Master Thesis

Does the weather influence ambiguity attitudes?

Abstract: In this thesis the effect of several weather conditions on ambiguity attitudes will be tested. A large representative sample is used to determine the ambiguity aversion and the a-insensitivity of individuals. Gender, age and the personality factor neuroticism are used in combination with a specific weather condition to analyse the effect. Evidence is found that through people's mood some weather conditions have an influence on ambiguity attitudes.

Keywords: Ambiguity aversion, a-insensitivity, good weather, bad weather, wind power, temperature, mood, neuroticism

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Preface

Proudly I present my Master Thesis that allows me to graduate for my Master in Behavioural Economics on the Erasmus University. The main topic concerning this thesis is the question if the weather has an influence on ambiguity attitudes.

The research in this thesis was very interesting and some results were found. So hopefully this can concur to the subject were still a lot can be investigated, because not much knowledge is known. The last couple of months I dedicated most of my time to writing this Master Thesis and I learned to carry out my own investigation, write a academic thesis and to think deep about a subject.

I especially want to thank my supervisor Aurelien Baillon for the excellent guidance and feedback during the process. Also I want to thank my family and friends for all their support and feedback if I asked for it.

I hope you enjoy your reading.

Lotte Roberts

Rotterdam, August 15, 2016

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1. Introduction

'I feel depressed because it is raining again' or 'I feel so happy because the sun is shining'. Does this sound familiar? Both are expressions, which indicate that people believe the weather could influence their humor and/or emotions. Does indeed the weather influence emotions? Is the weather able to influence decisions individuals make in their life? According to Simenon (2016) decisions are made based on brain development, experiences and activities. The amount of decisions an individual makes each day varies. The average amount of conscious decisions an adult makes every day is about 35,000 (Simenon, 2016). All these decisions have different consequences, varying from positive to neutral or negative. How or why individuals make certain decisions is dependent on different aspects such as personality, attitudes, circumstances, experiences and social pressure (Soane & Chmiel, 2005; Klein, 1999). In this thesis the main focus will be on the two factors attitudes and circumstances (in the sense of weather circumstances). Personality and other background variables of the individuals will also be taken into account but other aspects are not included in this thesis.

Defining attitudes is difficult therefore many different definitions exist. In general, attitudes are defined as the way people tend to evaluate things which is affected by what they have learned to believe about the world, their selves and others, what they have learned to like or dislike, and how they have learned to respond to people, things and situations (ACS Distance Education, n.d.). A well-known attitude is the risk attitude of people in different situations and a lot of research is already done about this attitude. A close linked attitude is the ambiguity attitude of people. The difference between the two is as follow: a situation with objectively known probabilities is called risky and a situation with unknown or uncertain probabilities is called ambiguous (Ellsberg, 1961). Real-life decisions are often characterized by unknown probability information (Brachinger et al., 2000) so that makes ambiguity attitudes interesting to investigate. The more is known about ambiguity attitudes and what can influence this attitude, the more is known about why people make certain decisions in their daily life and how the weather can influence these decisions. In the previous paragraph mentioned the weather could influence people's mood so interesting to investigate if it also influence an individual's ambiguity attitude. Therefore the research question in this thesis will be: Does the weather influence ambiguity attitudes?

To find answers on the questions, literature research is used. Search for relevant studies that provide information that could be interesting for the present thesis. Important focus is to find in which way(s) the weather could influence the ambiguity attitudes of individuals. Weather is a really broad concept so more specific weather conditions need to be defined. Only the weather conditions that seem to have an effect on the ambiguity attitudes of individuals will be used and investigate in the thesis. If all the information about weather and ambiguity attitudes is found in the expectations need to be tested on a sample to see if they are correct or not.

After the introduction, chapter 2 will start with a more detailed explanation and information of all the important concepts that are involved. Furthermore, the effect of several weather conditions on ambiguity attitudes will be described. Chapter 3 describes how the data will be collected and tested. Chapter 4 will consists of all the methods that will be used to test the hypotheses and chapter 5 will discuss all the results. The conclusion will be discussed in chapter 6 and in the last chapter (7) the discussion and limitations will be described.

2. Theory

2.1 Ambiguity attitudes

Decisions individuals make in their daily life are mostly uncertainty decisions because only vague information about the probabilities and the potential outcomes is available (Trautmann & Kuilen, 2014). A situation with unknown or uncertain probabilities and outcomes are called ambiguous (Ellsberg, 1961). According to Frisch and Baron (1988) ambiguity is the subjective perception of missing information. Also conflicting information can lead to ambiguity when people find it difficult to combine different types of information or to adapt information that they access from different sources (Cabantous, 2007; Einhorn, Hillel and Hogarth, 1985; Viscusi and Magat, 1992). All the different definitions of ambiguity (attitudes) have one thing in common: situations with one or more unknown factor(s). The attitudes individuals have towards ambiguity depend of different things like the likelihood of the uncertain situation, the source that generates the uncertainty, and the domain of the outcome (Einhorn and Hogarth, 1985).

In ambiguous situations people can react in two different ways because ambiguity consist of two dimensions. First, the motivational dimension, liking or disliking of ambiguity. This dimension is also called ambiguity aversion. People who are ambiguity averse they prefer risks (known probabilities) relative to ambiguity (unknown probabilities) (Dimmock, Kouwenberg and Wakker, 2015). The opposite or negative of ambiguity aversion is ambiguity seeking. For high likelihood situations most people are ambiguity averse and for low likelihood situations people are ambiguity seeking (Dimmock, et al., 2013).

The second dimension of ambiguity attitudes is the cognitive dimension, a-insensitivity. If individuals have a high a-insensitivity they tend to treat all ambiguous situations as a 50-50 gamble (Abdellaoui et al., 2011). This dimension measures how much a person can distinguish between different ambiguous situations. Low likelihood ambiguous outcomes are overweighed, and high likelihood ambiguous outcomes are underweighted (Dimmock, et al., 2013). So individuals are insensitive for normal signals but oversensitive for extreme signals (Dimmock, Krouwenberg, & Wakker, 2015). Due to loss aversion, the effect of overweighting will be stronger for the worst extreme outcome than for the best extreme outcome (Dimmock, Krouwenberg, & Wakker, 2015).

In this thesis both dimensions of ambiguity attitudes will be used to see if the weather has an influences on these two attitudes separately.

2.2 Mood

In this paragraph the term mood will be explained. Mood falls within the theoretical dimension of ‘affect’. This can be defined as ‘the specific quality of goodness or badness someone experience as a feeling state (with or without consciousness) and demarcating a positive or negative quality of a stimulus’ (Slovic et al., 2004). According to Sizer (2000, 762), mood affects a wide range of people’s thoughts, feelings, and attitudes in ways that are not constrained by subject matter or probable rules. The specific mood of a person can be influenced by the way people remember things. It can also effect how people deal with social information. According to Clark & Isen, 1982 and Sinclair & Mark, 1992 a positive mood decreases strenuous processing, while a negative mood increases strenuous and vigilant processing (Schwarz, 1990; Schwarz & Bless, 1991). Negative moods have a bottom-up processing; they focus on the details of the external world (Forgas, Goldenberg & Unkelback, 2009). In contrast, positive moods have a top-down processing and have a greater reliance on existing schematic knowledge and heuristics (Bless, 2000; Fiedler, 2001). Bottom-up processing is automatic, fast and non-volitional and generated through what is going on in the external world. This means it is an unconscious process. In contrast, top-down processing is controlled, slow and volitional and driven by inner processes so it is a consciousness process (Ramsøy, 2015).

2.3 Influences of daily weather on mood

Ambiguity aversion has been the subject of a large number of studies in psychology, economics, biology, neuroscience, and philosophy (Trautmann & Kuilen, 2014). From previous research it is know that the weather does influence the mood of a person (Grohol, 2016). Mood states are quite ephemeral and can easily be influenced by little things (Isen et al., 1982). For example, the plurality of people think they feel happier on days with a lot of sunshine and feel miserable or sad on dark days with a lot of rain (Denissen et al, 2008). So their mood is influenced by the weather of that moment or day.

When studying the association between daily weather and mood it is important the seasonal influences of weather must be distinguished from day-to-day influences (Denissen et al, 2008). This is important because mood reactions to day-to-day weather fluctuations may not generalize to reactions of people to seasonal weather fluctuations, and vice versa (Denissen et al., 2008). In this thesis the daily weather is used and the seasonal weather fluctuations are left out. Several studies already investigate the effect of daily weather on people's mood. First, Keller et al. (2005) investigated the effect of temperature and barometric pressure on single-moment explicit and implicit mood valence (positive and negative mood) and cognition (memory and cognitive style) (Denissen et al., 2008). Denissen et al. (2008) found no main effect of these two weather parameters on mood but they do found a moderator effect of season and the time participants spend in the open air. So on spring days when people spent a lot of time outside, their mood was positively associated with air temperature and also the barometric pressure was positively associated with mood. But on summer days when people spend more time outside on hot days it has a negative correlation and was associated with a decreased mood (Denissen et al., 2008). Second, Watson (2000) collected diary reports of subjects during the fall and spring between the years 1985 and 1993. He focused on the amount of sunshine and rain on a day, but found no consistent effect on the daily mood of people. To see the effect of sunshine on the mood of people he also investigated the difference of the effect of the amount of sunshine on mood. So he compared days with 0% sunshine with days with 100% sunshine and found that sunshine only influences the arousal (intensity) of the mood but not the valence (Denissen et al., 2008). Third, according to Bassi et al. (2013) feelings of joviality, self-assurance, and attentiveness increase during good weather conditions/days, and these feelings are correlated with a greater risk tolerance. The research discussed above provided measures of several weather parameters and effected different types of mood but most showed that weather in general can have an influence on the mood of people.

The concept 'daily weather' is really broad; therefore this needs to be specified. Different research are discussed to find out how the term 'daily weather' the best can be explained. A previous study on weather and its relation with psychological design took only one or two weather parameters into account (Bushman, Wang and Anderson, 2005; Keller et al., 2005). Though, it is important to examine a wide variety of weather parameters and, differentiate the effect of each parameter (Denissen et al., 2008). In the study of Denissen et al. (2008) the effect of six weather parameters (temperature, wind power, precipitation, sunlight, photoperiod and air pressure) on three different mood conditions (positive affect, negative affect and tiredness) was investigated. They did not found a statistical significant effect of all the weather parameters on positive mood situations. But they do found for the negative mood situation a statistical significant positive effect of temperature and a negative effect of wind power and sunlight. For the last mood situation, tiredness, they found a significant negative effect of sunlight.

Kliger and Levy (2003) also investigated the influence of mood in risk perception correlated with a weather parameter. They used the cloud coverage to control for the weather. Data is reported by the National Climatic Data Center on a scale from 0 to 10. Ten indicates the total cloud coverage. Almost all differences were found in comparing the two extreme cloud coverage groups. People were less risk tolerant under pleasurable weather conditions (no clouds or just a few clouds) and more risk tolerant during unpleasant weather conditions (overcast).

Bassi et al. (2013) found experimental evidence that sunlight and good weather conditions/days makes people behave more risk taking. So people become more risk tolerant on sunny days. They used three definitions for the quality of the weather: the amount of sunlight (objective weather condition), subjective weather conditions of people and the precipitation on a day. In order to objectively categorize weather conditions, they collected data the measure on how many times the sky was clear, partly cloudy and overcast (Bassi et al., 2013). They defined good weather as a day in which the sky was clear for the majority of the time (50% of the time) and so the sun was shining for more than 50% of the time (Bassi et al., 2013). The subjective weather condition was a questionnaire to analyze the perceived quality of weather. The last one measured was the precipitation in a day. A day, in which the amount of rainfall exceeds the daily average amount in that area, is defined as a rainy day or in other words a bad weather day (Bassi et al., 2013).

In the present thesis the same definition of Bassi et al. (2013) for good and bad weather will be used because only these authors provided definitions of both good and bad weather. Only subjective weather conditions can be measured because there is no possibility to do a questionnaire with the same participants. In the thesis various weather parameters will be used to find an answer on the research question. Since it can be concluded from the discussed research above that daily weather is not just one component but consist of several weather parameters.

2.4 Influence of mood on risk attitudes

Risk attitude is the attitude an individual has in situations with known probabilities and outcomes. In this paragraph the information that is already know about the effect of mood on risk attitudes will be discussed. According to various research, a positive mood is expected that people are more risk seeking (Isen, 1997; Isen et al., 1982; Nygren et al., 1996). The Affect Infusion Model (AIM) states that a positive mood is expected to increase the risk tolerance and a negative mood should lower the risk tolerance (Forgas, 1995). When people are in a good mood they focus on positive features of the situation while a bad mood shifts one's attention to the negative cues in the environment (Grable and Roszkowski, 2008). In contrast, the Mood Maintenance Hypothesis (MMH) expects that a good mood will lead to caution and a bad mood will foster greater foolhardiness (Isen & Labroo, 2003; Isen & Patrick, 1983). People in a good mood want to stay in that mood, so they do not take risky decisions that could result in losses and would shift them into a bad mood. But when people are in a bad mood they will take risks in the hopes of taking a change and obtaining a reward, which would give them a good mood again (Grable and Roszkowski, 2008).

There is several research that support the AIM. Wright and Bower (1992) found that people in a happy mood tend to be more optimistic and an optimistic person is more likely to have a higher probability for positive risk events and report a lower probability for a negative risk event. They found that mood states have a greater influence on judging events that were less frequent (Grable and Roszkowski, 2008). Sizer (2000) added that people in a happy and/or positive mood might be less cautious because these moods are correlated with wide information focusing and decrease concentration on details. Grable and Roszkowski (2008) investigated the effect of mood on the risk tolerance and found a positive correlation between being in a happy and/or positive mood and having a higher level of financial risk tolerance as compared to a neutral mood. Furthermore, people who are in a bad mood have a lower risk tolerance compared to a neutral mood, but this effect was extremely small and not significant. So this research suggests that a positive mood has greater influence on risk tolerance than people in a negative mood (Grable and Roszkowski, 2008). Another proof for the theorem that people in a good mood take more risky decisions is the research of Yuen and Lee (2002). They found that people in a depress mood (bad mood) would have a lower willingness to take risks than people in a neutral or in a positive mood.

Less evidence is found in the literature for the MMH. Kliger and Levy (2003) found that in real capital market decisions, investors during good weather conditions (good mood) are less risk tolerant under pleasant weather conditions but during unpleasant weather conditions (bad mood) investors are more risk tolerant.

In the present thesis it is not clear yet which of the two theories hold for ambiguity attitudes. Expected also the AIM because more evidence is found for this theory with risk attitudes but after the research of the data and the hypotheses a conclusion can be drawn in a later chapter.

2.5 Correlation between risk and ambiguity aversion

Having discussed the effect of daily weather on mood and the effect mood has on the risk attitudes of individuals; this thesis needs to explain the effect on ambiguity attitudes. Almost all studies about the relationship between risk and ambiguity report evidence of a positive correlation between risk aversion and ambiguity aversion. Like in the study of Charness and Gneezy (2010) they report that ambiguity seekers hold more risk portfolios and Kocher and Trautmann (2013) found that participants in ambiguous markets are more risk seeking than those in a risky market. So ambiguity aversion displays similar characteristics to risk aversion, but the effect is in a stronger extent (Trautmann & Kuilen, 2014). However, there are also some studies that found less or no positive correlation between risk and ambiguity aversion and Lauriola and Levin (2001) found only evidence of the positive correlation in the domain of losses. Akay et al. (2012), Cubitt et al. (2012), and Sutter et al. (2013) found a negative correlation between risk and ambiguity aversion. So not fully one conclusion can be drawn but most of the studies have overall evidence there is a positive correlation between risk and ambiguity aversion. In the present thesis it is therefore stated there is a positive correlation between risk and ambiguity aversion. This information is useful to predict later in this research the effect of weather and ambiguity attitudes.

2.6 Weather influences ambiguity attitudes

As explained previously, there are two different dimensions of ambiguity: ambiguity aversion and a-insensitivity. These different ambiguity attitudes can also react different on situations and individuals. So there is the possibility they also react different on various weather conditions. Stated there is a positive correlation between risk aversion and ambiguity aversion. This is the last link that is needed to establish the relationship with the weather and ambiguity aversion. For clarity, the link is as follows: the weather influences the mood of individuals → the mood influences their decisions and risk aversion → a positive relationship between risk aversion and ambiguity aversion. In §2.4 already the relationship between mood and risk aversion is explained. Because there is a positive correlation between risk and ambiguity aversion, the same relationship between mood and ambiguity aversion holds.

Below hypotheses 1 and 2 are created with the information that is explained in the previous paragraphs and have to do with the first dimension, ambiguity aversion. Creating the hypotheses based on previous research shows bad weather/bad mood makes people more risk averse. But Baillon et al. (2016) had found that bad weather makes people more ambiguity neutral. They found that people who are in a sad mood make wiser decisions because of enhanced information processing. This means they are more ambiguity neutral compared with reduced information processing when they feel happy. This is the only research with an immediate effect on ambiguity attitudes so needs to be taken into account when creating the hypotheses. The only thing that is known from all the different research is that bad weather has an influence on the ambiguity aversion of individuals but not in which strength. Therefore this will be tested in this thesis.

H1a: People are more ambiguity seeking when the weather is good.
H1b: People are more ambiguity seeking when the wind power is high.
H2a: Bad weather has an influence on the ambiguity aversion of a person.
H2b: People are more ambiguity averse when the temperature is high.

For the second dimension, no direct evidence is found that risk is correlated with the a-insensitivity. A-insensitivity is the cognitive dimension of the ambiguity attitudes so when people do some cognitive tasks the decisions they made are accomplished by using their cognitive skills. Decisions made under ambiguity are influenced by personal judgments and confidence, which again can influence emotional states (Bower, 1981; Forgas, 1995; Schwarz & Clore, 1983). A research of Cao and Wei (2005) has shown that temperature significantly affects mood, and mood changes in turn cause behavioral changes. They found evidence that fluctuations in the weather can have a reaction on the stock returns in the financial market (Cao & Wei, 2005; Hirshleifer & Shumway, 2003; Saunders, 1993). Cao and Wei (2005) also found that a lower temperature is related with a higher stock return because people are more aggressive and a high temperature is related with a higher or lower stock return because people can be aggressive but also apathy. In another research of Hirsleifer and Shumway (2003) in the financial market, they found that good weather is strongly significant correlated with stock returns. So less cloud coverage is associated with higher stock returns. The research of Baillon et al. (2016) can also be used to predict the effect of weather on the a-insensitivity because they mention that when people are sad they are more focused so probably these people make a more cognitive decision. So this can also have a small influence of the understanding of ambiguous situations. These research imply that weather can influence decisions of cognitive tasks or skills and therefore result in the following hypotheses:
H3a: Good weather influences a-insensitivity.
H3b: Temperature influences a-insensitivity.
H3c: Bad weather creates a neutral a-insensitivity.

2.7 Effect of gender and age on ambiguity attitudes

A lot of research can be found about the differences in risk attitudes of males and females. In general, females react more risk averse compared to males (Brachinger et al., 2000). This is generally known for risk attitudes. It is already stated that there is a positive correlation between risk and ambiguity aversion. It could therefore simply be said that females are also more ambiguity averse compared to males. However, first some research is analysed about the relationship of gender and ambiguity attitudes. Borghans et al. (2009) did a research about ambiguity attitude differences in gender and found that females are more ambiguity averse than men in the investment context, but the other way around in the insurance context. So according to that research there is not one conclusion that females or males are more ambiguity averse (Borghans et al., 2009). Because there is a positive correlation between risk and ambiguity aversion in that research and decisions in financial markets denote to cognitive tasks or skill, the same theorem is stated for both ambiguity attitudes. Females are more ambiguity averse and a-insensitive than males. This results in hypotheses four.

Furthermore, Fehr et al. (2007) found a gender difference in the impact of mood on decisions. Females with a good mood and in a gain and/or loss scenario assign a higher subjective probability (Fehr et al., 2007). This is consistent with the AIM. In contrast, males were not influences by good mood. To research this, hypotheses five is formed.

H4: The effect of good weather is stronger on the ambiguity aversion of females than of males.

H5: Good weather influences a-insensitivity for females.

The age of people can also influence the different approach of taking decisions in different mood states. Young people have the tendency to focus more on the negative rather than the positive aspects in a certain situation (Chou et al., 2007). Young people are defined as teenagers (between the ages of 13 and 19 years old) and young adults (between the ages of 18 and 32 years old). In another research it is found that elderly are more sensitive for several weather conditions (Kööts, Realo, & Allik, 2011). They also found that there is no difference in risk taking among young people between positive versus neutral moods, but they found a difference between negative and neutral states of people (Chou et al., 2007). The opposite occurred among the elderly. According to Roebuck (1979) the general definition of an old person is any person of 50 years and older. The difference in risk taking was greater between the positive and the neutral mood states compared to the difference between the neutral and the negative mood states. But when the neutral point is neglected, for both the young and old people, there is a greater risk taking among those in a happy mood than those in a sad mood (Fehr et al., 2007). In order to test these assumptions, the following hypotheses are formed:

H6a: Weather has a bigger impact on the ambiguity aversion of elderly compared to young and middle aged people.
H6b: Bad weather increases more the ambiguity aversion of young people than of middle aged and elderly.

2.8 The moderator effect of personality

Personality will be examined as well to understand if this has an effect on the sensitivity to weather. Personality can be seen as a moderator between daily weather and mood. It has already been discussed that mood can have an effect on the ambiguity attitudes of persons. In many research there is no evidence found between personality traits of people and the sensitivity of weather conditions (Denissen et al., (2008). But there are some studies that suggest a link between seasonality and personality. In a study of Murray et al. (1995) it is found that the personality trait neuroticism is relevant to Seasonal Affective Disorder (SAD). Seasonality and SAD are a type of depression that is related to changes in seasons. Most of the time the symptoms start in the fall and continue into the winter. The symptoms people experience are tiredness and moodiness. Also the study of Ennis & McConville (2004) found that an increased level of the neurotic personality trait is associated with more profound seasonal disturbances in mood and behavior. So it is interesting to examine whether there is a link between sensitivity to daily weather and personality.

The broad level of the Five Factor Model (FFM) also called the “Big 5 personality traits” will be used to measure the personality between daily weather and ambiguity attitudes (Cherry, 2016). The five broad personality traits described by the theory are extraversion, agreeableness, openness, conscientiousness and neuroticism (Cherry, 2016).

- Extraversion: positive emotions, excitability, assertiveness and sociability. High extraversion people are often characterized, as attention-seeking and low extraversion people are more reserved.

- Agreeableness: friendly, affection and trust. People who are high agreeableness are more cooperative and can be seen as naive. Low agreeableness people are often more competitive and manipulative.
- Openness (to experience): curious and a broad range of interests. People with a high openness are more adventurous, creative and pursue self-actualization. Low openness people are more pragmatic and traditional (close minded).
- Conscientiousness: efficient, easy-going and thoughtful. People who are high conscientiousness prefer planned rather than spontaneous behavior and more obsessive. Low conscientiousness people are flexible and spontaneous.
- Neuroticism: nervous, sadness and emotional instable. People with a high neuroticism experience mood swings, irritability and sadness. People with a low neuroticism are more stable and have often more dynamic persons.

In the present thesis only the personality trait neuroticism will be taken into account because this is the only trait where evidence is found that it can have an influence on the ambiguity aversion. The following hypothesis will test this assumption:

H7: The effect of weather on ambiguity aversion index is increasing in the degree of neuroticism.

3. Data

In this chapter all the different components that are needed to test the hypotheses are explained as well as how the data is obtained. The data used in the thesis is obtained from the Longitudinal Internet Study for the Social Sciences (LISS) data panel. This is a representative household survey in the Netherlands conducted by CentERdata at Tilburg University. To encourage participation the panel member get paid for every completed questionnaire. If necessary for participants to participate some households are even provided a computer and free Internet connection. According to Knoef and de Vos (2009) the LISS panel is representative for the Dutch population. More information about the data or the panel can be found on the follow website: https://www.lissdata.nl/lissdata/.

In January 2010, the LISS panel completed a questionnaire about choices a participant makes when he or she is confronted with a known (risk) and unknown (ambiguity) probability distribution. The questionnaire was presented to 2,491 people of all panel members but only 1,935 responded and 1,933 completed the questionnaire. These two questionnaires that were not completely filled in had one or more missing value(s), but the missing values are not important information for this thesis hence they could be kept. It is a comprehensive questionnaire that can measure different attitudes in different situations. In this thesis not all the questions of the questionnaire are needed to find some answers on hypotheses. For example the questions to find some financial data of the participants or questions to know more about the individual's risk attitude are not relevant in this case. Some observations are excluded because they can affect the results in a wrong way. In this thesis 170 respondents answer 'Indifferent' in all ambiguity questions and 44 respondents just spend three seconds or less on all set of questions. So the number of respondents in this thesis will be 1,721. These results are excluded because these participants likely did not put any effort in making their choices in the questionnaire.

The data set is comprehensives with some background components (gender, age and personality) and four weather parameters. This will be discussed in more detail in the next paragraphs.

3.1 Behavioral variables

The behavioral variables are variables in the data set that research the ambiguity attitude of the participants. Both the ambiguity aversion and the a-insensitivity are explored in this thesis. To find the ambiguity attitudes of the participants, matching probabilities are used. The matching probability of an ambiguous event is the objective probability of winning a prize at the moment a subject is indifferent between the urns. So subjects are indifferent between betting on the ambiguous event versus betting on the objective probability (Dimmock et al., 2015). In this thesis the Ellberg's paradox is used to find the matching probabilities. The subject can choose between two different urns, choice U and K, to pick the purple ball in an urn with two colors. Choice U is the urn with unknown probabilities and urn K with known probabilities. If the subject selected Choice K in the first round, this choice will be made less attractive in the second round. If the subject again select Choice K then it will be made again less attractive. But if the subject select Choice U, Choice K will be made more attractive. This process continued until the subject selected 'Indifferent' (Dimmock et al., 2015). So urn U is kept fixed and the number of yellow balls in urn K is changed until the subject select 'Indifferent', this number called X. Then, X/100 is called the matching probability. So if a subject select 'Indifferent' when urn K consists of 50 yellow balls, the matching probability is m(0.5)=50/100. In this thesis there are three matching probabilities that are found in all the final rounds of the three games.

The ambiguity aversion variable is called *b* in the thesis and can be found by a formula. This formula is derived from the study of Dimmock et al. (2015) but used in a simplified way. The matching probability can be found with the formula: m(p)=X/100. So to measure b if an urn consists of 2 colors the formula is: b=2x(0.5-m(0.5)). Participants with an outcome close to -1 are really ambiguity seeking, an outcome close to 0 shows ambiguity neutrality and an outcome close to 1 is really ambiguity averse.

The a-insensitivity variable is called *a* in the thesis and can be found by a formula. Also this formula is derived from the study of Dimmock et al. (2015) and used in a simplified way. M(0.9) is the matching probability of a-insensitivity of a game when the urn consists of 10 different colors and the change of winning a price is 9/10 (not pick the purple color). M(0.1) is the matching probability of a-insensitivity of a game when the urn consists of the same 10 colors but the change of winning is now just 1/10 (pick the purple color). So the formula is: 1-((m(0.9)-m(0.1))/0.8). If the outcomes of the participants are close to 0 participants behave as expected utility but when the outcomes are close to 1, the participants behave really a-insensitive and are extreme averse.

Figure 1 (Dimmock et al., 2015, p.9) displays possible shapes of matching functions m(p), illustrating the joint effect of ambiguity aversion and insensitivity. The x-axis shows the probability p and the y-axis the matching probability m(p). Index b_{so} is inversely related to the average height of the curve so it is the global index of ambiguity aversion. Index a_{so} is an index of the flatness of the curve in the interior domain (Dimmock et al., 2015). In the present thesis I only consider the bold curves to see the matching probabilities so all other symbols or text in the figure will not discussed in this thesis. In figure 1a *b* and *a* are both zero so shows ambiguity neutrality with matching probabilities equal to the ambiguity neutral probabilities. Figure 1b shows for *a* a neutral a-insensitivity but for *b* an amount of 0.22. This displays ambiguity aversion, with the ambiguity neutral probabilities matched with smaller objective probabilities. In figure 1c it is the other way around because *b* is zero so ambiguity neutrality and *a* have an amount of 0.22. So this displays a-insensitivity and all matching probabilities moved to 50-50, the graph becomes flatter. The last figure 1d is a combination of ambiguity aversion and a-insensitivity and the line is lower and flat in the middle.

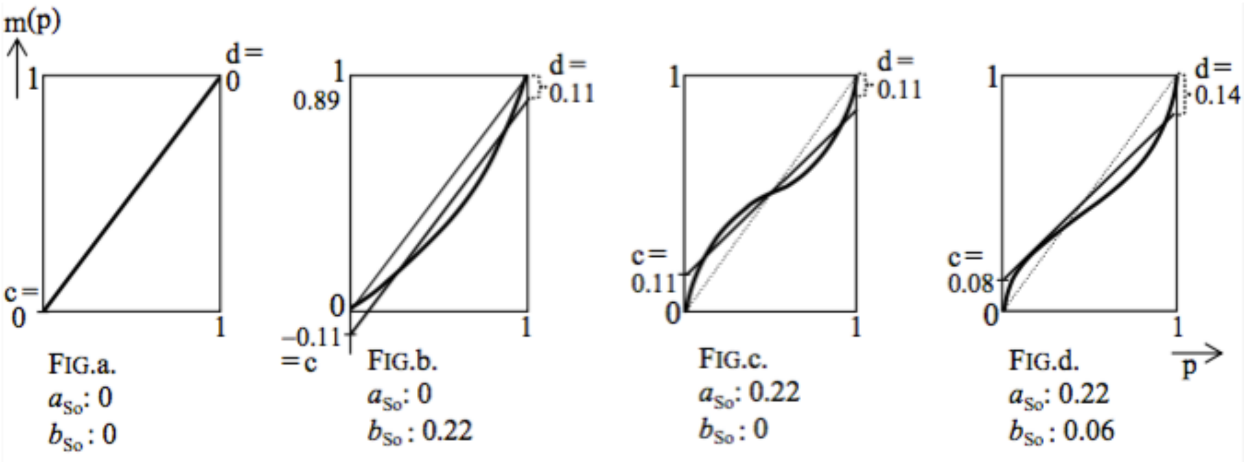

Figure 1*. Four possible graphs of some m(p) of ambiguity aversion and a-insensitivity. Reprinted from: "Ambiguity attitudes in a large representative sample," by Dimmock et al., 2015, *Management Science.

After explaining the variables *b* and *a* and how these variable can be measured some descriptive statistics about these variables. In this thesis the minimum amount for *b* is -0.94 and maximum amount for *b* is 0.94 so both extremes are present. The mean of *b* is 0.18 with a standard deviation of 0.48, so there is ambiguity aversion. Two different measures are needed to calculate *a*. So the minimum amount for m(0.1) is 0.025 and the maximum amount is 0.9719. So again both extremes are present. The mean is 0.24 with a standard deviation of 0.26. So participants are a-insensitive. For m(0.9) the minimum and maximum are the same as for m(0.1) but the mean is 0.29 with a standard deviation of 0.31 so again there is a-insensitivity. Using the formula to find *a*, in this thesis the minimum amount for *a* is -0.18 and the maximum amount is 2.18. The mean is 0.93 with a standard deviation of 0.57.

3.2 Participants background variables

Several background variables are added to the data set. In the next sub paragraphs it will be explained how they are measured and some descriptive statistics specific for this thesis. The overview starts with the variables gender and age and concludes with the variable personality.

3.2.1 Gender and age

Background variables of the participants are incorporated into the data set. The variable gender consists of two dummy variables. In the data set all the males are defined with the number 1 and all the females with the number 2. The amount of males and females in this thesis are representatively 800 and 921. The number of females is used for gender and the variable called *female*.

The second background component is the age of the participants. The youngest person in this thesis who filled in the questionnaire is 16 years old and the oldest is 89 years old. The mean of age is 48.77 years. I made seven age categories in the thesis, 1 = 14 years and younger, 2 = 15-24 years, 3 = 25-34 years, 4 = 35-44 years, 5 = 45-54 years, 6 = 55-64 years and 7 = 65 years and older. The frequencies per category are: no observations in category 1, 174 observations in category 2, 221 observations in category 3, 297 observations in category 4, 310 observations in category 5, 403 observations in category 6 and 316 observations in category 7. Figure 2 below represents these numbers in a visual overview. To test the hypotheses the differentiation must be made between young and old people. So two dummies are created into the data set. The first dummy *young* has the number 1 in the data set for all the participants between the ages 13 and 32 and 0 for middle aged and old people. The second dummy *old* has the number 1 in the data set for are all the participants of 50 years and older and a 0 for young and middle aged people.

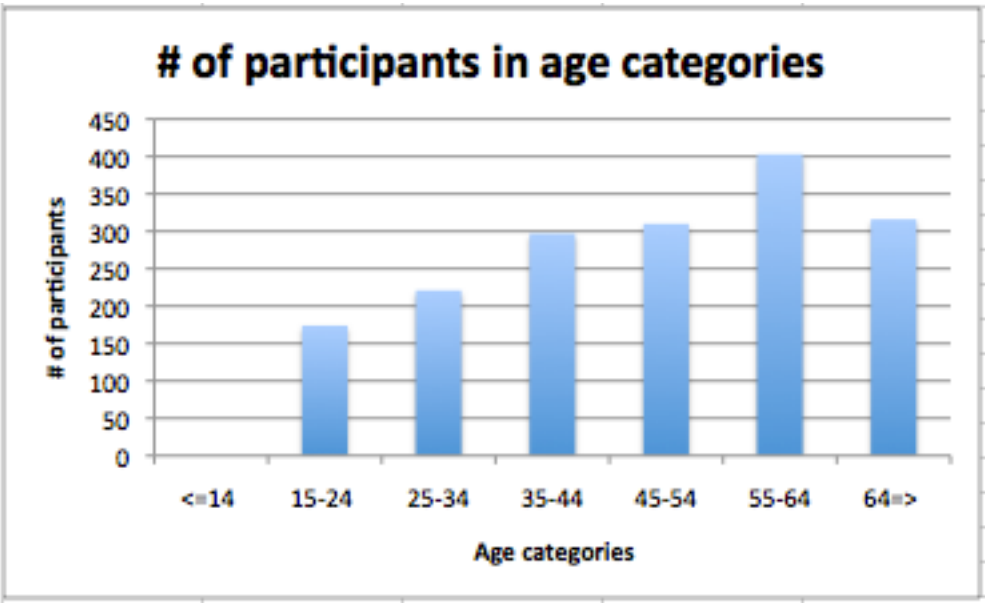

Figure 2. **Overview: number of participants per age category**

3.2.2 Personality

The total database for personality consists of 8 waves (timeslots), all with other dates of measuring. All these waves consist of 12 different components of personality, for example happiness, self-esteem and the Big Five personality traits. In the present thesis only the Big Five personality traits will be included in the regressions. The Big Five personality traits are measured in the questionnaire by using 50 different questions from the International Personality Item Pool (IPIP) (Goldberg, 1992, 1999; Goldberg et al., 2006). All these 50 questions are designed to capture the Big Five personality traits so 10 questions per trait. Five different answers are possible, 1 = very inaccurate, 2 = moderately inaccurate, 3 = neither inaccurate nor accurate, 4 = moderately accurate and 5 = very accurate. For each personality trait a total score was computed between the 10-50. Higher scores indicate that the participant is in a higher level of that specific personality trait.

Wave three of the metadata is used in the thesis because the measuring of this wave started on 03-05-2010 and ended on 30-06-2010. So this wave is used because the other variables in the data set are measured in January 2010 and this has the closest match with dates. The total number of observations of the Big Five personality traits is 323. This number of observations is much smaller compared to the other number of observations in the data set. Therefore are two reasons. First, the questionnaire to measure the personality of the subjects is not one big questionnaire but exactly there are two different questionnaires. The difference between the two is the amount of questions. Only in one questionnaire the questions to measure the Big Five personality traits are included. So not all the subjects filled in the 'long' questionnaire what means the number of observations is already less. Second, the subjects who filled in the 'long' questionnaire to measure the personality traits and the subjects who filled in the questionnaire to measure the ambiguity attitude need to match. After these two reasons just 323 subjects left.

Previous literature only found a statistical significant effect of weather on neurotic people. So only this personality trait (*neuroticism*) is interesting to use in this thesis. Ten questions are used to measure neuroticism and two of them measure reversed neuroticism (emotional stability) so to create unity these two measurements are reversed in the data set.

Table 1 shows the 10 questions that are used. In the thesis the minimal total score for *neuroticism* is 10 and the maximal total score for *neuroticism* is 44. The mean is 25.88 with a standard deviation of 6.46.

Number	**Question**
1.	Get stressed out easily.
2.	Am relaxed most of the time. (reversed)
3.	Worry about things.
4.	Seldom feel blue. (reversed)
5.	Am easily distributed.
6.	Get upset easily.
7.	Like order.
8.	Have frequent mood swings.
9.	Get irritated easily.
10.	Often feel blue.

***Table 1.* An overview of all the 10 questions to measure the degree of neuroticism of the subjects**

3.3 Weather variables

Previous research found evidence that the weather can have an influence on ambiguity attitudes. They found this evidence for four weather parameters. So only these four (good weather, bad weather, wind power and temperature) are added in the data set of this thesis. Via the website: http://projects.knmi.nl/klimatologie/daggegevens/index.cgi historic data about the weather in the Netherlands is found. The data that is used in the thesis is the data of one place in the Netherlands, called 'De Bilt', because this place is established in the most centre part of the Netherlands. Stated in the present thesis this is representative for all the observations. Because the Netherlands is a relative small country so the weather will be (almost) the same in the whole country. Below, the weather parameters will be discussed and explained how these are measured.

First, the variable good weather will be explained. The definition of good weather is already defined and is a day in which the sky was clear for the majority of the time (50% of the time) (Bassi et al., 2013). So if the sun is shining for 50% or more on a certain day it is a good weather day and if the sun is shining for less than 50% it is a not good weather day. In the data set the variable *good_weather* is actually a dummy variable. The variable is indicated with the number 1 when the weather is good and with a 0 when the weather is not good. In this thesis there are 429 observations of good weather days and 1,292 observations of not good weather days. Figure 3 is a visual reproduction of the *good_weather* in a pie chart.

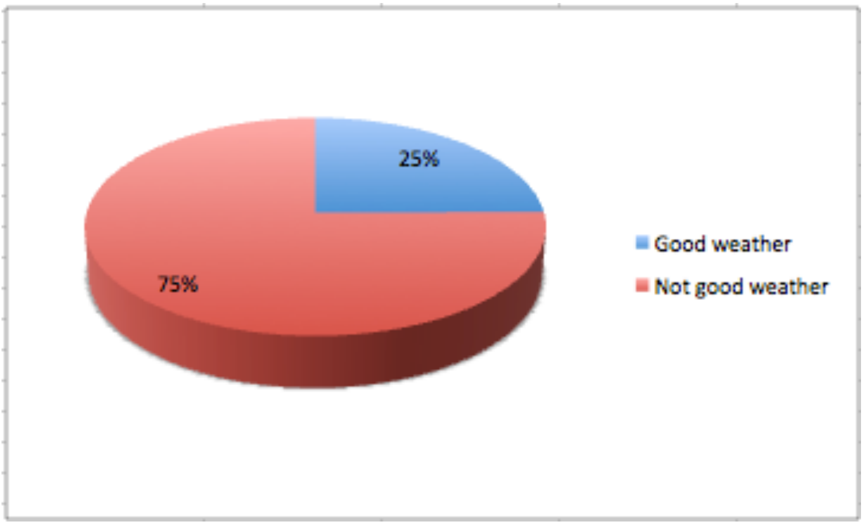

Figure 3. **The number of observations with good or with not good weather**

Bad weather is the second weather variable that will be explained. It is previously mentioned that the definition of bad weather is a day in which the amount of rainfall exceeds the daily average amount in that area (Bassi et al., 2013). For this data new information is needed about the daily average of rainfall. Using this website: https://www.knmi.nl/nederlandnu/klimatologie/geografischeoverzichten/ archief/maand/rd the average amount of rainfall in the period January 2010 can be found. The data was only available for the whole month of January so to know the daily average, the monthly amount of rainfall is divided by the number 31. The daily average of rainfall in 'De Bilt' in the period

January 2010 is 1.516 millimeter. If the rainfall is equal or more than 1.516 millimeter, the day is qualified as a bad weather day. The variable *bad_weather* is a dummy variable and a bad weather day is indicated with the number 1. If the rainfall is lower than 1.516 millimeter it is a not bad weather day and *bad_weather* is indicated with the number 0. In this thesis there are 187 observations of a bad weather day and 1,534 observations of a not bad weather day. Figure 4 is a visual reproduction of *bad_weather* in a pie chart.

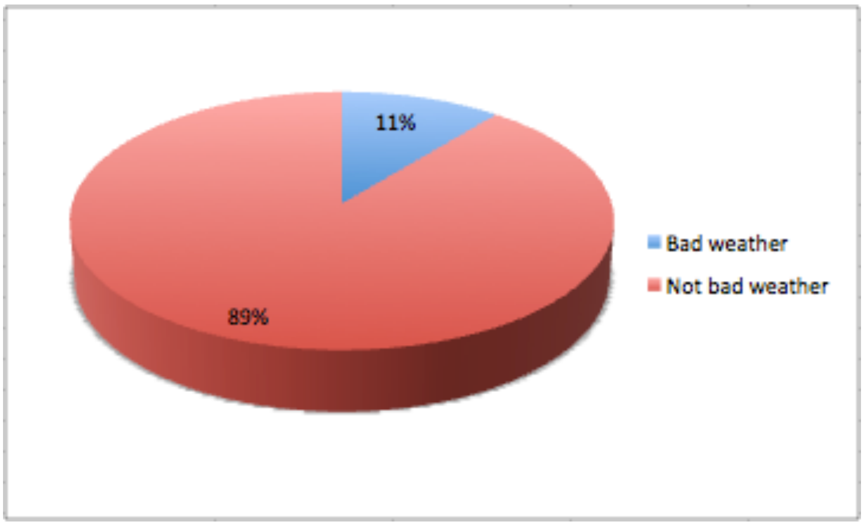

Figure 4. **The number of observations with bad or with not bad weather**

The third weather variable that will be explained is the amount of wind power. The wind power is expressed in the wind scale of Beaufort. On a Dutch website for national data and knowledge about the weather, climate and seismology (www.knmi.nl) is explained this scale is used to indicate the speed of the wind. An Irish man, Francis Beaufort, drafted the scale in 1805. He based the wind power on the amount of sail a big ship needs to use when there was a gentle breeze, storm or hurricane. The wind power was expressed in kilogram per square meter. The scale for the variable *wind_power* goes from 0 (still) till 12 (hurricane). See appendix A for a complete and more detailed overview of the scale of Beaufort. In this thesis the lowest value for *wind_power* that is measured is 2 and the highest value is 4 on the scale of Beaufort. The number of observations with a value of 2 is 1,170, with a value of 3 is 495 and with a value of 4 is 56. In figure 5 a visual overview of *wind_power* is displayed.

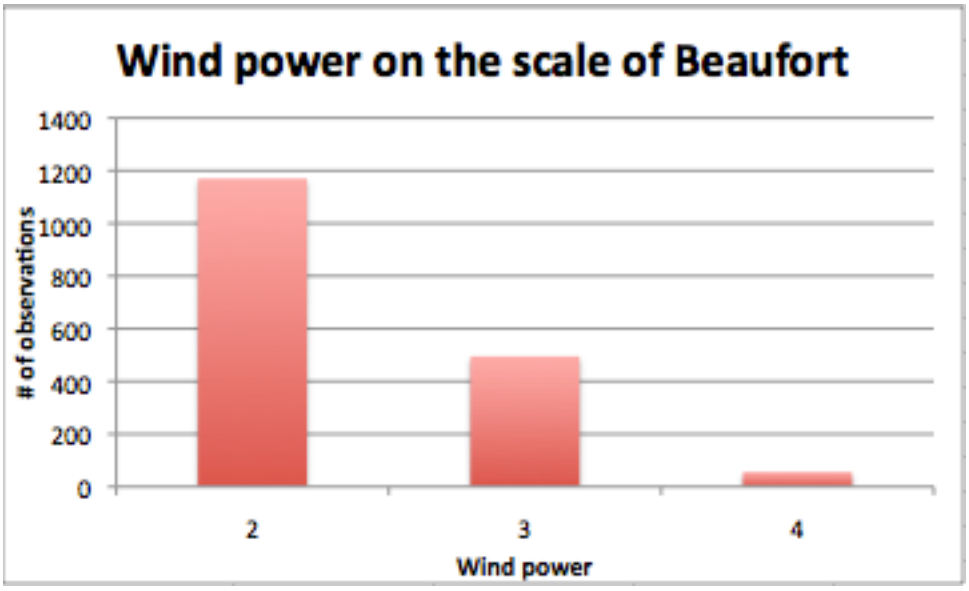

Figure 5. **The number of observations of the value for the wind power on the scale of Beaufort**

The last weather variable that will be explained is the temperature. This variable is expressed in degrees Celsius and is the average temperature of a day. In this thesis the lowest temperature that is measured for the variable *temperature* was -7.5 degrees Celsius and the highest *temperature* was 4 degrees Celsius in January 2010. The mean of *temperature* in that month is -1.34 degrees Celsius. Figure 6 shows the number of observation per temperature level in a graph.

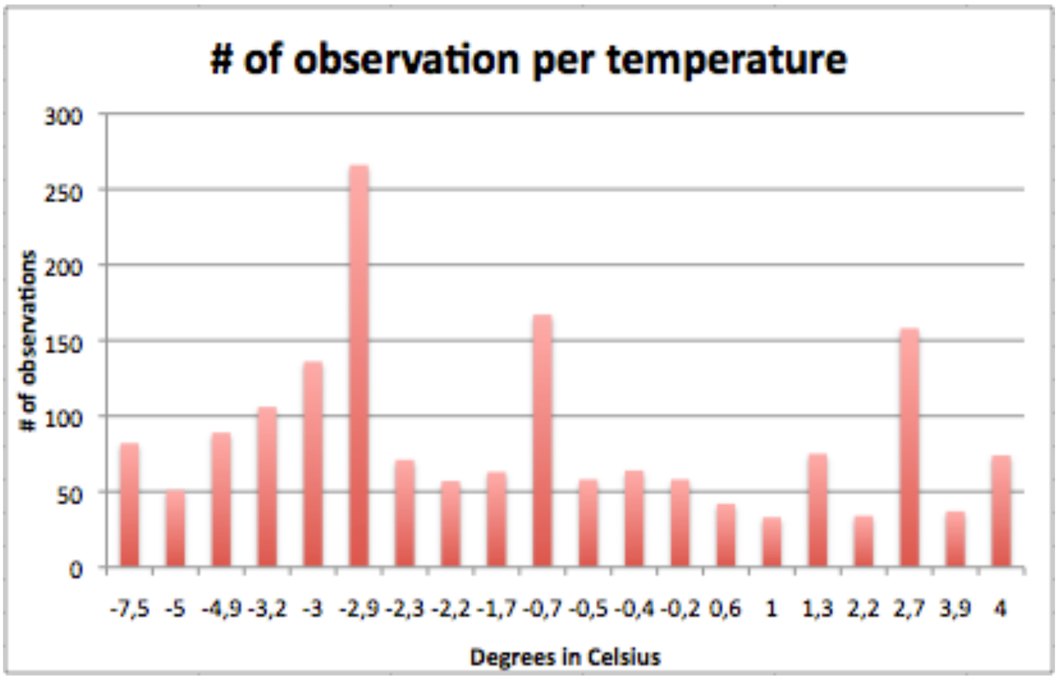

Figure 6. **The number of observations per temperature level**

3.4 Summary table of all the variables

Variable	Description variable	Description of data	Statistics
b	Ambiguity aversion	Between -1 and 1	Min = -0.94 Max = 0.94 Mean = 0.18 SD = 0.48
a	A-insensitivity	Between -1 and 2.2	Min = -0.18 Max = 2.18 Mean = 0.93 SD = 0.57
good_weather	If the sun is shining for 50% or more on a day	1 = good weather 0 = not good weather	N_1 = 429 N_0 = 1,292
bad_weather	The amount of rainfall exceeds the daily average	1 = bad weather 0 = not bad weather	N_1 = 187 N_0 = 1,534
wind_power	Wind power expressed in the wind scale of Beaufort	Between 0 and 12	Min = 2 Max = 4 Mean = 2.35 SD = 0.54 N_2 = 1,170 N_3 = 495 N_4 = 56
temperature	The temperature in degrees Celsius	All temperatures possible	Min = -7.5 Max = 4 Mean = -1.34 SD = 2.82
female	Gender of the subject	Male = 1 Female = 2	N_{males} = 800 $N_{females}$ = 921
young	Subjects between 13 and 32 years old	13 - 32 years = 1 33 - 89 years = 0	N_1 = 346 N_0 = 5,910

old	Subjects of 50 years and older	50 - 89 years = 1 13 - 49 years = 0	N_1 = 5,407 N_0 = 849
neuroticism	The degree of neuroticism of subjects	Between 10 and 50	Min = 10 Max = 44 Mean = 25.88 SD = 6.46 N = 323
female*good_weather	Days when the weather is good and someone is a female	1 = female and good weather 0 = male and/or not good weather	Mean = 0.13 SD = 0.34 N = 1721
female*bad_weather	Days when the weather is bad and someone is a female	1 = female and bad weather 0 = male and/or not bad weather	Mean = 0.06 SD = 0.24 N = 1721
female*wind_power	The amount of wind power on a day and someone is a female	Wind power on the scale of Beaufort (between 0 and 12) and gender	Min = 0 Max = 4 Mean = 1.26 SD = 1.24 N = 1721
female*temperature	The height of the temperature on a day and someone is a female	Average temperature on a day in degrees Celsius and gender	Min = -7,5 Max = 4 Mean = -0.70 SD = 2.19 N = 1721
young*bad_weather	Someone is young and the weather is bad	1 = young and bad weather 0 = middle aged or old and/or not bad weather	Mean = 0.02 SD = 0.14 N = 1721
old*good_weather	Someone is old and	1 = old and good	Mean = 0.12

	the weather is good	weather 0 = young or middle aged and/or not good weather	SD = 0.33 N = 1721
old*bad_weather	Someone is old and the weather is bad	1 = old and bad weather 0 = young or middle aged and/or not bad weather	Mean = 0.05 SD = 0.22 N = 1721
old*wind_power	Someone is old and the amount of wind power on a day	Wind power on the scale of Beaufort (between 0 and 12) and age	Min = 0 Max = 4 Mean = 1.19 SD = 1.23 N = 1721
old*temperature	Someone is old and the height of the temperature on a day	Average temperature on a day in degrees Celsius and age	Min = -7,5 Max = 4 Mean = -0.67 SD = 2.05 N = 1721
neuroticism*good_weather	The degree of neuroticism and good weather	The degree of neuroticism (between 10 and 50) and good or not good weather on a day	Min = 0 Max = 41 Mean = 6.32 SD = 11.62 N = 323
neuroticism*bad_weather	The degree of neuroticism and bad weather	The degree of neuroticism (between 10 and 50) and bad or not bad weather on a day	Min = 0 Max = 36 Mean = 1.73 SD = 6.57 N = 323
neuroticism*wind_power	The degree of	The degree of	Min = 22

	neuroticism and the amount of wind power on a day	neuroticism (between 10 and 50) and wind power on the scale of Beaufort (between 0 and 12)	Max = 164 Mean = 60.49 SD = 22.12 N = 323
neuroticism*temperature	The degree of neuroticism and the height of the temperature on a day	The degree of neuroticism (between 10 and 50) and the average temperature on a day in degrees Celsius	Min = -240 Max = 132 Mean = -36.52 SD = 71.54 N = 323

***Table 2*. Summary of all the variables that are used in this thesis**

4. Analyses

This chapter describes all the analyses that are done to test the hypotheses that are drafted. The first two hypotheses (1a and 1b) are about two weather conditions that make people more ambiguity seeking and the second two (2a and 2b) are about two weather conditions that make people more ambiguity averse. The third hypotheses are about the effect of several weather conditions on the a-insensitivity of people. In the other forthcoming hypotheses some personal background variables are added and/or the personality of a subject.

The first three hypotheses and their sub hypotheses are all almost the same kind of analyses because all the tests consist of just two variables. The only reason why three different tests are used is the difference in characteristics of the variables. The options are:

1. Mann-Whitney U test: if the dependent variable is an interval variable and the independent variable a categorical variable;
2. Kruskal-Wallis test: if the dependent variable is an interval variable and the independent variable an ordinal variable;
3. Spearman correlation: if both the dependent and the independent variables are interval variables.

The other hypotheses are all just normal regressions. Off course the variables or the number of variables depends on the hypothesis that needs to be tested. More details about the different regressions will be explained in chapter 5 when discussing all the results.

5. Results

In chapter 5 all the results of the tests will be discussed in detail. The first paragraph discuss all the results of the directs tests for the drafted hypotheses and the second paragraph will discuss the results from some extra regressions what also could be interesting in this thesis.

5.1 Direct tests

To test hypothesis 1a, the two variables that are needed to test this hypothesis are *b* and *good_weather*. After comparing the ambiguity aversion index between good and not good weather no difference is found (Mann-Whitney U test: $z = 0.238$, $p = 0.812$ and $n = 1721$). Hypothesis 1b is tested with the two variables *b* and *wind_power*. The effect of wind power on the ambiguity aversion index, no statistical significant effect is found (Kruskal-Walles test: $\chi^2 = 0.604$, $p = 0.740$, $n = 1721$).

To test hypothesis 2a the variables *b* and *bad_weather* are used. Comparing the ambiguity aversion index between bad and not bad weather it gave no difference (Mann-Whitney U test: $z = -0.964$, $p = 0.335$ and $n = 1721$). To test hypothesis 2b the index of *b* and *temperature* are used. A negative correlation is found at a statistical significance effect of 10% (Spearman: $\rho = -0.0468$, $p = 0.0523$, $n = 1721$). So if the temperature increases the ambiguity aversion index decreases and subjects become less ambiguity averse.

Comparing the a-insensitivity index between good and not good weather for hypothesis 3a no difference is found (Mann-Whitney U test: $z = 1.150$, $p = 0.250$, $n = 1721$). To test hypothesis 3b the effect of *temperature* on index *a* is needed. No statistical significant effect is found (Spearman: $\rho = 0.020$, $p = 0.410$, $n = 1721$). For hypothesis 3c the follow result is found: comparing the a-insensitivity index between bad and not bad weather it gave no difference (Mann-Whitney U test: $z = 0.240$, $p = 0.811$, $n = 1721$).

Hypothesis 4 is tested with a regression. The dependent variable is index *b* and the independent variables are *female, good_weather* and the interaction term *female*good_weather*. Table 3 below shows the results of three regressions. Three different regressions are done to analyze the robustness of the results. No statistical significant effect of the variables is found in one of the regressions so these regressions provide no support if good weather has a stronger effect on the ambiguity aversion of females compared to males.

	(1)	(2)	(3)
VARIABLES	b	b	b
good_weather	-0.0146	-0.0147	-0.00138
	(0.0267)	(0.0267)	(0.0392)
female		0.0157	0.0219
		(0.0232)	(0.0267)
female*good_weather			-0.0248
			(0.0535)
Constant	0.182***	0.173***	0.170***
	(0.0133)	(0.0182)	(0.0195)
Observations	1,721	1,721	1,721
R-squared	0.000	0.000	0.001

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. **Regressions to test if the effect of good weather is stronger on the ambiguity aversion of females than of males**

Hypothesis 5 is also tested with a regression and the dependent variable is the index of *a* and the independent variables are *female, good_weather* and the interaction term *female*good_weather*. The results are shown in Table 4 below. No statistical effect is found for this hypothesis so no support is provided if good weather influences a-insensitivity for females.

VARIABLES	(1) a	(2) a	(3) a
good_weather	-0.0260	-0.0260	-0.0324
	(0.0319)	(0.0319)	(0.0468)
female		-0.000530	-0.00350
		(0.0277)	(0.0319)
female*good_weather			0.0119
			(0.0640)
Constant	0.940***	0.940***	0.942***
	(0.0159)	(0.0217)	(0.0234)
Observations	1,721	1,721	1,721
R-squared	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. **Regressions to test if good weather influences a-insensitivity for females**

Hypothesis 6a is tested with multiple regressions because the hypothesis is quite general. The term weather can mean a lot of things and can also be tested in several ways. The dependent variable in all regressions is the ambiguity aversion index *b* whilst the independent variable(s) differ per regression. Also interaction terms are added to each regression. The results of hypothesis 6a are shown in table 5.

In table 5 all the regressions are presented with the four weather variables and their corresponding interaction terms with *old*. In regression 1 till 4 just one weather variable is added in the model but in regression 5 all the variables are put together in one regression. To test all the variables separately is done to control for multicollinearity.

Testing the VIF (variance inflation factor) is an indicator for the multicollinearity and shows when it is a problem or not. According to Wooldridge (2009), if the VIF is 10 or higher they concluded that multicollinearity is a problem for estimating x_j. Another way to detect multicollinearity is to look to the value of R_j^2. If the R_j^2 is close to 1 there is a high correlation between the two or more independent variables, which can be due to multicollinearity. So for example if the R_j^2 = 0.9 meaning that 90% of the sample variation in x_j can be explained by other independent variables in the regression model.

Testing all the VIF's of the regressions in table 5 and no multicollinearity problems occurred until the last regression (number 5). In this regression *old* and the interaction term *old*wind_power* highly correlated because the VIF is above the number 10. This can denote a problem. But also the R_j^2 in this model can be used to detect if multicollinearity exists and in this model it is 0.012 what is close to 0 and not highly correlated between the other independent variables. So in this case it is not clear if it is a problem or not. To be sure the effect is correct when interpreting the results, regressions 1 till 4 are used.

In these regressions only *old* and the interaction term *old*wind_power* are statistical significant. For hypothesis 6a the effect of the interaction term *old*wind_power* on the ambiguity aversion index *b* is interesting. In regression 3 the interaction term is statistical significant at a 10% significance level (p = 0.052). The coefficient is positive so the additional effect when the wind power increases has on average a bigger increase for old people than for young and middle age people. Because only this interaction term was statistical significant, only this weather condition provide evidence the weather has a bigger impact on the index of *b* of elderly compared to middle age and young people. But the other weather conditions provide no support for this hypothesis.

VARIABLES	(1) b	(2) b	(3) b	(4) b	(5) b
old	-0.0997***	-0.0840***	-0.272***	-0.0829***	-0.291***
	(0.0261)	(0.0246)	(0.101)	(0.0247)	(0.105)
good_weather	-0.0489				-0.0446
	(0.0322)				(0.0331)
old*good_weather	0.0644				0.0659
	(0.0543)				(0.0561)
bad_weather		0.0409			0.0555
		(0.0407)			(0.0447)
old*bad_weather		0.0123			-0.00580
		(0.0658)			(0.0722)
wind_power			-0.0375		-0.0434
			(0.0252)		(0.0269)
old*wind_power			0.0804*		0.0817*
			(0.0413)		(0.0437)
temperature				-0.00343	-0.00420
				(0.00496)	(0.00505)
old*temperature				0.000228	-0.000227
				(0.00818)	(0.00843)
Constant	0.233***	0.216***	0.309***	0.216***	0.322***
	(0.0158)	(0.0148)	(0.0612)	(0.0148)	(0.0640)
Observations	1,721	1,721	1,721	1,721	1,721
R-squared	0.009	0.008	0.010	0.008	0.012

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. **Regressions to test if the weather has a bigger impact on the ambiguity aversion of elderly compared to middle age and young people**

Hypothesis 6b is tested with three different regressions with the ambiguity aversion index *b* as dependent variable and *young, bad_weather* and their interaction term as independent variables. Table 6 below shows the results of these regressions. The interaction term is not statistical significant so no support is provided that bad weather increases more the ambiguity aversion index of young people than of middle aged and elderly. The statistical significant effect of *young* will be discussed in paragraph 5.2.

VARIABLES	(1) b	(2) b	(3) b
young	0.102***	0.103***	0.101***
	(0.0234)	(0.0234)	(0.0249)
bad_weather		0.0526	0.0492
		(0.0327)	(0.0376)
young*bad_weather			0.0197
			(0.0691)
Constant	0.157***	0.152***	0.152***
	(0.0136)	(0.0144)	(0.0147)
Observations	1,721	1,721	1,721
R-squared	0.007	0.008	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. **Regressions the test the effect if bad weather increases more the ambiguity aversion of young people than of middle aged and elderly**

The results of hypothesis 7 are shown in table 7 and 8 below. The personality variable *neuroticism* is added in the regressions. The multiple regressions have several weather variables and interaction terms.

Table 7 shows the results of two regressions with in the first regression all the weather variables and in the second regression also added *neuroticism*. Finding the differences of these two models the effect of adding *neuroticism* can be detected. Adding *neuroticism*, *bad_weather* became statistical significant at a 1% significance level. So neuroticism has an influence on the effect of bad weather on the ambiguity aversion of people. Table 8 shows the results of five regressions. Regressions 1 till 4 are regressions with the weather variable and their interaction term with *neuroticism* separately. Regression 5 is with all the weather parameters and interaction terms included in one model. In all regressions *bad_weather* and the interaction term *neuroticism*bad_weather* are statistical significant. The effect of *bad_weather* on *b* will be interpreted in paragraph 5.2. The coefficient with the lowest p-value will be used. The same holds for interpreting the interaction term. So an increase in the degree of neuroticism has on average a smaller effect on the ambiguity aversion index when the weather is bad than when the weather is not bad. For other weather conditions no effects are found. Also tested if multicollinearity exists and it can be a problem in this case. The VIF is for all the variables in the regressions above 10 but the R_j^2 is really low in all cases. So be aware the regression coefficients can be poorly estimated due to multicollinearity.

	(1)	(2)
VARIABLES	b	b
neuroticism		0.00498
		(0.00408)
good_weather	-0.0123	-0.0159
	(0.0278)	(0.0718)
bad_weather	0.0568	0.264***
	(0.0359)	(0.0967)
wind_power	-0.00360	-0.0542
	(0.0217)	(0.0624)
temperature	-0.00493	-0.00807
	(0.00412)	(0.0120)
Constant	0.177***	0.180
	(0.0525)	(0.191)
Observations	1,721	323
R-squared	0.002	0.020

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. **Regressions the test the effect of weather on b increasing in the degree of neuroticism**

VARIABLES	(1) b	(2) b	(3) b	(4) b	(5) b
neuroticism	0.00451	0.00578	0.0245	0.00756	0.0272
	(0.00490)	(0.00436)	(0.0181)	(0.00519)	(0.0195)
good_weather	-0.0343				0.0917
	(0.259)				(0.259)
neuroticism*good_weather	-2.46e-05				-0.00413
	(0.00954)				(0.00953)
bad_weather		0.747***			0.772**
		(0.285)			(0.306)
neuroticism*bad_weather		-0.0206*			-0.0204*
		(0.0112)			(0.0119)
wind_power			0.195		0.133
			(0.197)		(0.209)
neuroticism*wind_power			-0.00832		-0.00691
			(0.00746)		(0.00783)
temperature				-0.0519	-0.0648
				(0.0442)	(0.0452)
neuroticism*temperature				0.00185	0.00217
				(0.00168)	(0.00172)
Constant	0.100	0.0437	-0.377	0.00792	-0.413
	(0.130)	(0.117)	(0.484)	(0.139)	(0.524)
Observations	323	323	323	323	323
R-squared	0.004	0.018	0.008	0.006	0.029

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table 8.* Regressions the test the effect of weather on b increasing in the degree of neuroticism (included interaction terms)**

5.2 Regressions on index *b*

This paragraph will provide some regression with all an effect on the index *b* that are not used for the direct tests but still can be interesting in this thesis.

In table 6 above also *young* is statistical significant at a 1% significance level. So the effect young people have on ambiguity aversion can be interpreted. Hence, if people are young the ambiguity aversion index *b* increases with 0.10 compared to middle aged people and elderly ceteris paribus. So young people become more ambiguity averse.

Table 7 shows a statistical significant effect at a 1% significance level of *bad_weather* on index *b* when adding neuroticism into the regression. If the weather is bad the ambiguity aversion index increases with 0.26 ceteris paribus so people become more ambiguity averse. Also Table 8 shows a statistical significant effect of *bad_weather* on index *b* and in this case the interaction term *neuroticism*bad_weather* is added into the regression. If the weather is bad ambiguity aversion index *b* increases with 0.75 ceteris paribus at a statistical significance level of 1%.

Table 9 below consists of two regressions, the first one with the effect *old* on *b* and the second one also with the weather variables included into the model. No multicollinearity problems are found in these regressions. If someone is old his/hers ambiguity aversion index decreases with 0.083, ceteris paribus at a statistical significant level of 1%. So elderly are less ambiguity averse.

Table 10 is an addition model with the most statistical significant results. In this regression *old*, *bad_weather*, *wind_power* and the interaction term *old*wind_power* are statistical significant at a 10% significance level. Multicollinearity does not exist for these variables in the regression. *Old* and the interaction term *old*wind_power* already interpret. The variable *old* in the analysis of table 9 and the interaction term *old*wind_power* in the paragraph of analyzing hypothesis 6a. Start with *bad_weather* so if the weather is bad the ambiguity aversion index *b* increases with 0.058, ceteris paribus so people become more ambiguity averse. Second *wind_power*, if the wind power increases with 1 on the scale of Beaufort the ambiguity aversion index *b* decreases with 0.044, ceteris paribus. People become less ambiguity averse.

VARIABLES	(1) b	(2) b
old	-0.0832***	-0.0830***
	(0.0229)	(0.0229)
good_weather		-0.0154
		(0.0278)
bad_weather		0.0539
		(0.0358)
wind_power		-0.00435
		(0.0217)
temperature		-0.00488
		(0.00412)
Constant	0.220***	0.222***
	(0.0138)	(0.0526)
Observations	1,721	1,721
R-squared	0.008	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9.* Regression with the effect of the variables old and several weather parameters on the ambiguity aversion index *b

VARIABLES	(1) b
old	-0.273***
	(0.103)
wind_power	-0.0444*
	(0.0262)
old*wind_power	0.0800*
	(0.0415)
bad_weather	0.0579*
	(0.0350)
temperature	-0.00325
	(0.00504)
old*temperature	-0.00206
	(0.00821)
Constant	0.314***
	(0.0637)
Observations	1,721
R-squared	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table 10.* Additional model: a regression with the most statistical significant variables.**

5.3 Regressions on index *a*

This paragraph will provide some regression with all an effect on the a-insensitivity index that are not used for the direct tests to expand the research and can be interesting in this thesis. Very limited information is done about the effect of weather on a-insensitivity index so this paragraph will increase the knowledge about this. Table 11, 12 and 13 all show regressions about this effect included with several background variables.

Table 11 shows the results of the regressions with the gender variable included. In regression number 5 *wind_power, female*, the interaction terms *female*bad_weather* and *female*wind_power* are statistical significant. The following conclusions can be drawn from this:

1. If the wind power increases with an amount of 1 on the scale of Beaufort the a-insensitivity index decreases with 0.075 ceteris paribus at a significant level of 10%;
2. The extra a-insensitivity of females decreases with 0.218 compared to males, ceteris paribus, at a significant level of 10%;
3. A decrease of 0.186 of the extra aversion of a female in bad weather with respect to what a female would display if bad weather had the same impact on them as on males;
4. The extra a-insensitivity when the wind power increases is on average a bigger effect on females compared to males.

In this regression *female* and *female*wind_power* are highly correlated and multicollinearity can be a problem. Hence, the regression coefficients are poorly estimated for these two variables.

VARIABLES	(1) a	(2) a	(3) a	(4) a	(5) a
female	-0.00350	0.0130	-0.179	0.000908	-0.218*
	(0.0317)	(0.0295)	(0.123)	(0.0304)	(0.128)
good_weather	-0.0324				-0.0232
	(0.0466)				(0.0479)
female*good_weather	0.0119				-0.00461
	(0.0643)				(0.0669)
bad_weather		0.0504			0.0817
		(0.0652)			(0.0707)
female*bad_weather		-0.124			-0.186**
		(0.0835)			(0.0917)
wind_power			-0.0595		-0.0745*
			(0.0376)		(0.0399)
female*wind_power			0.0758		0.103*
			(0.0510)		(0.0540)
temperature				0.00192	0.00163
				(0.00666)	(0.00675)
female*temperature				0.00119	0.00283
				(0.00966)	(0.0100)
Constant	0.942***	0.929***	1.074***	0.937***	1.109***
	(0.0223)	(0.0207)	(0.0897)	(0.0216)	(0.0933)
Observations	1,721	1,721	1,721	1,721	1,721
R-squared	0.000	0.001	0.002	0.000	0.004

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11. **Regressions to test the effect of gender and weather conditions on the a-insensitivity index of the subjects.**

Table 12 shows the results of several regressions including the age variable. Only the variable *old* is statistical significant at a 1% or 5% significance level. To interpret *old*, the regression with the lowest p-value is chosen. Regressions 1, 2 and 4 have the same statistical significance level of 1%. Which of these regressions is chosen does not really matter so in this case regression 1 is chosen. So the a-insensitivity index of an old person increases with 0.139 compared to young- and middle-aged people, ceteris paribus, at a 1% significance level. To conclude, older people exhibit higher a-insensitivity. In this regression there are no problems due to multicollinearity.

VARIABLES	(1) a	(2) a	(3) a	(4) a	(5) a
old	0.139***	0.108***	0.245**	0.147***	0.339***
	(0.0313)	(0.0293)	(0.123)	(0.0302)	(0.128)
good_weather	0.0138				-0.00409
	(0.0406)				(0.0420)
old*good_weather	-0.0733				-0.0435
	(0.0643)				(0.0665)
bad_weather		-0.0754			-0.0807
		(0.0551)			(0.0595)
old*bad_weather		0.121			0.118
		(0.0801)			(0.0890)
wind_power			0.00907		0.0270
			(0.0314)		(0.0334)
old*wind_power			-0.0527		-0.0845
			(0.0512)		(0.0542)
temperature				-0.00650	-0.00584
				(0.00600)	(0.00615)
old*temperature				0.0190*	0.0165
				(0.00982)	(0.0103)
Constant	0.869***	0.881***	0.851***	0.863***	0.811***
	(0.0193)	(0.0180)	(0.0750)	(0.0188)	(0.0784)
Observations	1,721	1,721	1,721	1,721	1,721
R-squared	0.012	0.012	0.012	0.014	0.016

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12. **Regressions to test the effect of age and weather conditions on the a-insensitivity index of the subjects.**

Table 13 shows all the results from the regressions with the personality variable *neuroticism* included. No statistical significant effects were found so not providing any support for the effect of neuroticism on a-insensitivity.

VARIABLES	(1) a	(2) a	(3) a	(4) a	(5) a
neuroticism	7.62e-05	-0.00194	-0.00326	-0.00258	-0.000227
	(0.00486)	(0.00462)	(0.0166)	(0.00585)	(0.0175)
good_weather	0.0951				0.0366
	(0.293)				(0.300)
neuroticism*good_weather	-0.00451				-0.00296
	(0.0111)				(0.0114)
bad_weather		-0.485			-0.522
		(0.486)			(0.509)
neuroticism*bad_weather		0.0125			0.0134
		(0.0180)			(0.0186)
wind_power			-0.0389		0.0330
			(0.185)		(0.193)
neuroticism*wind_power			0.000920		-0.00106
			(0.00635)		(0.00649)
temperature				0.0208	0.0253
				(0.0540)	(0.0548)
neuroticism*temperature				-0.000857	-0.000932
				(0.00204)	(0.00206)
Constant	0.975***	1.033***	1.091**	1.036***	0.989**
	(0.128)	(0.122)	(0.468)	(0.156)	(0.500)
Observations	323	323	323	323	323
R-squared	0.001	0.006	0.000	0.001	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13. **Regressions to test the effect of neuroticism and weather conditions on the a-insensitivity index of the subjects.**

6. Conclusion

This chapter will summarize the most important results. The first paragraph consists of the results of the direct tests in which a statistical significant effect is found. The second paragraph will discuss the results from the regressions on index *b* and *a*.

6.1 Conclusions direct tests

Via the direct tests for three hypotheses support is found. Hypothesis 2b mentioned people are more ambiguity averse when the temperature is high. But no evidence was found for this theorem but for the other way around. So people are less ambiguity averse when the temperature is high.

Hypothesis 6a was about that weather has a bigger impact on the ambiguity aversion of elderly compared to middle aged and young people. The term weather is really broad and support is found for this hypothesis but just for a small component of weather. So for one weather parameter evidence is found. Wind power has a bigger effect on elderly than on young or middle aged people.

Hypothesis 7 mentioned the effect of weather on ambiguity aversion is increasing in the degree of neuroticism. Adding *neuroticism* into the regression with all the weather parameters and comparing this with the regression with only the weather parameters, the effect on *b* changes for all the weather parameters. Even, *bad_weather* became statistical significant. Another regression showed the following result: an increase in the degree of neuroticism has on average a smaller effect on the ambiguity aversion index when the weather is bad than when the weather is not bad. So the effect of weather on *b* is increasing in the degree of neuroticism but only evidence is found in situation of not bad weather. This is not one of the defined weather parameters but it is the opposite of *bad_weather.* 'Not bad weather' is also a form of weather so in this case there is evidence for hypothesis 7.

6.2 Conclusions regressions

The extra regressions on ambiguity aversion and a-insensitivity found some results. Two tables below show all the findings in a summarized overview. Table 14 are all the results of the regressions on ambiguity aversion and Table 15 all the results of the regressions on a-insensitivity.

Table	Variable	Ambiguity attitude	Effect
Table 6	young	b	b increases with 0.10
Table 7	bad_weather	b	b increases with 0.26
Table 8	bad_weather	b	b increases with 0.75
Table 9	old	b	b decreases with 0.083
Table 10	bad_weather	b	b increases with 0.058
Table 10	wind_power	b	b decreases with 0.044

Table 14. **All results of the regressions regarding ambiguity aversion.**

Table 14 summarizes the six results of the effect of different variables on ambiguity aversion. So young people are more ambiguity averse compared to middle aged and elderly and old people are less ambiguity averse compared to young and middle aged people. Three the same effects are found for bad weather on ambiguity aversion. So if the weather is bad people become more ambiguity averse. The last result is about the wind power on a day. If the wind power increases the ambiguity aversion decreases and people become less ambiguity averse.

All the results for ambiguity aversion are interpret but there is more to say. In this paragraph some results that are found can provide support for some hypotheses. For this hypothesis was no evidence found via the direct tests in §5.1. First, hypothesis 1b if testing this hypothesis with a Kruskal-Wallis test there is no statistical significant effect found but with a regression an effect is found. After adding some variables into the regression that is presented in table 10, *wind_power* became statistical significant. Via the direct tests I not found any support for hypothesis 1b but with the regression I do found evidence. Secondly, hypothesis 2a has the same story. Via the direct tests there was no support, but the with the regressions found an effect is found. Table 7, 8 and 10 all showed an effect of *bad_weather* on index *b*. All the three results show a positive effect of bad weather on ambiguity aversion only the magnitude of the coefficient is different. But via these regressions evidence is found for hypothesis 2a.

Table	Variable	Ambiguity attitude	Effect
Table 11	wind_power	a	a decreases with 0.075
Table 11	female	a	a decreases with 0.218
Table 11	female*bad_weather	a	a decreases with 0.186
Table 11	female*wind_power	a	If wind power increases, bigger effect on females w.r.t. males
Table 12	old	a	a increases with 0.139

***Table 15*. All results of the regressions regarding a-insensitivity.**

Table 15 summarizes the five results of the effect of different variables on a-insensitivity. So the following effects are found:

- If the wind power increases the a-insensitivity index of the subjects decreases;
- If someone is a female the a-insensitivity index decreases compared to the a-insensitivity index of males;
- Bad weather days decrease the a-insensitivity index of females only;
- The additional effect when the wind power increases has on average a bigger increase for females compared to males;
- The a-insensitivity index of old people increases compared to the a-insensitivity index of young and middle aged people.

One thing that still need to be taken into account is the poorly estimation of the coefficients of *female* and *female*wind_power* due to multicollinearity. So the exact magnitude of the effect of these two variables can be slightly different than mentioned in the table.

Knowing all the conclusions of the tests also a conclusion can be drawn which theory that are discussed in paragraph 2.4 is used with ambiguity attitudes. Just for a reminder the two theories were the Affect Infusion Model and the Mood Maintenance Hypothesis. For risk attitudes there was more evidence for the AIM model. Looking to the results in this thesis there is not a clear answer. So before a conclusion can be drawn about the theory for ambiguity attitudes probably more research need to be done. I think the problem of contradict results will always be the case but the same holds as for risk attitudes, it will probably the theory with the most founded evidence in the same circumstances.

7. Discussion & Further research

7.1 Limitations and further research

This thesis focuses on both ambiguity attitudes but by the lack of research of a-insensitivity less knowledge is known about this attitude. So just little information was available to create hypotheses. Just in general all new research about a-insensitivity would be really interesting. Questions that are related to this thesis and should be useful to investigate are for example: Is people's a-insensitivity influenced by mood? Is the effect of a certain weather variable the same for ambiguity aversion and a-insensitivity? In daily life knowing more about this attitude could help because people make every day multiple cognitive decisions in ambiguous situations. So how can these decisions be influenced in a direction that is preferred?

Furthermore, a lot of research was already done about the link between mood and risk attitudes. In previous research were found risk attitudes and ambiguity attitudes are positive correlated. So assumed mood also has an influence on the ambiguity aversion of people but not much research is done about the direct relationship between these two. The questionnaire that is used in this thesis does not analyze the mood of the participants. All the effects that are found in this thesis of weather on ambiguity attitudes is stated that this happens because of the participant's mood. Interesting for further research would be to investigate if indeed the mood influence people's ambiguity attitude. So the mood and the weather conditions need to be compared to investigate if people are in a bad mood it is also a bad weather day for example. This would provide more evidence and information of the link between mood and ambiguity attitudes.

Another limitation is about the distribution between the variable gender and age. There are more females in this thesis and the variable age is not normally distributed. More old people filled in the questionnaire. Both can influence the representativeness and reliability of the research. In order to have optimal results the best would be an equal distribution between females and males and if age is normal distributed.

In this indention limitations due to how the research in this thesis was done will be discussed. First, a closer look to the amount of weather variables that were taken into account in this thesis. The more weather conditions the more accurately the results and the information will be. Four weather parameters are used in this thesis to find the effects on ambiguity attitudes. Four weather parameters were used because in previous research these possibly have a link with ambiguity attitudes. For further research it would be interesting to define more weather parameters/conditions and analyses which of those have an effect on ambiguity attitudes of people. Second, in this thesis only the weather circumstances of one place in the Netherlands, called 'De Bilt' are used, on different days in January. In this thesis is stated that the weather will be the same for the rest of the country. To be more precise the weather data of the specific place of the participant need to be used. Maybe this is not the biggest problem but the participants filled in the questionnaire when they want it is. There were no restrictions when the participants need to fill in the questionnaire so it is possible they all filled in the questionnaire on a bad day for example. Because the Netherlands is quite small the variance between places will be smaller than the variance between dates. So for further research more rules need to be created when the participants need to fill in the questionnaire to decrease the variance. Later in this chapter an example if given of maybe a better way of testing and this component will be taken into account. Third, the definitions of good and bad weather are adopted from one previous study. These definitions are really important for a big part of the thesis. So if other definitions were found it could have changed a lot in the results. Therefore it would be better if there was more information about what people experience as a good weather day and a bad weather day. Comparing more results on this would create better and more thought definitions. Last, the Big Five personalities traits are used to add some extra personal background variables into the research of this thesis. Only the personality trait neuroticism is used to see if this has an effect of a weather parameter on an ambiguity attitude. People are really different and for sure not only neuroticism would influence people's attitude. So if there is more knowledge about which weather condition combined with a personality trait makes people for example the most ambiguity seeking. This can help people or companies to know in which way they need to approach these people. Another limitation of the Big Five personality factors is the number of observations. The observations were less because this information was only available if the participants filled in the 'long' questionnaire. So more observations will make the results more reliable and maybe a statistical significant effect could be found for a-insensitivity.

7.2 Other possible design

After this research and analyzing the limitations maybe a whole other design would be better. The design that will be discussed is not by definition the best design but a design that can solve some limitations.

Instead of doing a questionnaire also an experiment is possible. All the participants will be invited to participate in an experiment in a certain place. Ideal there are several spots in the Netherlands were the experiment could take place to have a dispersion of living places of the participants. The dates of the experiments will for example 10 specific days in one month and for all places the same. Ten days are used because several weather conditions needed to be measured. So the same 10 days will be used for all places because probably there is a bigger variance between dates than places. Another advantages of have specific dates, participants cannot choose by themselves when they fill in the questionnaire or when you want to do the experiment. This will be better for the results because people cannot be influenced by the weather when they participate. For example if the weather is bad they want to participate but when the sun in shinning they prefer to go to the beach. During the experiment also the mood of the participants can be tested or observed. This is useful to investigate to found out if indeed mood is the moderator between weather and ambiguity attitudes. Instead of let the participants fill in a questionnaire, in an experiment they actually can really test it. So they will carry out the exact same thing that is described in the questionnaire but then in a 'real' situation. The Ellsberg's paradox is used and every round the participants need to choose from which urn they want to pick the purple ball. When the participant chooses 'Indifferent', the ambiguity attitudes can be calculated. Choosing for an experiment with some restrictions will already reduce the limitations so this can be useful for further research if the resources exist.

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9. Appendix

9.1 Appendix A

Power	Name	Wind average speed about 10 minutes (km/u)	Wind average speed about 10 minutes (m/sec)	Effect above land and at people
0	Still	0-1	0-0.2	Smoke arise straight or almost straight
1	Weak	1-5	0.3-1.5	Wind direction well to ditract from smoke plumes
2	Weak	6-11	1.6-3.3	Wind noticeable in the face
3	Moderate	12-19	3.4-5.4	Dust blowing on
4	Moderate	20-28	5.5-7.9	Hair confused and clothes flapping
5	Quite powerfull	29-38	8.0-10.7	Blowing dust iritation for eyes
6	Powerfull	39-49	10.8-13.8	Umbrella's hard to hold
7	Strong	50-61	13.9-17.1	Hard to walk againt the wind
8	Stormy	62-74	17.2-20.7	Propel really hard
9	Storm	75-88	20.8-24.4	Tiles blow away
10	Heavy storm	89-102	24.5-28.4	Big damage at buildings
11	Really heavy storm	103-117	28.5-32.6	Enormuous damage on forests
12	Hurricane	>117	>32.6	Destructions

Source: Weergaloos Nederland. Publisher Kosmos/Z&K, Utrecht, 1997/2004