk) influences the size of the effect. Background ambiguity increased risk aversion compared to the control group, and albeit it did not differ significantly from the background risk group, background risk was not significantly different from the control group. Thus, the effect of background risk was weaker than the effect of background ambiguity. Third, background uncertainty does not alter the effect of framing or probability weighting in the present study. Our observation that the increase of risk aversion is affected by the type of uncertainty is in line with the finding that observed effect sizes in field studies investigating background ambiguity (e.g., Harrison et al. 2007) were larger than the effects in the laboratory studies investigating background risk (Herberich & List, 2012; Lusk & Coble, 2008). One limitation of the experiment is that background uncertainty and decision task were very similar, for this reason, we aimed to conceptually replicate our study in a more naturalistic context. In field studies, that examine the after-effects of natural disasters, the increase in risk aversion could also be explained with an unobserved variable caused by natural disasters and correlated with background uncertainty and risk aversion such as employment uncertainty. For example, social pressure or changes in the overall wealth could affect risk-taking (Guiso & Paiella, 2008). For this reason, we conducted Study 2 to investigate risk preferences in an immersive virtual environment, where we can simulate background uncertainty under controlled laboratory conditions in an ecologically valid way (Harrison et al., 2011).

Study 2

In study 2, we induced background uncertainty, in particular ambiguity, through elevation and compared risk preferences in the Balloon Analogue Task (BART; Lejuez et al., 2002) to a control group.

Methods

Participants and Design

Students ($N = 28$, 18 % women) were recruited via the recruitment software ORSEE (Greiner, 2015) and randomly assigned to either a *background ambiguity* group that was elevated on a small virtual platform or to a *control group* that was on the floor. Using virtual reality headsets, both groups were immersed in a virtual environment. Participants made repeated decisions in the balloon analog risk task (BART; Lejuez et al., 2002).

Measure of Risk Preferences

To measure risk preferences, we used the BART and adapted it to the virtual environment. As the right panel of Figure 2 shows, the virtual balloon is connected to a pumping machine installed on a trolley (the “pump station”). Participants virtually pumped up multiple balloons. Participants knew that the balloons could explode, but not at what point. Unknown to participants, the maximal number of pumps was 128. The maximal number of pumps per balloon was randomized and then the same for all participants in line with previous research (Lejuez et al., 2002; Schürmann et al., 2019; Walasek et al., 2014; White et al., 2008), to avoid variation of experiences due to explosion across groups. Participants received 0.05€ per pump. After each pump participants could decide whether to stop pumping and cash in their accumulated payoff from the current balloon or to continue pumping. If the balloon burst, all payoffs accumulated with this balloon so far were lost.

Figure 3

The BART on a 2D Screen and the 3D Adaptation in our Virtual Setting.

It is assumed that the number of pumps is a reliable measure of an individual's risk preference, and fewer pumps indicate higher risk aversion (Lejuez et al., 2002; White et al., 2008). In our study, the virtual BART consisted of two elements, the pump to which the balloon was attached, and the cash-in station, where participants had to walk to, to deposit their earnings. Participants pumped up the balloon by pressing a button on the handheld controller of the virtual reality system. Participants' pumps were counted as the dependent variable. More precisely, we used the adjusted BART score, i.e. the mean across all trials in which the balloon did not explode as the dependent variable (Lejuez et al., 2002). Additionally, we also used the number of explosions per participant as it is more strongly related to risk-taking behaviors (Schmitz et al., 2016). We also report the trial by trial analysis in the electronic supplementary materials C, as some authors (De Groot, 2020; Pleskac et al., 2008) strongly advise against using the aggregated adjusted BART scores as this overestimates the degree of risk aversion and treats missing values as randomly missing which is inaccurate. We followed recent suggestions (De Groot, 2020;

Weller et al., 2019; Young & McCoy, 2019), and additionally conducted all analyses using Bayesian multilevel Poisson regression analysis accounted for the right-censored data implemented in the brms package for R (Bürkner, 2018).

Experimental Groups

All participants were “immersed” in the virtual environment by wearing a virtual reality headset, the HTC Vive, visually perceiving that they are standing in a virtual warehouse. After a short time of acclimation, participants had to complete the BART.

The control group and the ambiguity group were immersed in the same virtual setting. Both groups faced the pump station with the balloon on one side and the cashpoint on the other. The stations were connected with a plank of 30 cm width, which participants had to cross to get to the pump station, and then to turn back to the cash-in station. Participants crossed this plank back and forth repeatedly, to cash in their payoffs in trials when the balloon did not explode. In the control group, participants stood on the plank, which was integrated into the floor. The participants in the ambiguity group entered the warehouse and stepped on an open elevator with no guards, which raised them approximately 7m overground. The left panel of Figure 3 shows the point of view of the ambiguity group (elevated participants), the perspective of the control group (non-elevated participants) is shown on the right panel.

Figure 4

The Left Panel Shows the View of a Participant in the Elevated Group (Ambiguity Group), the Right Panel Shows the Participant's View in the Non-Elevated Group (Control Group)

Procedure

Upon entering the lab participants were informed about the general procedure and potential side effects of VR. Then they gave their consent to participate and mounted the VR headsets and received the controllers. The procedure was in line with the guidelines of the IRB of the local university.

Instruction on how to navigate in the VR environment followed. After instructions were understood the experiment started. Participants completed 30 trials of the BART, received their payment, completed the questionnaire, and took their leave.

Results and Discussion

Comparing the number of pumps of experimental groups per trial indicated that the control group pumped up the balloon more than the ambiguity group (see Figure 5).

Figure 5*Adjusted Pumps and Explosions for Each Experimental Group*

Note. Panel a) shows the adjusted mean BART score. Panel b) shows the mean explosions. The Violin plot depicts the density of the distribution. The boxplot shows the first, second (median), and third percentile. The rhombus in each plot depicts the mean. The points are jittered individual average responses.

For the adjusted pumps, the normality assumption was violated, as indicated by the plotted residuals (see electronic supplement B Figure S1) and the significant Shapiro Wilk test ($W = .89, p = .007$) we used the non-parametric alternative to a linear model, the Wilcoxon test. The conditions did differ significantly in their adjusted pumps, $W = 155, n1 = 14, n2 = 14, p = .008, \eta^2 = .49$ 95% CI [.15, .77], and the adjusted pumps were lower in the ambiguity condition.

For the explosions, the normality assumption was not violated (see Q-Q plot in electronic supplement B Figure S2 and Shapiro Wilk test, $W = .97$, $p = .52$). The experimental condition did have a significant effect on the number of explosions, $F(1, 26) = 6.045$, $p = .021$, $\eta_g = .19$ 95% CI [.00, .44], and fewer balloons exploded in the ambiguity condition. Analysis taking censoring into account yielded the same results (see supplement C).

Study 1 and Study 2 both show consistent evidence in favor of the hypothesis, that background uncertainty alters risk preferences, individuals exposed to background uncertainty become more risk-averse than individuals in an environment without background uncertainty. However, the effect in Study 2 could also be explained by the specific nature of the risk preference measure. Responses across measures are often not consistent due to different possible processes underlying the decision in each task (Frey et al., 2017; Pedroni et al., 2017). Study 1 and Study 2 differed regarding the measurement of an individual's risk preferences as well as the induction method of background uncertainty. Thus, to test the robustness of the effects observed in Study 1 and Study 2 the manipulation of background uncertainty of Study 1 and the BART as a measure of risk preferences as in Study 2 were both used in Study 3.

Study 3

Study 3 addresses the question of whether the effect of background uncertainty (ambiguity and risk) is task-independent in terms of the behavioral measure, and the method to induce background ambiguity/risk. The pre-registration of Study 3 can be found here: https://osf.io/v4ak8/?view_only=c4d376acb5c84e15a8471fb34cb48b79. As in Study 1, we expect the effect of background risk to be smaller than the effect of background ambiguity when comparing risk preferences in the experimental groups (*risk* and *ambiguity*) to a *control* group.

Participants and Design

The number of participants was determined based on the following assumptions. Each participant performs the BART 30 times according to the standard procedure. The retest reliability of BART is .77 (White, Lejuez, & Wit, 2008). We aimed for a test power of .9 and an effects size of $f = .3$, based on our Study 1. The sample size calculated for an ANOVA with repeated measures and a between-subjects factor with three types calculated with GPower (Faul, Erdfelder, Lang, & Buchner, 2007) was $N = 102$. Participants were recruited via ORSEE from the local participant pool (Greiner, 2015). Because one subject had to be discarded due to a computer crash, we had a final sample of $N = 101$ (43.6 % female, age $M = 24.29$ years, $SD = 6.56$, $Range = [18, 64]$) and participants were randomly assigned to one of three experimental groups based on which experimental session they were in. The dependent variable was the number of pumps in the BART.

Experimental Groups

We used the same experimental manipulation of the background risk and ambiguity as in Study 1 using a wheel of fortune, partitioned in green and red, which was spinning while participants made their decision. Participants in the ambiguity group did not see the full wheel and did not know the distribution of red and green. Participants in the risk group saw the distribution. Participants in both background uncertainty groups won an additional 10 € if the wheel stopped at the green. If it stopped at the red, they received no additional payoff. Importantly, participants already received the 10 € at the beginning of the experiment and either lost it or were able to keep it. The control group received 5 € for sure and the wheel spun with no consequence.

Measures

Risk preferences were measured using the decisions in the Balloon Analogue Risk Task (BART; Lejuez et al., 2002; White et al., 2008). In this task, subjects have to inflate a virtual balloon with repeated “pumps”. The BART task had the same properties as in Study 2, the only difference was that it was executed using a flat 2D monitor.

We also measured emotion regulation with the ERQ (Abler & Kessler, 2009), Neuroticism with the NEO FFI (Borkenau & Ostendorf, 2008) for exploratory reasons.

Procedure

After signing up online for a testing session, all participants completed an online version of the ERQ (Abler & Kessler, 2009), and the NEO FFI (Borkenau & Ostendorf, 2008) at least 24 hours before the laboratory session took place. In the laboratory, participants were tested in groups of 8-12. Participants were seated in individual cubicles and received written instructions. In each session, we tested the participants of the same experimental group. The instructions were standardized and differed only in the group-specific parts, i.e., the instructions referring to the background lottery. In case of questions regarding the procedure, participants were allowed to ask the experimenter. Participants were informed that their decisions would determine one part of their compensation. Furthermore, participants in the control group were informed that they would receive an additional payoff of 5 € which was placed in front of them. In the background lottery groups, 10 € was placed in front of the participants, and they were told that they could either keep these 10€ or lose the money depending on if the wheel of fortune showed a green or red area at the marker. When participants were ready, the wheel of fortune was started, and participants completed the computerized decision task. When participants signaled that they finished the decision task, the wheel of fortune was stopped by the experimenter and the position

was recorded. At the end participants saw their final counted pumps, the resulting payoff and the additional payoff they received from the background lottery. Participants then were paid and left the laboratory.

Results and Discussion

Comparing the number of pumps of experimental groups per trial indicated that the groups did not differ in their pumps (see Figure 5).

Figure 6

Adjusted Pumps and Explosions for Each Experimental Group

Note. Panel a) shows the adjusted mean BART score. Panel b) shows the mean explosions. The Violin plot depicts the density of the distribution. The boxplot shows the first, second (median), and third percentile. The rhombus in each plot depicts the mean. The points are jittered individual average responses.

For the adjusted pumps, the normality assumption was violated, as indicated by the plotted residuals (see electronic supplement D Figure S4) and the significant Shapiro Wilk test ($W = .93, p < .001$) we used the non-parametric alternative to a linear model, the Kruskal-Wallis test. The conditions did not differ significantly in their adjusted pumps, $\chi^2 = 0.72, df = 2, p = .7, \eta^2 = -.01$ 95% CI [-.02, .09].

For the explosions, the normality assumption was not violated (see Q-Q plot in electronic supplement D Figure S3 and Shapiro Wilk test, $W = .98, p = .21$). The experimental condition did not have a significant effect on the number of explosions, $F(2, 98) = 1.522, p = .22, \eta_g = .03$ 95% CI [0.00, 0.11]. The trial-by-trial analysis accounting for data censoring is found in the electronic supplementary E – results are consistent with the main analysis.

Study 3 only found weak evidence for the effect of background uncertainty. Two possible explanations come to mind. First, the manipulation of uncertainty was not as strong as in Study 2, and second, the induction method of background uncertainty which is based on a lottery, as the wheel of fortune used, does not influence tasks that are governed by more automatic processes, which are supposed to underlie decision making in the BART (Buelow & Blaine, 2015). To test, whether the effect of background uncertainty on risk preferences differs between tasks, we carried out Study 4.

Study 4

In Study 4 we carried out an online study where participants responded to four measures of risk preferences, of which three are generally based on lottery decisions and one is based on a more direct behavioral measure. The pre-registration of Study 4 can be found here:

https://osf.io/gn395?view_only=fde6342ec47f45e6b84ee8ce86e9f7f5. Participants were assigned to one of two experimental groups, a *control* group, and a *background ambiguity* group.

Participants in the control group received a fixed showup fee of 4€. Participants in the ambiguity group were informed that they would either receive an additional 0€ or 8€ depending on a lottery that would be played during the experiment. All participants completed all four measures of risk preferences. The experimental group (control group and the background ambiguity group) will serve as our first independent variable, while the measure of risk preferences is our second independent variable. If the effect of background uncertainty is similar across measures, we expect only a main effect for the experimental group. If the effect of background risk differs across measures, we expect an interaction between the measure and the presence of background uncertainty.

Methods

Participants and Design

We planned to recruit 90 subjects per experimental group, in total 180. The power calculation is based on the simplistic assumption of a repeated measures design with a power of .8 with an Alpha of .01 for an effect of $f = .2$ in a repeated-measures ANOVA design (2x4) given a correlation of .5 between measures (GPower; Faul, Erdfelder, Lang, & Buchner, 2007).

Participants were recruited via ORSEE (Greiner, 2015) from the local participant pool. The final sample of $N = 185$ (62 % female) was randomly assigned to one of two experimental groups. The experiment was conducted online using oTree (Chen et al., 2016) and all participants completed all four behavioral measures of risk preferences.

Experimental Groups

In Study 4 a control group was compared to an ambiguity group. In the ambiguity group, participants were told that at the end of the experiment they would either receive an additional 8€

or nothing. Participants were told whether they gain nothing or an extra 8€ would be determined by a random mechanism that is visible through the shifting logos of the universities in the header at the top of the page. If the logo of the participant's university is on the right when getting to the final payoff page, the participant would receive the payoff, if the logo is on the left, their additional payoff would be zero. The likelihood of switching was unknown to the participant and logos switched at irregular intervals. In the control group, the logos switched sides in the header too, but participants were not instructed about the relevance of these switches.

Measures

Risk preferences

Risk preferences were measured with four different methods utilizing the ready-made applications for Otree by Holzmeister and Pfurtscheller (2016). We used the measures and followed the same procedures as Holzmeister and Stefan (2020) but we downscaled the payoffs by factor 0.5. We utilized the bomb risk elicitation task (BRET), certainty equivalent method (CEM), multiple price list (MPL), and single choice lottery (SCL). In the following, $x, p; y$ denotes a two-outcome lottery that assigns probability p to outcome x and probability $1 - p$ to outcome y . Subscripts h and l refer to “high” and “low” lottery outcomes.

The BRET is a visual risk preference elicitation method requiring subjects to decide on how many boxes to collect out of a matrix containing n boxes. Each box collected yields a payoff γ ; but in one of the boxes, a “bomb” is hidden, erasing all prospective earnings. Thus, potential earnings increase linearly but are zero if there is a bomb in one of the collected boxes. The BRET elicits (within-method) consistent decisions in $n + 1$ lotteries $\left(\gamma k, \frac{n-k}{n}; 0\right)$. The number of boxes collected is a single parameter $k \in \{0, 1, \dots, n\}$, which reflects a participants risk aversion. We used the dynamic version of the BRET (Crosetto & Filippin, 2013), where

after pressing the start button boxes are collected randomly until the stop button is pressed. The location of the bomb was only revealed at the end of the task. In our experiment, we set $n = 100$ (that is 100 boxes are displayed) and $\gamma = 0.25\text{€}$ (that is per box participants gain 0.25€), implying an expected payoff of 6.25€ for a risk-neutral decision-maker.

The CEM determines the point of indifference between a lottery $L_a = (h_a, p; l_a)$ with $h_a > l_a$ and n varying degenerated lotteries (lotteries with one sure outcome) where the payoff changes in each step i , $L_{b,i} = (b_i, 1)$, with $h_a \leq b_i \leq l_a$ for all $i = 1, 2, \dots, n$. We implemented the parametrization used by Abdellaoui et al. (2011), with $n = 9$ binary choices, scaled by factor .25; hence, $h_a = 7.50\text{€}$, $l_a = 2.50\text{€}$, and $b_i = \{2.50\text{€}, 3.125\text{€}, \dots, 7.50\text{€}\}$. A risk-neutral subject expects to earn 5.695€.

The MPL is characterized by a menu of ten binary choices. In each choice, two lotteries are depicted with fixed payoffs but varying probabilities of high and low outcomes for each option. Hence, subjects face multiple binary choices i between lottery $L_a = (h_a, p_i; l_a)$ and lottery $L_b = (h_b, p_i; l_b)$ for $i = 1, 2, \dots, n$, where $h_b > h_a > l_a > l_b$. We used the parametrization with $n = 10$ lotteries as proposed by Holt and Laury (2002) but scaled the payoffs by a factor of 2.5 which resulted in $h_a = 5.00\text{€}$, $l_a = 4.00\text{€}$ and $h_b = 9.625\text{€}$, $l_b = 0.25\text{€}$ with $p_i = \{0.10, 0.20, \dots, 1.00\}$. A risk-neutral individual expects to earn 6.07€.

The SCL offers subjects a menu of different lotteries, asking them to choose the one they prefer to be played out. The menu consists of six lotteries which are similar to the implementation proposed by Eckel and Grossman (2002, 2008). The payoffs were for $L1 = (4.50\text{€}, 0.50; 4.50\text{€})$, $L2 = (3.75\text{€}, 0.50; 6.00\text{€})$, $L3 = (3.00\text{€}, 0.50; 7.50\text{€})$, $L4 = (2.25\text{€}, 0.50; 9.00\text{€})$, $L5 = (1.50\text{€}, 0.50; 12.00\text{€})$, and $L6 = (0.00\text{€}, 0.50; 12.00\text{€})$. Lotteries L5 and L6 have the same expected payoff but differ in standard deviation. That is,

choosing L5 implies that the decision-maker is either (weakly) risk-averse or risk-neutral; choosing L6 reveals risk neutrality or risk-seeking preferences. Hence, a risk-neutral decision maker opts either for lottery L5 or lottery L6, implying an expected payoff of €6.00. One of the tasks was randomly chosen and determined part of the final payoff for each participant. The order in which the tasks will be presented will be randomized to avoid order and learning effects.

The tasks used differed regarding the number of possible risky choices and the payoffs but in all tasks, participants switch from risky options to a safer option (from safe to risk) at some point in the task. For this reason, the ratio of risky and safe choices in each measure is an empirical measure of the participant's risk preference. Because ratio measures have a lower bound of zero and the upper bound infinity, we log-transformed them so that they are linear and follow a normal distribution with a mean of zero in case of risk neutrality (i.e., the same proportion of risky to safe choices). We did not preregister this transformation as we overlooked this problem of comparability when designing the study.

Perceived risk and confidence

After making their decision in the respective task, participants were shown their decisions and asked about the perceived risk of their decision and their confidence in their choice. We did not include these measures in the analysis as they were only for exploratory purposes.

Personality measures

Additionally, we asked participants to answer two questionnaires when they signed up for the study. We measured emotion regulation using the ERQ (Abler & Kessler, 2009) and personality using the NEO FFI (Borkenau & Ostendorf, 2008). However, these questionnaires were part of another project.

Procedure

After signing up online for a testing session, all participants completed an online version of the ERQ (Abler & Kessler, 2009), and the NEO FFI (Borkenau & Ostendorf, 2008) at least 24 hours before the online experiment took place. Participants received a second email with a personalized link to the online experiment. Participants had to enter a code that they received after completing the survey during the registration. Participants in the control group were informed that they would receive an additional payoff of 4 € for sure. In the background ambiguity group, participants were told that they either receive an additional 8€ or no additional payoff depending on the position of the logo of their university at the top of the screen. Then the decision tasks started. Each task commenced with instructions followed by comprehension tests. Then participants made their decisions. In the end, one of the tasks was randomly selected and one randomly chosen decision played out and paid. Here, participants saw their decision, the resulting payoff, and the additional payoff they received from the background lottery or the additional payoff. Participants were paid according to their payoffs in Amazon Gift cards with the respective value.

Results and Discussion

As can be seen in Figure 6, participants were significantly more risk-averse in the BRET than in all other measures. To test the effect of the experimental group on each measure we ran a mixed-effects linear regression with the log ratio of risky choices as the dependent variable and a random intercept for each participant accounting for the repeated measures. The experimental groups and measures were added fixed effects as dummy variables. The experimental condition did not affect risk preferences in the BRET, $b = 0.05$ 95% [-0.19, 0.29], $p = .705$. However, a significant interaction between the experimental group and MPL was observed, $b = -0.36$ 95% [-

0.68, -0.05], $p = .02$, which shows the influence of the experimental groups differed for the MPL compared to the BRET and all other measures. Background uncertainty resulted in a risk preference characterized by increased risk aversion in the responses in the MPL compared to the control group, $t(167.69) = 2.52$, $p = .013$, $d = 0.38$ [0.08, 0.68] (for all coefficients see Table 5). However, the observed interaction effect does not increase the model fit significantly, indicated by the test of deviance comparing a main effects only model to the interaction model, $\chi^2(3) = 5.75$, $p = .12$.

Figure 7*Comparing Risk Preferences Across Measurements and Experimental Groups*

Note. The risk preference reflects the log ratio of choices in favor of the option with more risk. The horizontal line at $y = 0$ shows the value of risk preference given risk neutrality, i.e. the ratio of risk / safe is 1 and the $\ln(1) = 0$. The Violin plot depicts the density of the distribution. The boxplot shows the first, second (median), and third percentile. The rhombus in each plot depicts the mean. The points are jittered individual responses.

Table 5*Regression Results for Risk Preference on the Experimental group and Measurement.*

Predictors	<i>B</i>	95% <i>CI</i>	<i>p</i>
(Intercept)	-0.79	[-0.96, -0.62]	<0.001
Experimental group	0.05	[-0.19, 0.29]	0.705
CEM	0.49	[0.25, 0.73]	<0.001
MPL	0.66	[0.44, 0.88]	<0.001
SCL	0.69	[0.47, 0.92]	<0.001
Experimental group * CEM	-0.15	[-0.49, 0.20]	0.410
Experimental group * MPL	-0.36	[-0.68, -0.05]	0.022
Experimental group * SCL	-0.08	[-0.40, 0.24]	0.629
Random Effects			
σ^2	0.56		
τ_{00} participant	0.13		
ICC	0.18		
$N_{\text{participant}}$	185		
Observations	647		
Marginal R^2 / Conditional R^2	0.093 / 0.259		

Note. Regression was fitted using linear regression. The intercept reflects the response in the BRET and the control group. σ^2 shows the within-subjects standard deviation. τ_{00} shows the between-subject standard deviation. ICC indicates the intra-class correlation, i.e. the proportion of variation between individuals (τ_{00}) explained by the overall variance ($\sigma^2 + \tau_{00}$). Marginal R^2 provides the variance explained only by fixed effects and conditional R^2 provides the variance explained by the entire model, i.e., both fixed effects and random effects.

General Discussion

We reviewed research from psychology and economics that investigated the effect of background uncertainty on risk preferences. Some studies find an effect and others do not. We argue that two types of background uncertainty should be distinguished: background risk and background uncertainty. If one makes this distinction, a much clearer pattern emerges: background risk has a smaller effect on risk preferences than background ambiguity.

We conducted four experiments and tested how consistently background uncertainty alters risk preferences, and whether the type of background uncertainty matters. In two of four studies, we found strong support for the hypothesis that introducing background uncertainty increases risk aversion. One of four studies provided only weak support for the hypothesis, and the last study failed to reveal the effect at all. Together, the results show an effect of background uncertainty on risk preferences, but the effect is small and seems to depend on the measure used to elicit risk preferences and the type of uncertainty (risk or ambiguity).

In line with our hypothesis derived from the review of the economical and psychological literature, we found background ambiguity has a stronger effect on risk preferences than background risk. The findings of the four studies suggest that risk preferences, revealed through binary choices, are not solely a function of those options, but they are also affected by the context in which these choices are presented and not just properties of the options themselves like framing effects (de Martino et al., 2006). Our finding, that uncertainty which is unrelated to the decision itself, i.e., background uncertainty, alters decisions is in line with the proposition that risk preferences are constructed at the moment of the decision (Mata et al., 2018; Pedroni et al., 2017), and are trait-like (Frey et al., 2017).

In psychology, it is assumed that traits, while being relatively stable, underly a certain degree of variation which is caused by variations in the situation (Fleeson, 2001, 2007). Thus, our findings support the general assumption in psychology but oppose the frequently held assumption in economics, that risk preferences are stable over time. However, our findings are in line with the recent proposition by economists that risk preferences should be considered parameters in a distribution that is affected by situational factors (Schildberg-Hörisch, 2018). Our findings add background uncertainty as a situational factor that influences risk preferences

next to aspects such as framing the decision in terms of gains and losses (Kahneman & Tversky, 1984), or the labeling of choices as an insurance or a gamble (Johnson et al., 1993).

Our results also indicate that domain specificity of risk preferences (Weber et al., 2002) may not be a sufficient explanation for the lack of predictive validity of behavioral measures on actual behavior or self-reports (e.g., Dohmen et al., 2005; Frey et al., 2017). Behavioral differences might also be explained by the difference in perceived background uncertainty. This may be especially important when decisions are made in real-world settings.

It has been assumed that decision processes underlying the choices might differ depending on the task used (Mata et al., 2018; Tisdall et al., 2020). This fact may explain why some measures are more likely than others to be affected by background uncertainty. Whereas lottery decisions might be rather sensitive to small changes in the underlying risk preferences, behavior in the real world might be more elastic, i.e., less sensitive to changes in the underlying risk preferences. The large effects from Study 1 can be explained by the fact that the expected values of the binary options are equivalent. As a result, a small change in the risk preference leads to qualitatively different choices. We also see this effect in the multiple price list decision in Study 4, where background uncertainty shifted the choices by one row, which is a small but consistent effect across participants. In both tasks, the decision concerns clearly defined probability and consequences, which might be sensitive to the context. The decisions in the BART or BRET in Study 3 and Study 4 respectively, were not influenced by the context, which may be because the options are less clearly defined, and the decision making task is repeated. This may in turn mean that participants might become more immersed in the task, or the task provides a more fine-grained measure of the risk preference. Furthermore, our findings in Study 4 show, consistent with Holzmeister and Stefan (2020), that risk preferences differ between

measures. Our results also indicate that the effect of background uncertainty differs between measures, i.e., different measures yield different background uncertainty elasticities. Future research should investigate if decisions between a lottery and a safe payoff with the same expected value are particularly susceptible to effects of background uncertainty.

It has been shown that uncertainty alters choice by altering the underlying neurological processes (Weber & Johnson, 2008). So far research has mostly focused on uncertainty inherent in the decision options and found that it increased risk aversion (Feldmanhall et al., 2016). We add to this research by showing that also uncertainty in the environment increases risk aversion. The influence of such background uncertainty may be explained in two ways: it alters the reward system which could be an effect at the neuronal level (Critchley et al., 2001; Singer et al., 2009) or it could influence risk preferences on a more general level by altering the information processing in the endocrine system. In that vein, it has been observed that individuals exposed to high levels of environmental uncertainty have high levels of cortisol which should in turn result in higher risk aversion (Coates & Herbert, 2008). Future research could use the concept of background uncertainty toward a better understanding of how and when choices are altered by specific or more general neurological processes.

Limitations and Future Research

We only used between-subjects designs, thus our results rest on the assumption that our randomly allocated experimental groups did not differ regarding their risk preferences, so the observed differences are due to the experimental manipulation. Our interpretation of the results also rests on the assumption, that our manipulation actually induced a heightened feeling of uncertainty. However, we did not measure if this was the case.

We did not examine the effect of unfair background uncertainty or uncertainty that could result in real losses. Background uncertainty in the field studies was characterized by the possibility of losses due to natural disasters and unfair background risk in the laboratory was induced through skewed payoff distributions with a higher likelihood of losses (Lusk and Coble (2008) – and found a significant effect of background risk. Possibly our manipulations in studies 3 and 4 were too weak to elicit a response as strong as in Study 2 Future research should strive to measure a wider range of background uncertainty variations and use strong induction methods, such as background lotteries which involve losses.

Conclusion

We reviewed research from economics and psychology on the effect of background uncertainty on risk preferences. We argue that heterogeneity of observed effects is due to the different types of background uncertainty investigated in the studies. With four experiments, we tested whether background uncertainty breeds risk aversion and if the type of uncertainty moderates the effect of background uncertainty on risk preferences. Our results suggest a small but consistent positive effect, that is background uncertainty increased risk aversion. The type of background uncertainty, however, seems to have moderated the observed effects: background ambiguity as compared with background risk resulted in a stronger increase of risk aversion. We also found that measures of risk preferences differed regarding their background uncertainty elasticity as some measures reacted strongly to added uncertainty whereas others were more robust and did not change.

Acknowledgments

We thank Valentin Baumann for conducting Study 1 as part of his BSc. Thesis. We thank Lucas Braun for supervising Study 3.

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