Erasmus Universiteit Rotterdam

Erasmus School of Economics

A Master Thesis, submitted to the

Erasmus University Rotterdam

Erasmus School of Economics

Master thesis programme Behavioural Economics

The effect of emotion on judgement capabilities in risky choice situations

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Date: 09-03-2022

Wordcount: 9367

Abstract

Previous research found that an individual's emotional state affects their risk-taking behaviour. A person in a positive emotional state is expected to behave in a more risk-seeking way. Whereas plenty of research exists on this matter, research on people in a negative emotional state is lacking. It is however expected that people in such an emotional state tend to avoid risk. Moreover, this research has aimed to find whether the experienced weather has an intensifying effect on the emotional state. By means of a survey, data on self-reported emotion and self-reported weather was collected from 144 subjects. This data was then analysed with use of several regression analyses. Contradicting previous literature, an adverse association between positive affect and risk-taking behaviour was found. For negative affect, the results found were statistically insignificant. These findings are discussed in relation to previous literature and further suggestions for future research are made.

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1. Introduction

As a society, we are more than ever concerned with the assessment of risky choices, considering health situations (due to Covid-19), investment situations and even safety with regards to, for example, terrorism and war. Affective state is known to influence judgement and information processing under certainty and uncertainty. Most findings within this domain suggest that people engage in more systematic processing when in negative emotional states or moods, whereas people in positive moods or emotional states engage in more heuristic processing. The relevance of findings on the consequences of affective state on judgement in risky choice behaviour can be widely interpreted. First, betting behaviour of individuals can be analysed and predicted in hindsight, or this behaviour could even be influenced beforehand. Moreover, in economic choice moments with uncertainty, such as investing in the stock market on individual level or even mergers and acquisitions on corporate level, behaviour can be predicted, stimulated, and analysed. Lastly, general behaviour in risky situations can be analysed further and expectations can be formed on the overall influence of emotion on risky choices.

To this date, most research on the effect of an affective state on the decision-making process has been with relation to positive emotions. Moreover, the vast majority of research is related to risk-attitude in situations with positive outcomes. A lack of knowledge and clarity, however, exists with regards to the effect of a negative affective state on judgement in risky choice situations and the effect of emotions on risk-attitudes in negative outcomes. The latter is difficult to examine, as people tend to hide their negative emotions for outsiders. Sommers (1984) discovered that people who display negative emotions are perceived to be less liked, less social, and less popular than those who do not. Based on the data Sommers argues that the acceptable emotional range appears to be narrow, strongly favouring positive affective experiences. A possible way of examining negative affective states more precisely would be to induce negative emotions upon subjects. This, however, is often found to be unethical. This research attempts to uncover possible association between both positive and negative affect on behaviour in risky choice situations, by researching;

"*The effect of emotion on judgement capabilities in risky choice situations*"

In addition, research also lacks possible mediators between affect and risk-taking behaviour. For a third factor to be of influence on the relation between two other variables, it does not have to influence both variables directly. These variables could be of moderating nature, strengthening, or weakening the relation between two variables. Moreover, suppressing variables could increase the predictive validity of another variable when included in a regression equation. Natural occurrences, and the weather specifically, are found to influence an individual's state of mind (Connoly, 2013). Results of a study that finds an association between the weather and a person's willingness to take risks could be relevant for multiple reasons. Firstly, it could partially explain a difference in risk taking behaviour between different regions, allowing for policy makers to adapt regulations accordingly. Moreover, insurance companies could, to a certain degree, adapt their rates according to the results of such a study. Besides the difference between regions, a study on the mediating effect of experienced weather on risk-attitude could possibly give explanations for different behaviour in different periods of the year. If the weather is found to be of significant influence on the intensity with which affect is experienced, this could have an aggravating influence on risk taking behaviour in certain periods of the year. Sunshine and temperature are known to influence affective states (Kööts et al., 2011 & Clark et al., 1988). Granted that either of those conditions significantly influenced an individual's affective state, such a factor could by use of mediation then influence risk attitude. For policy makers, but also for insurance companies or (online) casinos, this could lead to different strategies that could be adapted to the period of the year. So, by adding such a natural occurrence to the equation, this research could add to the existing literature, by answering the sub-hypothesis;

"Does experienced weather increase the intensity of the experienced affective state, amplifying its effect on risk attitude?"

2. Theoretical basis

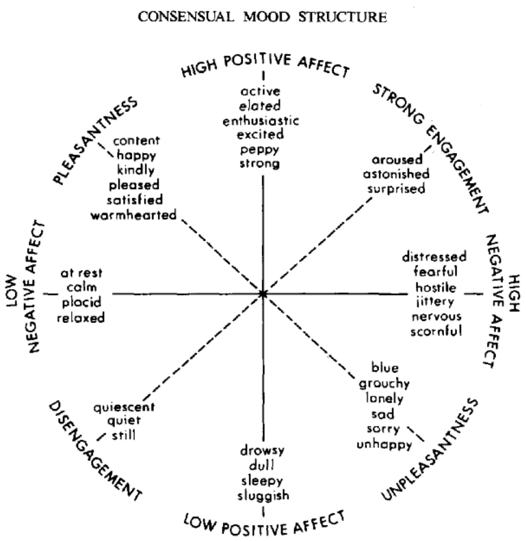
In behavioural economics, the study of economics which applies psychological insights into human behaviour, bounded rationality is one of the key building blocks. The concept of bounded rationality is based on the idea that the cognitive, decision-making capacity of humans cannot be fully rational because of several limits that we face (Simon, 1990). One of the limits that humans face in this concept are emotions, which cloud judgement of choices that can otherwise be made rationally (Jones, 1999). Psychological literature suggests that human passion, otherwise known as emotional or affective states, can impart a series of biases and irrationalities into human behaviour (Kaufman, 1999). In many of the initial economic theories emotions are largely overlooked, as those theories are based on the rational agent. However, an abundance of empirical evidence shows that this idea of fully rational actors is highly inaccurate (Thaler, 1991). In Simon's theory of bounded rationality, he introduces a number of cognitive constraints, such as limited computational ability and selective memory and perception. Kaufmann (1997), through illustrations, adds an additional source of bounded rationality. This bounded rationality arises from insufficient or excessive emotional arousal, so a change in affective state. Moreover, an individual's risk-taking tendencies are considered to develop and change over time (Boyer, 2006). Effectively, this means that an individuals' course of action in precarious situations is not necessarily stable over time. If the influence of affective state on decisions in risky situations is found to be significant, this effect could show a factor of stability in the long-term behaviour of individuals.

2.1 Definition of affective state

Despite a significant body of research dedicated to the study of affective state, there is little consensus on the most basic principles of affect. It is agreed however, that mood and emotion are both a part of the affective state (Schnall, 2010). Although similar in some respects, there are differences between mood and emotion based on their object and temporal constraints. Emotions are formed by both external and internal stimulus events that are relevant to the individual. Moreover, the duration of emotions must be relatively short, to allow behavioural flexibility, as emotions are easily influenced (Scherer, 2005). Moods on the other hand can often emerge without an evident reason linked to a specific event. To add, they could last for hours, days or even weeks (Frijda, 2000). As the current affective state, which is not influenced by a specific event in the research, will be investigated, the affective states that will be considered for the remainder of this research are more closely related to mood. Additionally, an affective state can be experienced both negatively and positively, depending on the event that has caused the mood over a period (Brewer et al., 1980).

In an attempt to characterise affect at the most general level, Watson and Tellegen (1985) have proposed a basic schematic approach, which is depicted in Figure 1.

Figure 1.



Words that are 90° apart are essentially unrelated, whereas words that are placed opposite of each other are also opposite in meaning. Generally speaking, Watson and Tellegen (1985) conclude that Positive and Negative affect can be interpreted as higher order dimensions that are related to discrete mood states in several theories of emotion. Hence, this research will continue to make use of Positive and Negative affect and the emotions and moods connected to them as defined by Watsen and Tellegen (1985), to analyse the effect on risky choice situations.

2.2 Incorporation of naturally occurring circumstances

Different methods exist in order to incorporate emotional states into research. One of the four basic approaches, as described by Parrot and Hertel (1999), is to make use of naturally occurring circumstances for the purposes of creating temporary emotional reactions. The weather is a naturally occurring circumstance of such kind, as this is an exogenous variable which is proven to have an effect on the intensity with which a person experiences well-being (Connoly, 2013). To determine the magnitude of the effect of temperature on emotional well-being, he found that a temperature of 90 degrees Fahrenheit or higher (compared to 70 degrees Fahrenheit) had a larger effect on the intensity of an affective state than being divorced or widowed compared to being married. Thus, on a rainy, cold day people are more likely to feel less excited (Positive Affect), but also less sad (Negative Affect), whereas on a sunny, hot day people are likely to feel more excited (Positive Affect) but are also likely to feel increased sadness (Negative Affect) (Connoly, 2013). Moreover, Kööts, Realo and Allik (2011) find that temperature has a significant effect on the frequency with which Positive and Negative affect are experienced. Temperature was positively related to Negative Affect, as well as to Positive Affect. This further confirms the idea that weather influences the intensity of affect, with a positive correlation. Moreover, Clark and Watson (1988) found that the amount of sunshine a person actively experiences on a day is also positively correlated with the intensity of affect.

In order to use the self-reported affective state as an independent variable, one must believe that emotional states are conscious. But not all researchers believe that emotional states need be conscious (Ekman & Davidson, 1994), so when analysing the self-reported affective state, the weather could be of interest for exploring whether it influences the intensity of the experienced affective state and the risk taken.

Hypothesis 1; "The experienced weather increases the intensity of the experienced self-reported affective state, amplifying its effect on risk attitude".

2.3 Positive affect and risk-taking tendencies

People in a positive emotional state have an increased expected risk-taking tendency, in case of positive outcomes (Nygren et al., 1996). This is also supported by most research on the effect of emotion on behaviour in certainty and uncertainty situations. Additionally, positive affect signals that the situation is safe and, thus, general knowledge constructs are a sufficient basis for judgement (Bless et al., 1996; Tiedens et al., 2001). Moreover, with the mood priming effect an individual becomes more vulnerable to access thoughts about the positive aspects of the risky situations than those in neutral affective state. Hence, in the way of evaluating such a risky situation, people would perceive the outcomes more favourable than people in a neutral emotional state. Besides being willing to take more risks, individuals with a positive mood cue are also more likely to overestimate probabilities of winning when it comes to a neutral-to-positive situation. This supposed overestimation is not expected to be carried on towards negative material situations, as there are hardly any positive cues in such a situation. However, positive affect can result in ‘cautious optimism’ causing an underestimation of the probability that a negative outcome occurs (Nygren et al., 1996). Based on this, it is expected that subjective utility information rather than the objective probability information of the potential outcome is more salient and significant in the decisions of people with positive emotions (Isen et al., 1988).

When it comes to negative expected outcomes, people in a positive emotional state are as a matter of fact more likely to self-protect and behave accordingly, by choosing a more conservative option in real life situations, where losses can be real and meaningful (Isen, Nygren & Ashby, 1988). This is explained by literature which suggests that people who are happy are more motivated to maintain their feeling of happiness. Thus, they feel like they have more to lose than people in a neutral or negative state of mind, as their reference point is adapted. This can also be explained with respect to subjective expected utility theory, as greater disutility is connected to outcome of losses, especially for the reference point of an individual with a positive emotion. Evaluation of negative material is not biased upwards by positive affect, and, in fact, we know that negative outcomes, once they are focused upon, actually seem worse to people in positive affect states (Nygren et al., 1996).

In hypothetical situations, however, positively affected individuals are still more likely to show risk-seeking behaviour as the chances of experiencing real losses are still relatively low (Arkes, Herren & Isen, 1988).

Hypothesis 2; “Individuals in a positive affective state tend to take more risk than those in a neutral state”.

2.4 Negative affect and risk-taking tendencies

Whereas there is plenty of research on the influence of positive affect on risky choice situations, not as much was written on negative affect. It is known, as Jorgensen (1996) states, that people in a negative emotional state are more likely to view the world as threatening, causing them to carefully process information, in order to avoid possible loss. The "affect as information" approach argues that when negative affect is induced, a situation is evaluated as threatening to the achievement of desired goals, thus, this situation requires systematic and attentive processing. People in a negative affective state would thus be more likely to make a conservative decision. However, different emotional states can lead to different behavioural responses. It is expected that, for example, anger and disgust (both considered negative emotions) would have opposite effects on risk taking, since anger functions to deter transgression through aggression, while disgust functions to ward off contamination (Fessler et al., 2003). Hence it is of utmost importance to correctly determine the induced emotion in an experiment, before coming to conclusions. Contradicting, the 'mood repair hypothesis' (Morris & Reilly, 1987) explains that people with a negative state of mind are supposedly preoccupied with repairing this negativity and are thus more likely to take a risk in a situation with positive outcomes. Sadness is one of the emotions, found by Raghunathan and Pham (1999), which supports this 'mood repair hypothesis'. Similar to the situation with positive affect, this could be explained by SEU, as individuals who are feeling bad view a potential gain as more pleasant, because they not only win but they also elevate their negative emotional state. When it comes to estimating probabilities, negatively affected individuals are more likely to pessimistically view the probability of a gain, compared to people in a neutral emotional state. This can partially be explained by mood congruent theory, which states that when humans store memories, they not only store the event, but they also store a memory of the mood they were in at the exact time of that event, creating a vicious cycle of negativity (Isen et al., 1978)

Hypothesis 3; "Individuals in a negative affective state tend to take less risk than those in a neutral state".

3. Method

In the experiment conducted to gather the necessary data, subjects have been asked to fill in a Qualtrics survey. A cross-sectional survey set-up was used in order to measure self-reported affective state, demographics, and the experienced weather conditions. Moreover, all subjects were, by means of lottery questions, asked to elicit an indifference point in a choice list in order to determine their risk attitude.

First of all, some general demographics, such as gender, age and educational level were asked for, in order to be able to provide an accurate description of the research sample. The subjects were then asked to elicit the extent to which they have experienced four different emotions (2 for Negative Affect: sad and fearful, and 2 for Positive Affect: enthusiastic and joyful). The exact way of eliciting emotional states can be found in the appendix. Sadness, fear, and enjoyment were chosen for their relative strength with relation to Positive and Negative Affect as found in Watson & Tellegen (1985). Enthusiasm is included in Watson & Tellegen's affect scale, as a High Positive Affect emotion. Moreover, it is repeatedly used as a high pole for Affective state in another research (e.g., Zevon & Tellegen, 1982; Watson, Clark & Tellegen, 1984). Hence this was the second measure of Positive affect in this research. Kellerman and Plutchik (2013) found that a questionnaire is the right way to overcome possible biases, such as an interviewer bias, when it comes to researching self-reported affective state. In order to reduce the possibility of bias, the questionnaire in this research has been designed similar to that of Kellerman and Plutchik (2013, P.66). Specifically, the first two questions of their subsection *'Description of your emotional reaction'*, have been readjusted slightly and were used to determine the current mood of the subject (one of four options), as well as the intensity which they experience the affective state with. Instead of using the 9-point scale in Kellerman and Plutchik's research, this questionnaire has made use of a Likert scale to determine the intensity, as the data that a Likert scale answer provides can be profitably compared and combined with qualitative data-gathering techniques in the case of self-reported participant observation (Nemoto & Beglar, 2014).

After determining the affective state, subjects were asked to describe the weather which they have experienced based on two questions. The exact questions can be found in the appendix. Both temperature and sunshine were deemed relevant (Connoly, 2013; Kööts et al., 2011; Clark et al., 1988) for the intensity of affect. Hence, the subjects have been asked to rate both the temperature which they have experienced for the past week, as well as the amount of sunshine which they have actively experienced. These questions have both been posed with use of a Likert scale, which has proven to be an effective scale for self-report questions.

Subsequently, subjects were given two multiple price lists (MPL's). To be more specific, a certainty equivalence choice list and a probability equivalence choice list were used, which has allowed for the determination whether a difference between the estimation in terms of money (direct utility) and probabilities exists when it comes to a risky choice situation. Nygren et al. (1996) found a difference in risk taking between the outcome estimates and the probability estimates, so I have also controlled for this. These lists have been used as they are an appropriate way of eliciting 'not induced' self-reported preferences of subjects (Andersen, Harrison, Lau & Rutström, 2006). MPL's have a couple of pitfalls as identified by Andersen et al. First of all, it only elicits interval responses, instead of showing a true point at which risk-preferences change. The second is that subjects can switch back and forth between rows, implying potentially inconsistent preferences. However, this risk has been eliminated, as the subjects in this study were only allowed to choose a switching point once. Thirdly, subjects could be susceptible to framing effects, as subjects are drawn to the middle of the ordered table irrespective of their true values. If specific boundary values at either end of the table are used, these could signal to the subject that the experimenter believes that these are reasonable upper and lower bounds, hence they will try to find a point that lies somewhere in the middle. This effect is not as strong in a task where probabilities are given, as the probabilities are, by law of nature, bounded between o and 1. Therefore, the first and last values are not recognized as reasonable upper and lower bounds (Andersen, Harrison, Lau & Rutström, 2006).

Table 1, (taken from Andersen, Harrison, Lau & Rutström, 2006, P. 388) shows the first choice list that has been presented to the subjects. This choice list was first presented by Holt and Laury (2002). Expected values are given in the fourth and fifth column. These two columns, as well as the last column which shows the difference between the expected outcome of lottery A and B, were not shown to the subjects. The subjects have been asked to indicate the point at which they would consider switching from Lottery A to Lottery B, or vice versa.

Table 1: Payoff Matrix from the Holt and Laury Risk Aversion Experiments (Holt and Laury, 2002)

Lottery A				Lottery B						
p($2)		p($1.60)		p($3.85)		p($0.10)		EV^A	EV^B	Difference
0.1	$2	0.9	$1.60	0.1	$3.85	0.9	$0.10	$1.64	$0.48	$1.17
0.2	$2	0.8	$1.60	0.2	$3.85	0.8	$0.10	$1.68	$0.85	$0.83
0.3	$2	0.7	$1.60	0.3	$3.85	0.7	$0.10	$1.72	$1.23	$0.49
0.4	$2	0.6	$1.60	0.4	$3.85	0.6	$0.10	$1.76	$1.60	$0.16
0.5	$2	0.5	$1.60	0.5	$3.85	0.5	$0.10	$1.80	$1.98	−$0.17
0.6	$2	0.4	$1.60	0.6	$3.85	0.4	$0.10	$1.84	$2.35	−$0.51
0.7	$2	0.3	$1.60	0.7	$3.85	0.3	$0.10	$1.88	$2.73	−$0.84
0.8	$2	0.2	$1.60	0.8	$3.85	0.2	$0.10	$1.92	$3.10	−$1.18
0.9	$2	0.1	$1.60	0.9	$3.85	0.1	$0.10	$1.96	$3.48	−$1.52
1	$2	0	$1.60	1	$3.85	0	$0.10	$2.00	$3.85	−$1.85

Note: The last three columns in this table, showing the expected values of the lotteries, were not shown to subjects.

Lottery A is less risky compared to Lottery B. A risk-neutral subject is thus expected to initially choose Lottery A, and to switch at the point where the difference between Lottery A and B becomes negative. Any subject who switched before this point is considered risk-seeking, whereas all subjects who have switched after this point are considered risk-averse. The extent to which someone is considered risk-averse/risk-seeking, can be concluded from the point at which they decide to switch.

Holt and Laury propose this choice list to find the degrees of risk aversion, in a situation with relatively low payoffs. Drichoutis and Lusk (2016) suggest that this choice list is likely to be more accurate at eliciting the shape of the probability weighting function. Therefore, they have designed a different multiple price list that is likely more accurate at eliciting the shape of the utility function, thus the risk attitude. By holding the probabilities constant but changing the monetary payoffs of the lotteries each time, which was also used in an approach by Wakker and Deneffe (1996), Drichoutis and Lurk are able to determine an interval of relative risk aversion. In Table 2 (taken from Drichoutis and Lusk, 2016, P.8), the second MPL is shown. Only the first two columns, Lottery A and Lottery B, have been shown to the subjects. They have, once presented with the PL, been asked to elicit the point at which they would switch from Lottery A to B, or the other way around.

Table 2: Payoff-varying MPL with Constant Probabilities (Drichoutis and Lusk, 2016)

Lottery A				Lottery B				EVA	EVB	Difference	Open CRRA interval if subject switches to Lottery B (assumes EUT)	
p	€	*p*	€	*p*	€	*p*	€	(€)	(€)	(€)		
0.5	1.68	0.5	1.60	0.5	2.01	0.5	1.00	1.640	1.506	0.13	−∞	−1.71
0.5	1.76	0.5	1.60	0.5	2.17	0.5	1.00	1.680	1.583	0.10	−1.71	−0.95
0.5	1.84	0.5	1.60	0.5	2.32	0.5	1.00	1.720	1.658	0.06	−0.95	−0.49
0.5	1.92	0.5	1.60	0.5	2.48	0.5	1.00	1.760	1.738	0.02	−0.49	−0.15
0.5	2.00	0.5	1.60	0.5	2.65	0.5	1.00	1.800	1.827	−0.03	−0.15	0.14
0.5	2.08	0.5	1.60	0.5	2.86	0.5	1.00	1.840	1.932	−0.09	0.14	0.41
0.5	2.16	0.5	1.60	0.5	3.14	0.5	1.00	1.880	2.068	−0.19	0.41	0.68
0.5	2.24	0.5	1.60	0.5	3.54	0.5	1.00	1.920	2.272	−0.35	0.68	0.97
0.5	2.32	0.5	1.60	0.5	4.50	0.5	1.00	1.960	2.748	−0.79	0.97	1.37
0.5	2.40	0.5	1.60	0.5	4.70	0.5	1.00	2.000	2.852	−0.85	1.37	+∞

Last four columns showing expected values and implied CRRA intervals were not shown to subjects

Again, Lottery A is considered less risky compared to Lottery B. A risk-neutral subject is thus expected to switch at the point where the difference between Lottery A and B becomes negative. Any subject who switches before this point is considered risk-seeking, whereas all subjects who switch after this point are considered risk-averse. This second task, which our subjects have been presented with, allows for a more detailed estimation of the shape of *U(x)* whereas the first task gives a more detailed representation of *W(p).*

The Holt and Laury choice list entails choices made over only four different dollar amounts. A utility function is unique only up to an affine transformation. Accordingly, one must fix two points in the utility curve and can only identify the relative difference implied by the other two. Therefore, this choice list explains relatively little information about the curvature of the utility function. On the other hand, the choice list gives choice over 11 different probabilities. This choice list thus contains more detailed information on the potential shape of the probability weighting function. Oppositely, the Drichoutis and Lusk choice list has more monetary amounts and fewer probabilities to choose from. Consequently, this choice list is better suited to explain the utility function. Hence the combination of both tasks will give us a complete insight into the risk-attitude of subjects.

Lastly, the subjects have been asked to state their understanding of all questions. The understanding of both price lists is especially interesting as these might be more difficult to understand.

In terms of the sample size, an ex-post calculation of the statistical power was opted for as Hoenig and Heisey (2001) show that any significant estimate from a study will, mechanically, exhibit ex post power that is greater than 50%. The ex post optimal sample size based on the R-squared of the reduced and the full model was 171, under the assumption of a default power of 0.8 and significance level $\alpha = 0.05$. This number was reached, however, as a significant part of the observations in the full sample had to be omitted due to missing variables the total number of observations came up short. A detailed analysis of the effect of the lack of observations will be in the discussion of this research.

4. Data

4.1 Demographics

In total, 189 subjects started the survey. However, 45 of those did not manage to complete the entire survey. After removing the data of the unfinished surveys, there were 144 participants left who managed to completely answer the survey. As mentioned, the subjects were first asked to answer some demographic questions, to form a clear view of the subject pool. The age range of the 144 study participants was between 16 and 64 years with a mean age of 26.2 and the majority of the sample aged between 20 and 25[1]. Additionally, 74 of our participants identified themselves as male, 67 as female, two subjects preferred not to declare their gender and one identified as 'other'[2]. In the dummy variables '*male*' and '*female*', the three subjects who identify themselves with something other than male or female will automatically belong to the reference category. Lastly, subjects were asked to answer a question about the highest form of education that they have finished. Almost 70% of the subjects have a university degree of some form (99 out of 144)[3], in my model this will be presented by the dummy variable '*university*', or by the categorical variable '*education*' which allows for more detail as to which specific form of education the subject has completed.

4.2 Weather variables

To create the weather variables in the regression model, subjects had to rate the weather which they have experienced based on the past two weeks. Firstly, subjects were asked to rate the temperature which they have experienced over the last two weeks, based on a Likert scale. The answers to this question were turned into a scale variable

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[1] **Appendix graph 1**
[2] **Appendix graph 2**
[3] **Appendix graph 3**

'*temperature_experience'*, where 1 is extremely unpleasant and 5 is extremely pleasant. Secondly, participants were asked to answer a similar Likert scale variable on their exposure to sunshine, which became the scale variable '*sunshine_experience'.* Together, they were summed together into the scale variable '*experiencedweather'* which runs from 2 until 10, where 2 is extremely unpleasant and 10 is extremely pleasant[4]. In order to measure the strength and direction of the association between the two ranked variables of the Liker-scale questions, the Spearman's rank correlation was used. The Spearman's rank correlation is a preferred option when the measure consists of two items (Eilsinga, Grotenhuis & Pelzer, 2013). Spearman's ρ took a value of 0.4592, showing a positive monotonic relation between the two variables. Moreover, the null hypothesis of independence between the two variables is rejected. As the two variables have positive relation with ranked outcomes, it seems appropriate to combine both variables into one. In order to also test the internal validity of the variables, Cronbach's alpha is tested. The α equals 0.6161 for these two variables. According to a scale by George and Mallery (2003) any alpha above 0.6 is questionable. However, it is known that increasing the number of items in a scale increases alpha with diminishing returns. Hence, reaching alpha above 0.6 in a two-item scale is acceptable (Gliem & Gliem, 2003).

4.3 Affective state variables

To measure the affective states, subjects were asked to report the extent to which they have experienced sadness, fear, enthusiasm, and joy on a Likert scale. All of the affective states are turned into separate scale variables, where one indicates that a subject has barely experienced that emotion, whereas five means that a subject has severely experienced these emotions[5]. In my data I found a restriction of range on the positive affect items, which could be due to a 'ceiling effect' (Diener & Emmns, 1984 P.1114), pushing the subjects to cluster towards the higher end of the measure in positive situations. Oppositely, there is a 'floor effect' for the negative affect variable, as subjects are pushed to cluster towards the lower end of a 'negative' measure.

As described previously in the theoretical basis, sadness and fear should have similar effects on risk-taking attitudes. Hence it is possible to take the sum of the two variables, in order to combine them into one '*negativeaffect'* variable[6], with a scale of 2 to 10. Similar tests as to the combination of weather variables can be used for combined variables of

[4] **Appendix table 1**
[5] **Appendix table 1**
[6] **Appendix table 1**

negative effect. Spearman's ρ has a value of 0.3701 showing a positive monotonic relation between the two variables. Moreover, the null hypothesis of independence between the two variables is rejected. Both variables should thus form a comprehensive combined variable. On the other hand, joy and enthusiasm can be combined into one 'positiveaffect'[7] variable. This is done by taking the sum of the individual variables. Spearman's ρ has a value of $\alpha=0.6$ showing a strong positive monotonic relation between the two variables. Again, the null hypothesis of independence between the variables is rejected, so the positive affect variables should form an informative combined variable.

For both pairs of items, Cronbach's alpha was also tested to check the internal validity of the items. Enthusiasm and joy got a reliability coefficient of 0.769, which in George and Mallery's (2003) scale is seen as acceptable (close to good). Fear and sadness reached a reliability coefficient of 0.5164, which is fairly low. However, considering there are only two variables in the scale and the Spearman's rho is

4.4 Risk attitudes

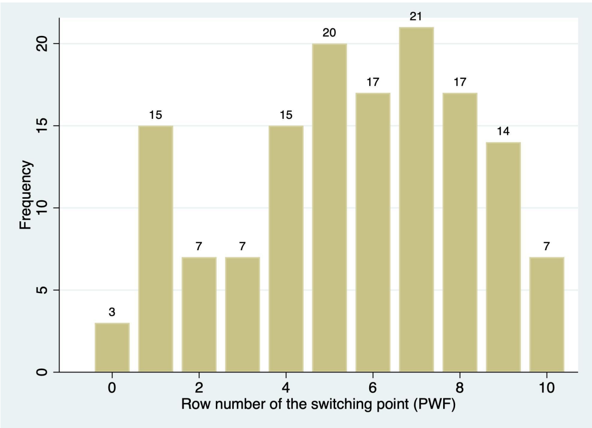
Risk attitudes are determined through the multiple choice lists in the survey. Subjects are asked to choose between two lotteries, similar to the lotteries in Holt and Laury (2002) and Drichoutis and Lusk (2017). Participants move along a path of decision, in order to determine at what point in the table they would switch from Lottery A to Lottery B. This switching point represents the risk-taking attitude for a subject. When a subject chooses Lottery B immediately in the first row, their switching point is denoted as 1, as their switching point apparently has been reached in the first row. If a subject chooses Lottery A in row one, but Lottery B in row 2 the switching point is denoted as 2, as the switching point is situated in the second row. This is repeated for every row in the table. A lower value for the switching point is equivalent to a more risk-seeking attitude, whereas a higher switching point relates to a more risk averse attitude. If a subject decides to stick with Lottery A throughout the entire path, his or her risk attitude will become 0. In this last row the obvious choice would be Lottery B, because the absolute value in B is higher than in A. If someone still chooses A in that row, their risk attitude will thus become 0, as they seem completely unwilling to consider switching to lottery B even though the risk in this choice set has been reduced to zero. An individual who consistently chooses lottery A breaks the monotonicity assumption, as they prefer a sure gain of €2 over €3,85. This is found more frequently in

[7] **Appendix table 1**

relation with expected utility theory (Ingersoll, 2008). A more detailed explanation of the possible issues with nonmonotonicity will be available in the discussion section

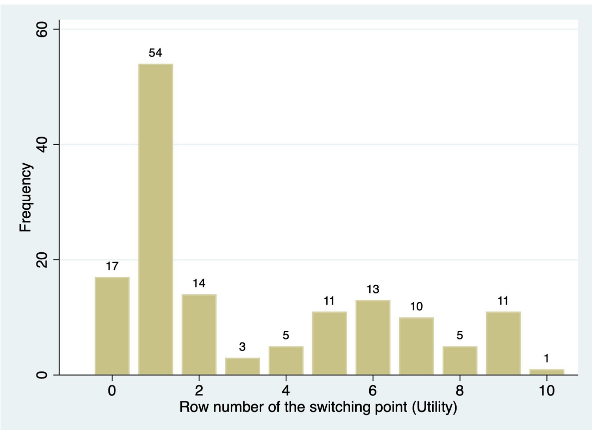
This way of eliciting switching points works for both the utility focused MPL (Drichoutis & Lusk, 2017) and the probability weighting function (PWF) focused MPL (Holt & Laury 2002). Histograms of the switching points shows us that in the Holt and Laury MPL, the risk preferences are clustered towards the centre (a switching point/risk attitude of 5) with a slight skewness to the right, as can be seen in the histogram below. In terms of behaviour, this histogram shows that for the PWF choice list individuals behave slightly risk seeking than a switching point of 5, which would be risk neutral. There are 15 extreme outliers who choose to seek the maximum risk.

Graph 1; Histogram of switching points (PWF)



On the other hand, for Drichoutis & Lusk choice list the preferences are clustered towards earliest rows. In the constant-probability task, subjects appear to be risk loving, whereas in the traditional H&L task, they appear to be risk averse. Interesting to note is that Drichoutis and Lusk, when they first introduced this MPL, found that over half of their subjects chose lottery B in the first row.

Graph 2; Histogram of switching points (Utility)



5. Results

5.1 Correlation between weather and emotion

Table 3 shows the correlation between the weather variables, the negative affect variables and the combined positive affect variable. The variables sad and fearful were analysed separately because of their opposing relations with the weather variable. On the other hand, the positive emotions were combined as their effects were very similar. Most noticeable are the different signs in the correlation of the variable sad with temperature (negative) and sunshine (positive), which was not expected. However, the correlations were not found to be significant on a 10% level.

Table 3; Correlation table weather

Variables	Sunshine	Temperature
Sad	0.044	-0.008
Fearful	0.113	0.035
Positive affect	0.040	0.143

**** p<0.01, ** p<0.05, * p<0.1*

In addition to the correlation matrix, four linear regression models provided the effects of the experienced weather variables on the way in which subjects denoted their own emotional states. This enables us to identify whether a change in the self-reported weather experience could lead to a change in the self-reported emotional state, as predicted in the first hypothesis. Hypothesis one expected that a more intense experience of the weather increases the intensity of the experienced effect. For the simplified Positive Affect model, the way in which subjects experienced sunshine has a significant positive effect. This means that the positive emotions are intensified in case subjects believe that they have experienced more sunshine. However, in the full model, which included three control variables (age, a dummy for male/female and a dummy for whether a subject went to university) none of the variables seemed to be significant.

For the simplified Negative Affect model, neither of the weather variables were significant. This would mean that the subjective assessment of the weather does not influence the negative emotional state of the participants. In the full model, the significance for the experienced weather variables does not change. However, two of the control variables do show significant results. An increase in age of one year decreases the experienced negative affect by 0.039 points on a scale of 2 to 10 with a 10% significance level, ceteris paribus. Moreover, being male compared to being female also decreases the experienced negative effect by .603 points on a scale of 2 to 10 with a 10% significance level, ceteris paribus. To give further explanation, an increase in age and being male compared to being female decrease the experienced negative affect. This does not necessarily mean that the overall emotional state is also more positive. It merely means that the negative affect variables are experienced less intensely. Moreover, a low adjusted R-squared indicates underfitting and adding additional relevant features or using a complex model might help. To add, additional observations could increase the goodness of fit of the current model. Adjusted r-squared was used to be able to interpret the differences in r-squared between the models, without the additional variables affecting the r-squared. Effectively, the adjusted r-squared shows that the models are not good enough to predict the dependent variable, but merely allows for understanding of the relationship between the independent and dependent variables.

Table 4;
Experienced Weather Regression Table

	Positive Affect	Positive Affect (full)	Negative Affect	Negative Affect (full)
Experienced Temperature	.223*	.21	-.065	-.023
	(.132)	(.134)	(.165)	(.161)
Experienced Sunshine	-.038	-.046	.147	.176
	(.102)	(.103)	(.127)	(.124)
Age		.006		-.039**
		(.013)		(.016)
Male		.201		-.603**
		(.251)		(.302)
University		.055		.061
		(.272)		(.327)
Cons	7.45***	7.203***	3.977***	5.06***
	(.35)	(.491)	(.437)	(.59)
Observations	142	142	142	142
Adj R^2	.007	-.007	-.005	.055

Standard errors are in parentheses

*** $p<.01$, ** $p<.05$, * $p<.1$

5.2 Risk attitudes

Examination of the switching point variables with use of linear regression models showed us the coefficients and significance of the affect variables and several control variables, independently and conditional on the experienced weather. This examination allows for a more in-depth analysis of the risk attitudes of the subjects. Based on the literature, people in a positive emotional state are expected to show an increased risk-taking tendency, hence the positive affect variable should cause a decrease in the switching point variable and thus an increased risk attitude. This was represented in hypothesis two. On the other hand, people in a negative emotional state show more conservative behaviour, hence the negative affect variable should cause an increase in the switching point variable and thus a decreased risk attitude, which was predicted in hypothesis three. A distinction between the switching points elicited by the Holt & Laury choice list and the Drichoutis and Lurk choice list were made, as the latter is better suited to explain utility preferences whereas the first is more accurate in providing a subject's probability weighting function. Nevertheless, the outcomes are expected to be quite similar for both choice lists.

Firstly, Holt and Laury's choice list is examined in five different linear regressions. All of them use adjusted r-squared to determine the reliability of the correlation and how much it is determined by the addition of independent variables. As mentioned previously, this choice list is best suited to determine the probability weighting function of subjects, rather than the utility curve. Generally, the dependent variable can be interpreted as a risk-attitude on a scale of 0 to 10. If the dependent variable approaches zero, the risk-attitude can be considered risk-averse. On the other hand, as explained by Drichoutis and Lusk, for a person with risk-neutral preferences a low value for the dependent variable could mean that they weight probabilities non-linearly.

To examine the effects of the independent variables of interest, they are tested separately as well as combined (Table 5). The models with one independent variable show the crude effects of these variables and the others show adjusted effects. The crude models show very different results. Contradicting the literary prediction, positive affect shows a positive coefficient with a significance at the 5% level. It is predicted that, if positive affect increases by 1 on a scale of 2 to 10, the switching point increases by 0.371 points, ceteris paribus. This shows that people in a more positive emotional state are likely to behave more conservatively compared to individuals in a neutral or negative emotional state. On the other hand, negative affect also shows an unexpected (negative) sign of the coefficient. However, this coefficient is not significant at 10% level, so it cannot be interpreted correctly.

In the adjusted models which follow, the coefficient for positive affect stays very similar to the coefficient in the first model. Moreover, it remains significant at the 5% level. On the other hand, negative affect remains insignificant in the adjusted model. The coefficient is very close to zero for two of the adjusted models and is negative in the full model. Besides the affect variables, the first full model includes three control variables (age, male and university). This model shows a significant effect for age at the 10% level, with a coefficient of -0.044. In other words, as age increases by 1 year, the switching point moves down by 0.045 points, ceteris paribus. Accordingly, age seems to increase the risk-taking tendency. Moreover, whether or not a subject went to university has a significant positive effect on the switching point. Going to university increases the switching point variable by .961compared to not going to university at a 10% significance level, ceteris paribus. In addition, this means that going to university, on average, decreases the risk-taking tendency.

The second full model uses the same variables, however, it is conditional on the self-reported experienced weather. Both self-reported weather variables have to be equal to 3 or more, as the intensity of affect should be positively correlated with the exposure to sunshine and higher temperatures. Consequently, the coefficients of Positive and Negative affect are expected to be more extreme in the final model.

In the final column of Table 5, this increased intensity is represented in the values of the coefficients of both affect variables. The expected positive correlation between the weather and affect is shown as the sign of the coefficients does not change and both coefficients become more extreme. Even though the level of significance decreases slightly, positive affect still shows a positive coefficient with a significance at the 10% level. It is predicted that, for individuals with positive exposure to sunshine and temperature, if positive affect increases by 1 on a scale of 2 to 10 the switching point increases by 0.524 points, ceteris paribus. Negative effect remains insignificant but has a more extreme coefficient.

Both affect coefficients show unexpected signs. An increase in positive affect was expected to increase risk-taking. Hence, a negative coefficient was expected. Oppositely, the conservative behaviour connected to a more negative emotional state was expected to result in a positive coefficient.

Table 5;

Switching point (PWF)
Regression table

	Switching point (positive)	Switching point (negative)	Switching point (affect)	Switching point (full)	Switching point (full, conditional on intense weather experience)
Positive affect	.371**		.373**	.378**	.524*
	(.153)		(.154)	(.153)	(.302)
Negative affect		-.012	.017	-.029	-.23
		(.126)	(.124)	(.127)	(.236)
Age				-.044*	-.065
				(.024)	(.039)
Male				.015	-.223
				(.451)	(.836)
University				.947*	1.134
				(.488)	(.903)
Constant	2.632**	5.613***	2.542*	3.194**	3.33
	(1.226)	(.581)	(1.389)	(1.554)	(2.882)
Observations	142	142	142	142	51
Adj R^2	.034	-.007	.027	.081	.139

Standard errors are in parentheses

*** *p<.01,* ** *p<.05,* * *p<.1*

Secondly, the Drichoutis and Lusk choice list is examined to see whether a task that is more focussed on utility gives similar results to the task that explains more about probability weighting function. Similar to the Holt and Laury choice list, this choice list is also examined in five different linear regressions. All of them use adjusted r-squared to determine the reliability of the correlation and how much it is determined by the addition of independent variables. The dependent variable is similar to that of the previous regressions, except for the different choice lists that were used to collect the data for the switching rows.

Most noticeably, there are no significant coefficients and the adjusted r-squared is either negative or very close to zero for all models. Hence, the coefficients of the variables cannot be interpreted correctly. Interesting to notice is that positive affect does have a negative coefficient in the full and the conditional model, whereas negative affect still has an unexpected sign in front of the coefficients.

Table 6.
Switching point (Utility)
Regression table

	Switching point (positive)	Switching point (negative)	Switching point (affect)	Switching point (full)	Switching point (full, conditional on intense weather experience)
Positive affect	.026		.008	-.001	-.169
	(.174)		(.174)	(.176)	(.331)
Negative affect		-.151	-.151	-.136	-.113
		(.14)	(.141)	(.147)	(.259)
Age				-.008	.033
				(.027)	(.043)
Male				.563	.839
				(.518)	(.916)
University				-.324	-.98
				(.561)	(.99)
Constant	3.046**	3.897***	3.828**	4.022**	4.765
	(1.394)	(.644)	(1.573)	(1.787)	(3.159)
Observations	142	142	142	142	51
Adj R^2	-.007	.001	-.006	.021	.062

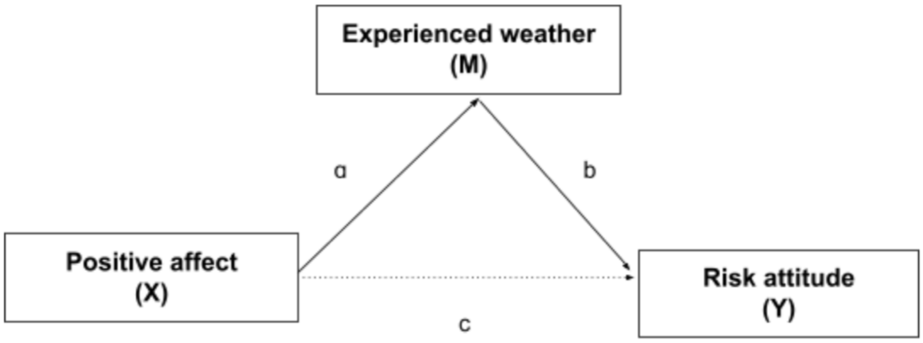
Standard errors are in parentheses

*** *p<.01,* ** *p<.05,* * *p<.1*

5.3 Mediation analysis

The procedure of a mediation analysis is one way that a researcher can explain the process or mechanism by which one variable affects another. Mediating variables are behavioural, biological, psychological, or social constructs that transmit the effect of one variable to another variable (MacKinnon, Fairchild, & Fritz, 2007). In this research, that would be the effect of experienced weather on affect, which transmits this effect on to risk attitude. The following scheme provides a visual explanation of this;

Figure 2. Schematic of mediation analysis



A mediator is a variable that is in a causal sequence between two variables. In the case presented above, this mediator variable would be experienced weather. Baron and Kenny's (1986) establish that the first step in mediation analysis is to probe that the independent variable X has a significant zero-order effect on the dependent variable Y. It might seem logical to assume that, if there is no impact to be mediated, there is no purpose in continuing to investigate whether the effect of X on Y is mediated by M. In this original approach, all coefficients of the following regression functions should be significant;

$$M = i_1 + aX + e_1. \qquad \textbf{(1)}$$

$$Y = i_2 + c'X + e_2. \qquad \textbf{(2)}$$

$$Y = i_3 + cX + bM + e_3. \qquad \textbf{(3)}$$

Baron and Kenny state that to establish mediation, the following conditions must hold: “first, the independent variable must affect the mediator in the first equation; second, the independent variable must be shown to affect the dependent variable in the second equation; and third, the mediator must affect the dependent variable in the third equation”. (1986) However, this statement is incorrect. To prove mediation, there does not need to be a strong zero-order influence of X on Y (Zhao, Lynch & Chen, 2010). Moreover, Hayes (2017) finds that it is possible to state that the product of path a and b is significantly different from 0, even though one of the paths itself might not have a significant coefficient. Table 7 shows the results of the different regression functions shown above. Model 1 provides the coefficient for path a (function 1). Model 2 shows the relation between the X variable and the Y variable (function 2), whereas model 3 shows coefficients for the mediation effect of the M variable (function 3).

Table 7. Mediation analysis

	Experienced Weather	Switching point	Switching point
Positive affect	.14	.371**	.357**
	(.12)	(.153)	(.154)
Experienced weather			.102
			(.108)
Constant	4.403***	2.632**	2.181*
	(.96)	(1.226)	(1.316)
Observations	142	142	142
Adj R^2	.003	.04	.047

Standard errors are in parentheses

****** p<.01, ** p<.05, * p<.1*

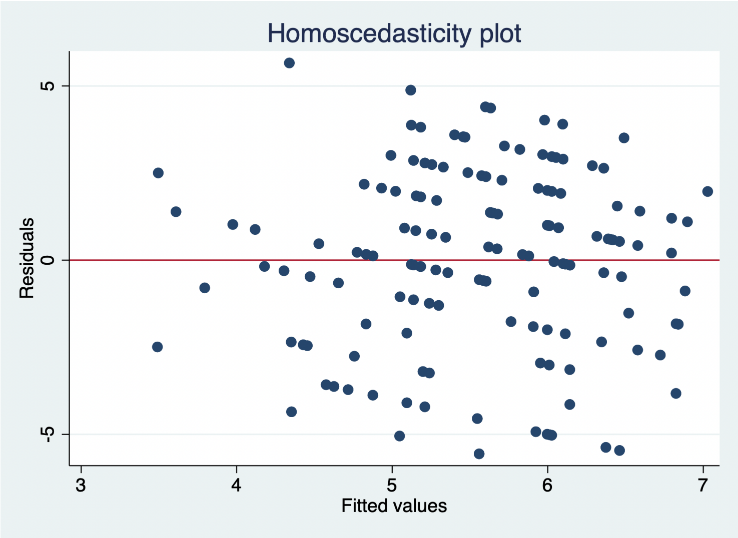
From these regression results it is found that there is a significant direct effect of our X variable on our Y variable (c' from function 2). However, there is no significant relation between the X variable and the M variable (path a). Moreover, there is no significant effect found in the relation between the mediator variable and dependent variable (path b). Based on the decision tree by Zhao, Lunch & Chen (2010)[8] and by performing a mediation analysis in STATA[9], a direct only non-mediation effect is found. This means that the direct effect (path c0 is found to be significant, but no mediation is found. Hence, we can conclude that there is no association between the weather and behaviour in risky choice situations.

5.4 OLS assumption tests

In order to develop a well-functioning OLS regression, several assumptions have to be met. As only the PWF switching point regressions were found significant, the assumptions will be tested for that full model. Firstly, to check for normality of residuals an IQR test was used (written by Lawrence C. Hamilton, Dept. of Sociology, Univ. of New Hampshire) the detailed result of this test can be found in the appendix[10]. The general result showed that there

[8] Appendix figure 1
[9] Appendix table 3
[10] **Appendix table 4**

are no severe outliers, thus the distribution seems fairly symmetric. The residuals have an approximately normal distribution. Secondly, a test for homoscedasticity is performed. If the model is well-fitted, there should not be a pattern to the residuals plotted against the fitted values. The following plot clearly shows that there is no pattern to be found.

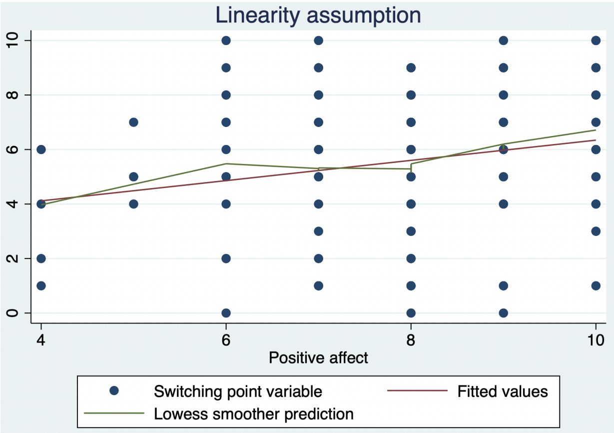


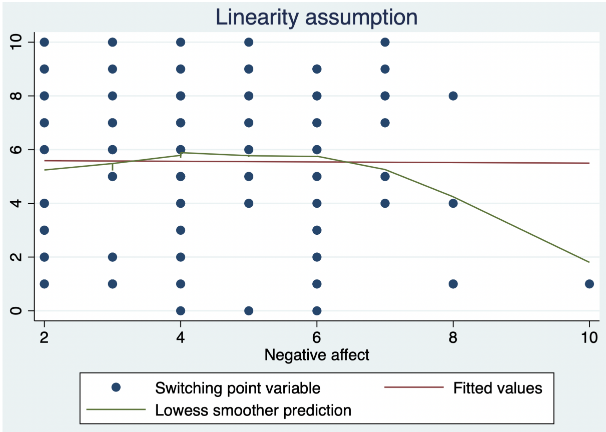
Moreover, a Breusch-Pagan for heteroskedasticity test, assuming normal error terms, is used to test the null hypothesis that the variance of the residuals is homogenous.
As the P-value of the chi-squared test is very high (P=0.9076), the null-hypothesis is not rejected, and homogenous variance is found. Thirdly, the multicollinearity assumption has to be controlled for. A perfect linear relationship among the predictors would cause a regression model to become biased, as the unique estimates cannot be computed correctly. The results of a STATA variance inflation factor test are shown below;

Table 8. VIF

	VIF	1/VIF
Age	1.11	0.898999
Negative affect	1.08	0.922267
University	1.06	0.946109
Male	1.05	0.952178
Positive affect	1.02	0.983902
Mean VIF	1.06	

O'brien (2007) has set a VIF of 5 as an acceptable threshold. Therefore, we can conclude that the regression used in this research shows no multicollinearity. Lastly, in a linear regression it is assumed that the relationship between the response variable and the predictors is linear. This is the linearity assumption, which will be tested by scatterplots of the predictor variables against the dependent variable. Both graphs clearly show a degree of nonlinearity.





6. Discussion

An individual's risk-taking tendencies are considered to develop and change over time. In this research, I have tried to determine a more constant factor which influences this attitude towards risky situations. Historically, affective states are defined by an abundance of mood states describing the specific emotional connection with an occurrence. In order to simplify the basic schematic approach by Watson and Tellegen, Positive and Negative affect are used, as they are higher order dimensions that are related to discrete mood states. In an attempt to find the influence of the aforementioned emotional states on risk tendencies, subjects were asked to complete multiple choice lists based on utility and probability weighting function. Whilst examining the effect of self-determined affective states on these choice lists, the moderating or intensifying effect of the weather on mood states was also researched. In previous literature, the weather was found to have significant effects on the intensity with which emotional states were experienced. The magnitude of the coefficient for positive effect of the sub-sample of individuals who intensely experienced the weather remained significant and was found to be larger than the magnitude of the coefficient of the entire sample. This is in line with the expectations based on previous literature.

Conversely, the second and third hypotheses are not supported by this research. Hypothesis two, expects that individuals in a positive affective state tend to take more risk than those in a neutral state. This is based on previous literature which says that, in the way of evaluating a risky situation, people in a positive emotional state would perceive the outcomes more favourable than people in a neutral emotional state. In terms of the coefficient in our regression analysis, the sign was expected to be negative, as this would lead to a lower outcome for risk-attitude. What we find however, is a positive sign for positive affect in the PWF models. Relating this to previous literature, Isen, Nygren and Ashby (1988) illustrate that for individuals in a positive mood, the relative degree of misery is larger when risking a loss. Thus, a person could consider playing a lottery with a reduced risk in order to exclude this relative degree of misery and maintain a positive emotional state. An individual in such a state could be under the impression that they have a lot to lose, causing them to behave cautiously. Moreover, relating to behavioural economics theories, decision making in risky choice situations makes use of cumulative prospect theory (Tversky and Kahneman, 1992). According to CPT, the utility function has a reference point that represents a current situation, such as wealth level (Gurevich, Kliger & Levy, 2009). Moreover, at the individual level, household wealth has been shown to improve individual well-being. Wealth also affects emotional states through the generated consumption flows that it generates (Senik, 2014). For the aforementioned reasons, it is possible that current wealth has an effect on both risk attitude as well as the positive affect variable in the regression used in this research. Current wealth could be a confounding factor leading to spurious results of the regression.

Hypothesis three predicts that individuals in a negative emotional state experience the world as threatening, causing them to take more cautious decisions (Jorgensen, 1996). This is, however, not in line with the findings of this research. Even though the results are not found to be significant, the negative coefficient contains a similar contradiction as noted in the second hypothesis. Again, relating this back to the article by Isen, Nygren and Ashby (1988) individuals in a negative mood, could experience the relative degree of misery when risking a loss as smaller than individuals in a positive emotional state. Thus, a person could consider playing a lottery with a higher risk in order to have a chance to increase their current emotional state. Simplified, this means that people in a more negative emotional state feel like they have less on the line, so they are more inclined to take a risk.

As mentioned, the negative affect variable was not found to be significant in both the PWF and the utility measuring model. This paper aimed to study the difference between positive and negative emotional states on risk-attitude. Possibly, the lack of results could be due to a disability of recognizing one's negative emotions. In research on emotional intelligence (EI) Fischer, Kret and Broekens (2018) found that people often overestimate their ability to control and recognize their emotional state, causing them to underestimate the negative emotions that they feel. A solution, and direction for further research, could be to split the samples in order to induce negative and positive emotions on the different samples. For ethical reasons, this was not done in this study, although results would be interesting.

Moreover, a clear distinction in significance can be made between the results of the PWF choice list and the utility choice list. In the PWF choice list, subjects were asked to choose from different probabilities, which can easily be transferred to real-life situations. Bostyn, Sevenhant and Roets (2018) find that responses to hypothetical dilemmas are not predictive of real-life dilemma behaviour, but they are predictive of affective and cognitive aspects of the real-life decision. As these situations become closer to real-life decisions, the hypothetical situation becomes more representative. In the utility choice list by Drichoutis and Lusk, subjects are asked to choose between low stakes with constant probabilities. As this situation is strictly hypothetical and the decision over small amounts of money is not a conscious decision in real-life, the outcome of this choice list has less powerful results. A way of improving on this set-up would be to either increase the monetary values of the hypothetical situation, or to go from a hypothetical situation to a real-life decision where actual prizes are involved. For budget reasons, this was not done in this study.
Additionally, a limitation in the data that should be touched upon, is that of the violation of the assumption of monotonicity of preferences by observations in the data. Monotonicity of preferences implies that any increase in consumption will be welcomed by a consumer, independent of the reference consumption bundle. Therefore, choosing a 100% chance of winning $2 should never be preferred over a 100% chance of winning $3.85 A tabulation of the switching point variable related to the first choice list shows that 3 individuals violate the monotonicity assumption in the first choice list. A robustness check, without the observation that violate monotonicity can be found in the appendix[11]. Results were found to be robust.

Lastly, as a final suggestion for further research on the influence of weather on emotional states, a between-subjects match of exchange students could be studied to control for the change of emotional state when moving from one climate or weather condition to another. As subjects would be matched on characteristics, this would reduce the chances of an influential variable skewing the results by negating it.

[11] **Appendix table 5**

7. Conclusion

This research discusses the findings of a simple lottery-choice experiment which allows me to assess risk aversion across a range of payoffs. Behaviour under hypothetical incentives is studied for both a utility related choice list and a choice list which focuses on the probability weighting function. Moreover, the intensifying effect of positively experiencing weather circumstances is tested.

In assessing risky situations with changing probabilities, positive affect is found to have a positive effect on the risk-taking behaviour. Contradicting most findings, in previous literature (Nygren et al., 1996 & Isen et al., 1988), this research finds that an increase in the level of positive affect seems to decrease risk taking. Moreover, this effect seems to be larger for people who have reported positive weather experience. The latter was predicted by theory, as positive weather experience leads to an intensified effect of emotion. Besides finding a significant effect of one of my main variables, significant effects were also found for two control variables. Age has a negative effect on the risk-taking variable, which results in higher levels of risk taking. On the other hand, going to university decreases the level of risk taking compared to not going to university.

This study does not have many direct practical implications. However, it should form a strong theoretical basis for further research on the matter. In order to transform this research to a more practically applicable example, a larger pay-off should be considered. If done correctly, this could offer an interesting insight for organisations that are looking for investors, as risk taking behaviour could be considerably different from the expectancies created in previous literature.

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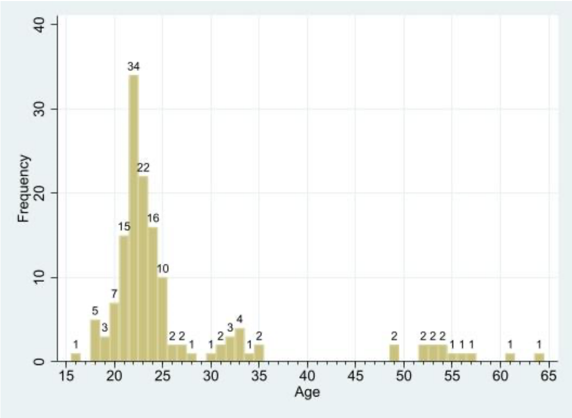
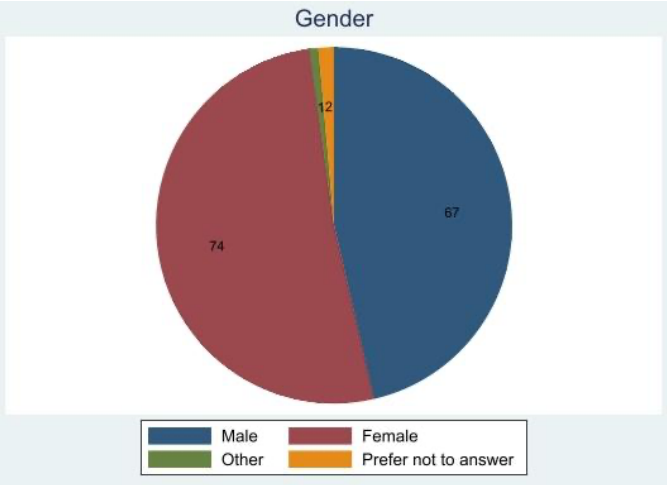
Appendix

Graph 1; Histogram of age



Graph 2; Pie chart of gender



Graph 3; Pie chart of education

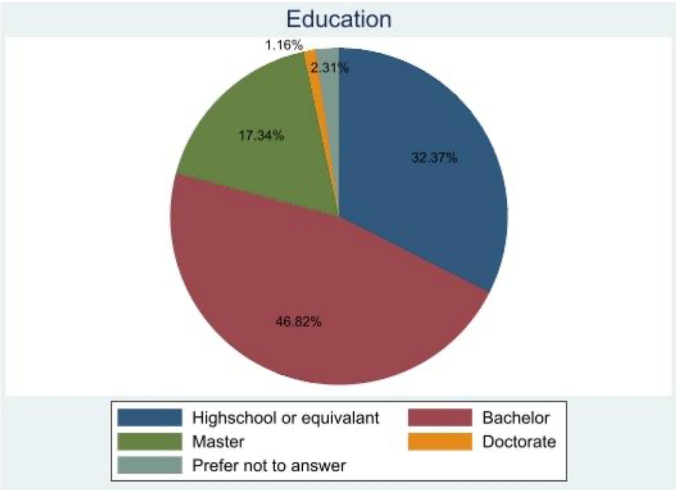


Figure 1. Mediation analysis decision tree by Zhao, Lunch & Chen (2010)

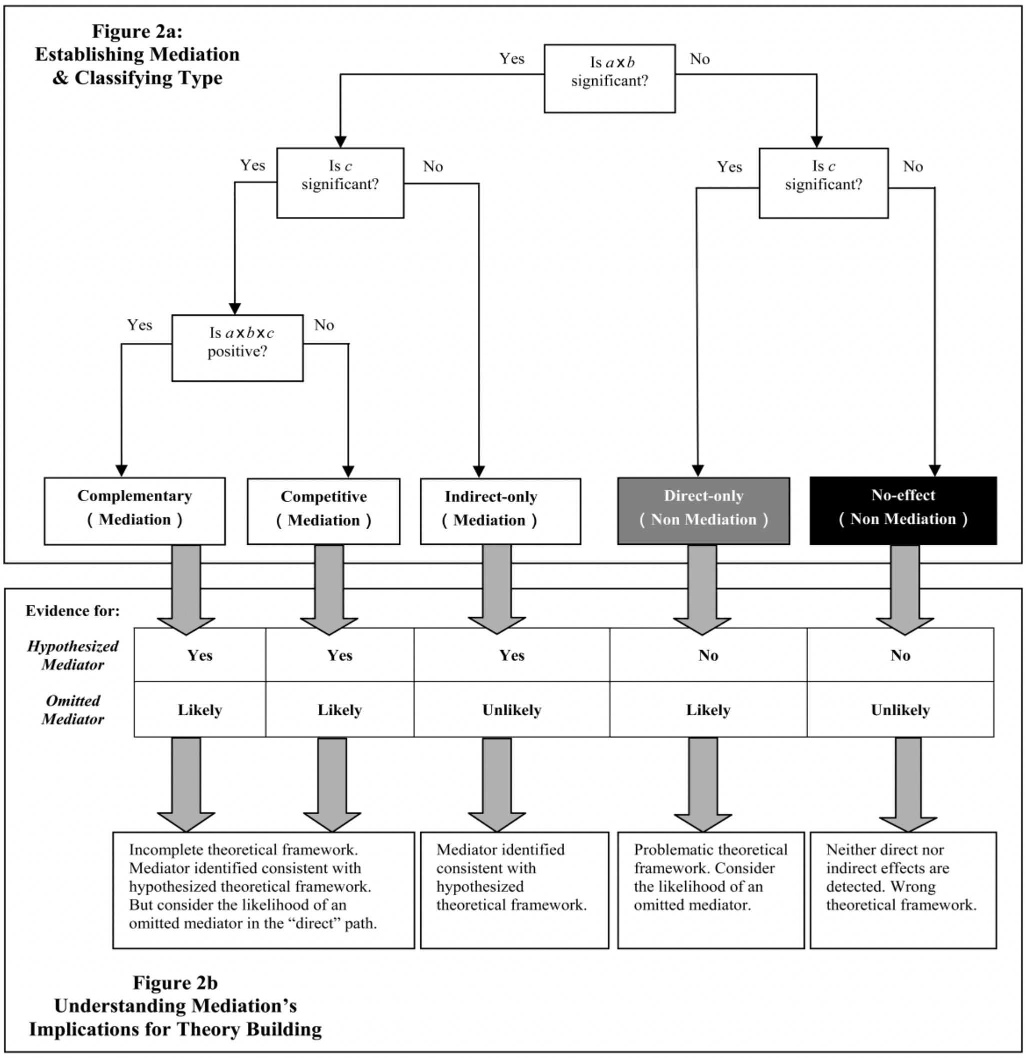


Table 1; descriptive statistics of all variables
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
age	144	26.201	9.685	16	64
gender	144	1.569	.587	1	4
sad	142	2.408	1.174	1	5
fearful	142	1.845	1.013	1	5
enthusiastic	142	3.88	.829	2	5
joyful	142	4.014	.781	2	5
temperature experience	144	2.514	1.044	1	5
sunshine experience	144	2.986	1.354	1	5
understood explanation	144	2.882	.364	1	3
understood diagrams	144	2.861	.403	1	3
switching point row a	143	5.531	2.698	0	10
switching point row b	144	3.215	2.983	0	10
university	144	.688	.465	0	1
positive affect	142	7.894	1.452	4	10
negative affect	142	4.254	1.8	2	10
experienced weather	144	5.5	2.055	2	10
male	144	.465	.501	0	1
female	144	.514	.502	0	1
highschool	144	.292	.456	0	1

Table 2.
Experienced Weather
Regression Table

	Positive Affect	Positive Affect (full)	Negative Affect	Negative Affect (full)
Experienced Temperature	.223*	.21	-.065	-.023
	(.132)	(.134)	(.165)	(.161)
Experienced Sunshine	-.038	-.046	.147	.176
	(.102)	(.103)	(.127)	(.124)
Age		.006		-.039**
		(.013)		(.016)
Male		.201		-.603**
		(.251)		(.302)
University		.055		.061
		(.272)		(.327)
Cons	7.45***	7.203***	3.977***	5.06***
	(.35)	(.491)	(.437)	(.59)
Observations	142	142	142	142
Adj R^2	.007	-.007	-.005	.055

Standard errors are in parentheses

**** $p<.01$, ** $p<.05$, * $p<.1$*

Table 3. Mediation analysis

Significance testing of indirect effect

Estimates	Delta	Sobel	Monte Carlo*
Indirect effect	0.014	0.014	0.015
Std. Err.	0.019	0.019	0.023
Z-value	0.743	0.743	0.635
P-value	0.457	0.457	0.525
Conf. Interval	-0.023 , 0.052	-0.023 , 0.052	-0.023 , 0.070

***Mcreps is set to number of observations**

Table 4. IQR test

IQR Test

Estimates	Low	High
Inner fences	0.014	0.014
No. of mild outliers	0	0
% of mild outliers	0.00%	0.00%
Outer fences	0.457	0.457
No. of mild outliers	0	0
% of mild outliers	0.00%	0.00%

Table 5.
Switching point (PWF)
Regression table

	Switching point (positive)	Switching point (negative)	Switching point (affect)	Switching point (full)	Switching point (full, conditional on intense weather experience)
Positive affect	.364**		.37**	.377**	.501*
	(.148)		(.149)	(.149)	(.283)
Negative affect		.016	.046	.006	-.133
		(.122)	(.12)	(.124)	(.226)
Age				-.027	-.032
				(.024)	(.04)
Male				-.219	-.77
				(.44)	(.804)
University				.872*	1.348
				(.476)	(.847)
Constant	2.806**	5.614***	2.569*	2.88*	2.613
	(1.189)	(.56)	(1.346)	(1.537)	(2.743)
Observations	139	139	139	139	49
Adj R^2	.035	-.007	.029	.04	.062

Standard errors are in parentheses

*** *p<.01,* ** *p<.05,* * *p<.1*