The Effect of Weather on Ambiguity Attitudes: An Analysis on The United States of America

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Abstract

Individuals are often confronted with decisions in life, that involve the lack or absence of information about decision outcomes. If not enough information is provided to form several probability distributions at all, this is known as ambiguity. Existing literature shows that ambiguity affects decision making, which is also affected by the emotional state. This research investigates weather as a factor that may influence ambiguity attitudes via the emotional state, by combining data on decision making under ambiguity and the weather for the United States of America. Evidence shows a positive effect of the average daily wind speed on ambiguity-averse behaviour. However, precipitation, snowfall and temperature are not significant. When considering the four state regions of the United States, the results show that there is a difference in significance for several weather conditions between state regions. However, only the effect of snowfall on the ambiguity attitude for low likelihoods in the northeast region is statistically larger than in other state regions. Additional findings show that individuals are more ambiguity-averse for high likelihoods than for low likelihoods. Besides, having more trust in the financial stock market (decision making under ambiguity) makes individuals less a-insensitive.

Keywords: *ambiguity attitudes, ambiguity-aversion, a-insensitivity, weather conditions, emotional state, mood*

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1. Introduction

Agents are often confronted with decisions in life, that are based on beliefs concerning the likelihood of uncertain outcomes (Tversky & Kahneman, 1974). Such events involve the lack or absence of information about decision outcomes (Platt & Huettel, 2008). For instance, individuals need to make intertemporal decisions for their retirement without knowing how much their future earnings and rates of return will be (Delavande & Rohwedder, 2011). Furthermore, financial firms suffer from imperfect information due to volatility in idiosyncratic shocks, which might change the initial expected value of an asset (Avery & Zemsky (1998); Rigotti & Shannon (2005)). Besides, one could also think about an uncertain event, such as the result of an election (Tversky & Kahneman, 1974).

Bayesian networks are developed for decision making under uncertainty, to represent a scheme for probabilistic knowledge and beliefs (Shafer & Pearl (1990); Pearl (1996)). For example, they are used to explain smoothing and prediction, and to make plans in uncertain environments (Dean & Wellman, 1991). Bayesian networks are in general used by individuals to attach their own subjective probabilities leading to behavioural decisions, when information about the objective probabilities is absent (Gilboa & Marinacci, 2013). The Bayesian method namely shows, that present axioms cause individuals to make necessary decisions by maximizing their expected utility relative to a certain probability measure (Gilboa & Marinacci (2013); Savage (1954)). That is, in absence of probabilities, axioms cause individuals to come up with certain probabilities to base their decisions on. According to Savage (1954), Bayesian networks do not provide a way of how the updating of prior (original) probabilities is measured. So, Savage (1954) developed the subjective expected utility model to find choice-based subjective probabilities from decision making behaviour representing individuals' beliefs (Karni, 2013).

There have been discussions about whether rational decision making under uncertainty should be based on such Bayesian beliefs (Gilboa & Marinacci, 2013). Uncertainty can be defined as events wherein decision outcomes and/or the probability of each decision outcome are not fully predictable (Knight, 1921). Keynes (1921) and Knight (1921) both state that it is not always possible to attach numerical probabilities to uncertain events. For that reason, uncertainty is subdivided in two different aspects; risk and ambiguity. Knight (1921) distinguishes risk from ambiguity, in that risk occurs in events wherein all the alternatives and their objective probabilities are known, which is not the case under ambiguity. Namely, ambiguity is known as a more uncertain situation, wherein no specific information is present to attach any subjective probability distribution to the decision outcomes (Ellsberg, 1961). Decision making behaviour under ambiguity can be subdivided in three kinds of attitudes: ambiguity-averse, ambiguity-neutral and ambiguity-seeking (Dimmock, Kouwenberg, & Wakker, 2016). These attitudes indicate two different aspects. The first aspect of ambiguity-aversion corresponds to the motivational part of behavioural decision making, whether individuals like or dislike ambiguous events (Abdellaoui, Baillon, Placido, & Wakker, 2011). For instance, an ambiguity-averse individual likes decision making under known probabilities more than decision making under unknown probabilities. The second aspect of a-insensitivity corresponds to the cognitive part, whether individuals discriminate between likelihood levels (Abdellaoui, Baillon, Placido, & Wakker, 2011). A-insensitive people do not make a sufficient distinction between different ambiguity likelihood levels, by considering them all as 50-50. Ellsberg's paradox indicates that such behaviour is sometimes not rational and therefore deviates from subjective expected utility (Dimmock, Kouwenberg, & Wakker, 2016). This research focuses on decision making under ambiguity for which probabilistic information about the alternatives is absent, to form any probability distributions to the decision outcomes (Etner, Jeleva, & Tallon, 2012).

Existing literature shows that ambiguity affects decision making, by analysing different models of ambiguity (Etner, Jeleva, & Tallon, 2012). Ellsberg (1961) mentions that ambiguity is determined by several aspects that affect information, but more importantly causes a level of confidence in attaching certain probabilities to different decision outcomes. Felson (1981), Epstein and Schneider (2007), and Hsu et al. (2005) all find that confidence is an important aspect for decision making under ambiguity. For instance, Hsu et al. state that the level of confidence could change a lot in attaching probabilities to decision outcomes. For example, one could be more confident due to the decisions made in the past. With the use of functional brain imaging, they provide evidence that a higher ambiguity level leads to a higher brain activity in the amygdala and orbitofrontal cortex, and a lower brain activity in the striatal system. So, it seems that the individual's emotions may also be important, since the function of the amygdala is connecting information gathered by senses with different emotional states (Ramsøy, 2015).

Bower (1981) shows that emotional states affect decision making under ambiguity. The reason for this is that mood causes a biased decision making, because individuals refer to categories that are connected to the emotion. Moreover, Potamites and Zhang (2012), and Yusef and

Feinberg (2016) discuss several emotional states that affect the ambiguity attitude. Furthermore, it follows from Kugler, Connolly and Ordóñez (2012) that the individual's emotional state affects risk-taking or risk-seeking behaviour, dependent on the individual's type and level of uncertainty. Finally, also Forgas (1995), and Schwarz and Clore (1983) show that mood affects the way individuals think about their decision making. It is of great interest in behavioural economics to find out what psychological factors affect the individual's emotional state and how this is related to the individuals' ambiguity attitudes.

There is evidence for several factors that may influence the individual's emotional state and decision making, such as; day length (Rosenthal et al. (1984); Kamstra, Kramer & Levi (2000)), lunar phases (Yuan, Zheng & Zhu (2006); Dichev & Janes (2001)), religious holidays (Fields (1934); Frieder & Subrahmanyam (2004)), sport results (Edmans, Garcia, & Norli, 2007) and the weather (Cunningham (1979); Hirshleifer & Shumway (2003); Mills (1934); Saunders (1993); Digon & Bock (1966); Cao & Wei (2005); Goldstein (1972); Persinger (1975)). For instance, Persinger (1975) finds that people feel less happy, when there is less sunshine. Moreover, Cunningham (1979) provides evidence that people feel more happy, when the temperature is higher. Saunders (1993) relates the temperature to stock prices and finds that returns are higher, when the temperature is higher. Finally, Hirshleifer and Shumway (2003) also show that temperature affects the stock returns.

Baillon, Koellinger and Treffers (2016) also investigate the effect of emotional states on ambiguity attitudes. They use two laboratory experiments and vary the emotional states of individuals. They find that individuals are more ambiguity-neutral, when they are sad. However, individuals who feel joy and fear are less payoff-maximizing. Furthermore, Bassi, Colacito and Fulghieri (2013) experimentally investigate the effect of weather and mood on risk-taking behaviour in financial decision making. They especially focus on the relationship between weather and the individual's risk-taking behaviour. The results show that a higher temperature and more sunshine lead to more risk-seeking behaviour, which is controlled for both objective and subjective measures of the weather. Moreover, they also find that a lower temperature and less amount of sunshine lead to more risk-averse behaviour. This research focuses on weather, because there is only little evidence on whether and how weather affects ambiguity attitudes via emotional states. Therefore, the research question is as follows: *"What is the effect of weather on ambiguity attitudes?"*

Since there is only little evidence on the effect of weather on ambiguity attitudes via emotional states, this research tries to fill that gap. I use data from the RAND American Life Panel (ALP 2012), which includes a survey on ambiguity attitudes. The ALP has come into existence in 2003 and is a regular, nationally representative panel among 6,000 individuals from the United States of America, who are 18 years and older. The probability-based survey on ambiguity attitudes was conducted in 2012 and includes a sample of 3,290 observations. It is a rich dataset on decision making under uncertainty, in which several important demographics are present. Ambiguity attitudes are measured with the method introduced by Dimmock, Kouwenberg and Wakker (2016), using matching probabilities derived from Ellsberg's paradox (Ellsberg, 1961). Matching probabilities are the objective probabilities where the subject is indifferent between the ambiguous and the objective alternative, given a certain price. Since the data includes information about the state the individuals reside at the moment of filling in the survey, and the timestamp for beginning and completing the survey, it is possible to match the ALP data to weather data from the National Centers for Environmental Information (NCEI 2016).

Evidence shows that a higher average daily wind speed leads to more ambiguity-averse behaviour. Though, precipitation, snowfall and temperature are not significant. When looking more specifically at the four state regions of the United States of America, the findings indicate that there is a difference in significance for several weather conditions between state regions. However, only the effect of an increase in snowfall on the ambiguity attitude for low likelihoods in the northeast region is statistically larger than in other state regions. Additional results show that individuals are more ambiguity-averse for high likelihoods than for low likelihoods. Also, there is evidence that having more trust in the financial stock market (decision making under ambiguity) makes individuals less a-insensitive. Finally, the order of the questions on ambiguity-aversion and risk-aversion are very important for measuring ambiguity attitudes.

The rest of this paper is built up as follows. In the next chapter, different related economic papers are reviewed to provide theoretical insights for testing the hypotheses and answering the research question. Then, the data on ambiguity attitudes and the weather are described in detail. After that, the empirical strategy will be designed and used for statistical testing, of which the results are described in the fifth chapter. In the discussion, the results will be summarized and discussed by taking the existing literature into consideration. Possible shortcomings and future recommendations are also mentioned in this chapter. Finally, the research question is answered in the conclusion.

2. Related literature

In this section, existing papers that are related to the research topic are reviewed and considered. First of all, existing literature on ambiguity attitudes is described. Thereafter, the relationship between emotional states and ambiguity attitudes is analysed in more detail. Then, the weather is considered as a factor that may influence the ambiguity attitudes via the individual's emotional state. Finally, several hypotheses are formed based on expectations from the related literature, which will be tested later on.

2.1 Ambiguity attitudes

Bayesian networks are developed to make decisions under uncertainty (Shafer & Pearl (1990); Pearl (1996)). However, Savage (1954) argues that Bayesian networks are not successful in providing a way of how the updating of prior probabilities is measured. For that reason, Savage developed the subjective expected utility model with the purpose of finding choice-based subjective probabilities from decisions, that represent the individuals' beliefs. He bases his model on updating beliefs according to the Bayesian method, for uncertain events wherein numerical probabilities are absent. His intention is to realise the attachment of measurable, subjective probabilities to the decision outcomes, which expresses the individual's beliefs.

However, due to the implication of the subjective expected utility theory, Ellsberg (1961) makes a clear distinction between uncertainty, risk and ambiguity. First of all, Knight (1921) and Keynes (1921) both argue that it is not always possible for individuals, to attach numerical probabilities to the outcomes of decisions. Namely, they make a clear distinction between events wherein numerical probabilities are present and not present. So, it is important to define the three aspects related to such events based on existing literature; uncertainty, risk and ambiguity. Uncertainty can be defined as situations in which the outcomes of decisions and/or probabilities of the alternatives are not fully predictable (Knight, 1921). Therefore, uncertainty is subdivided in two different aspects: risk and ambiguity. Risk occurs in situations wherein all the different alternatives are known and it is possible to attach objective probabilities to the alternatives (Knight, 1921). Ambiguity differs from risk, in that information about the objective probabilities is unknown to the decision maker (Knight, 1921). Ellsberg (1961) also makes a distinction between risk and ambiguity, in that there are uncertain events wherein it is not likely to base the decision making on subjective expected utility and wherein not enough information is provided to form several probability distributions at all.

Ellsberg (1961) designed thought experiments to test the axioms that have been made by Savage (1954) and other existing papers. Such a well-known hypothetical experiment is the Ellsberg two urn thought experiment, also known as Ellsberg's paradox, and works as follows. Identical to the survey questions in the dataset of this research (ALP 2012), a subject is asked to choose between two different boxes, a known box (Box K) and an ambiguous box (Box U). Both boxes consist of orange balls and purple balls, and both contain a total number of 100 balls. In Box K, the number of orange and purple balls are equally divided. In Box U, there is a total number of 100 balls for which the number of orange and purple balls are completely unknown to the subject. Then, the subject is asked to choose between the known urn and the ambiguous urn, and what winning colour is preferred. Now, assume that the preferred winning colour is purple. A ball will randomly be drawn from the box the subject has chosen, with a chance of winning when a purple ball is drawn. In that case, the individual wins when the drawn ball from the chosen box is purple and will not win anything when the drawn ball is orange. At the end, the individual is ambiguity-averse when 'Box K' is chosen over 'Box U'. On the other hand, the individual is ambiguity-seeking when 'Box U' is chosen over 'Box K'.

Ellsberg (1961) calls it a paradox, since individuals prefer decision making under known probabilities over decision making under unknown probabilities, regardless of the fact that a gamble on the unknown probabilities would lead to a higher winning chance. Therefore, individuals do not always behave according to subjective expected utility. Based on Ellsberg's paradox in this survey, this can be explained as follows. O_K and P_K are respectively the events of an orange ball and purple ball drawn from the known Box K, whereas O_U and P_U are respectively the events of an orange ball and purple drawn from the unknown Box U. Assume that the preferred colour of the subject is orange. Then, we know that the following holds for the probabilities of an orange and purple ball in Box K and Box U:

$$[P(O_K) = P(P_K) = 0.5]$$

$$[P(P_U) \leq P(O_U)]$$

If the subject chooses for the known Box K, this implies:

$$0.5 = P(O_K) > P(O_U) \geq P(P_U)$$

$$P(O_U) + P(P_U) < 1$$

Therefore, the individual's choice indicates a contradiction. There are many papers on ambiguity attitudes that use Ellsberg's paradox. First of all, Camerer and Weber (1992) review previous papers, theoretical insights and several studies on ambiguity attitudes and subjective expected utility. They clearly explain Ellsberg's paradox and mention several studies that have been using this paradox. For instance, Becker and Brownson (1964) were the first who investigated ambiguity attitudes using the two urn experiment of Ellsberg, with an option to pay for avoiding ambiguity (ambiguity premium). Furthermore, Hogarth and Einhorn (1990) study ambiguity attitudes based on Ellsberg's paradox. However, it differs in that they give the opportunity to subjects to look into the ambiguous urn before they need to make a decision, so individuals can make an estimation. Their findings show that individuals are less ambiguity-averse for a loss than for a gain. Abdellaoui and Wakker (2005) provide a likelihood method for making decisions under uncertainty, using an analysis on Ellsberg's paradox. Besides, Halevy and Feltkamp (2005) show how to investigate uncertainty-aversion. They use the two urn experiment as a basis, but slightly change it by drawing more than one ball from the chosen alternative. Later on, Halevy (2007) tests this provided theory and extends Ellsberg's paradox by conducting two experiments. Another paper written by Dominiak, Duersch and Lefort (2012) also uses Ellsberg's experiment, but changes it to a dynamic setting.

There is only little evidence on the relationship between ambiguity attitudes and decision making behaviour, since Ellsberg's paradox is mainly used to investigate ambiguity-aversion (Dimmock, Kouwenberg, & Wakker, 2016). Dimmock et al. (2016) design a way to measure ambiguity attitudes with the use of matching probabilities. Such probabilities, under ambiguous decision making, are the objective probabilities where the subject is indifferent between the ambiguous and the objective alternative, given a certain price (Dimmock, Kouwenberg, & Wakker, 2016). Based on the matching probabilities, it is possible to determine whether individuals are; ambiguity-averse, ambiguity-neutral, ambiguity-seeking and a-insensitive. In the dataset that is used in this research (ALP 2012), it is possible to calculate the matching probability by analysing the individuals' choices between the ambiguous and known urn. If the known urn is chosen over the ambiguous urn, then it follows that the matching probability is less than 50%. In addition, a lower matching probability indicates that the subject is more ambiguity-averse. The method introduced by Dimmock et al. (2016) is used in this research and will be described more in detail in the fourth chapter including the empirical strategy.

2.2 Emotional states and ambiguity attitudes

Ellsberg (1961) states that ambiguous information is affected by several factors, but also leads to a level of confidence in attaching certain probabilities to the outcomes of decisions. There are several other papers that show how the level of confidence is affected by ambiguous situations (Felson (1981); Epstein & Schneider (2007); Hsu et al. (2005)). In Hsu et al. (2005), it is mentioned that the individual's level of confidence is highly affected by the attachment of probabilities to the outcomes of decisions. For instance, attaching the decision outcomes from the past to current ambiguous events, leads to a higher level of confidence. By testing subjects with the use of functional brain imaging, their results show that a higher ambiguity level positively affects the brain activity in the amygdala and orbitofrontal cortex. On the other hand, a higher ambiguity level negatively affects the brain activity in the striatal system. This last finding in the amygdala is especially important, because the function of the amygdala is connecting information gathered by senses with different emotional states (Ramsøy, 2015). It therefore seems that the individual's emotions may also be affected by ambiguous situations.

The findings by Bower (1981) indicate that emotional states indeed influence decision making under ambiguity. This stems from the fact that mood leads to a biased decision making by individuals, caused by referring to categories that are connected to the emotional state. Schwarz and Clore (1983), and Forgas (1995) also provide evidence that mood has an impact on the way individuals think about decision making. Furthermore, Potamites and Zhang (2012) show with an experiment that individuals who have a higher level of anxiety, also have a higher level of ambiguity-aversion. Besides, Kugler, Connolly and Ordóñez (2012) show that the emotional state influences risk-seeking behaviour, which is determined by the type of the individual and the level of uncertainty. Finally, Yusef and Feinberg (2016) mention certain emotional states that affect ambiguity attitudes of individuals, such as happiness and trust. Based on the findings from existing literature, it is very interesting to find out whether and how psychological factors have an impact on mood, and what the relationship is between these psychological factors and ambiguity attitudes.

Existing literature has shown that there are different factors that may affect the individual's mood and decision making. First of all, Rosenthal et al. (1984), and Kamstra, Kramer and Levi (2000) both find that day length affects the emotional state and decision making. Secondly, Yuan, Zheng and Zhu (2006), Dichev and Janes (2001) show that lunar phases affect stock market returns, which is characterized by uncertainty. In addition, it follows from Frieder and Subrahmanyam (2004), and Fields (1934) that religious holidays also have an effect on the stock market returns. Edmans, Garcia and Norli (2007) provide evidence, that results of several famous sport games have an impact on stock markets. Finally, there are many papers that investigate the effect of weather on mood and financial markets (Cunningham (1979); Hirshleifer & Shumway (2003); Mills (1934); Saunders (1993); Digon & Bock (1966); Cao & Wei (2005); Goldstein (1972); Persinger (1975)). First of all, the findings of Persinger (1975) show that individuals feel less happy, when there is less sunshine. Besides, it follows from Cunningham (1979) that the individual's happiness is positively related with a higher temperature. Saunders (1993) relates the temperature to the financial markets and finds that stock returns are also positively affected by the temperature. Finally, Hirshleifer and Shumway (2003) also investigate the effect of weather on stock returns and indeed find a positive effect.

2.3 Weather and ambiguity attitudes

According to the historical literature, it clearly stands out that weather is a factor that may affect the mood and decision making of individuals. This research studies the impact of weather on ambiguity attitudes, because there is only little evidence on whether and how weather influences ambiguity attitudes via mood. However, there is only some literature about the effect of mood on ambiguity attitudes or risk-seeking behaviour.

The most recent and related paper is written by Baillon, Koellinger and Treffers (2016). They also investigate the effect of emotional states on ambiguity attitudes, in particular fear and sadness, since they argue that this affects decision making more. They used two laboratory experiments and varied the emotional states of individuals. The first study was a two random assignment, wherein subjects saw a short video to induce emotions. Thereafter, subjects were confronted with ambiguous situations, in which their betting behaviour allowed to calculate the matching probabilities using the approach by Dimmock et al. (2016). The second study was additional to the first study, wherein two control groups were used. The first group was confronted with a neutral affect by showing them a short video. In the second group, they made the subjects aware of their emotional state. After that, the subjects needed to answer several questions about the short videos to avoid any experimenter demand effect. Finally, the ambiguity attitudes were measured by using different probabilties for the winning bet, than the 50% that was used in the first study. The findings indicate that individuals are more ambiguity-neutral, when they feel sad. On the other hand, individuals who feel joy and fear, are less behaving as they maximize their payoff.

Trautmann and Van de Kuilen (2016) also study the relationship between ambiguity attitudes and the decision making of individuals. They show several ways of testing ambiguity in experiments. Besides, existing literature is reviewed to provide evidence on ambiguity attitudes in the decision making under ambiguity. Furthermore, they analyze the external validity of the existing findings, by providing evidence on whether and how the experimental results reflect the decision making in the field. More important, they notice that several sources of uncertainty could influence the decision making of individuals, such as the weather. In the review of existing literature, Trautmann and Van de Kuilen mention the related paper by Stahl (2014). Stahl investigates the differences in ambiguity attitudes by individuals, based on different situations. Therefore, he uses a two-colour and three-colour Ellsberg paradox and consecutively finds that a two-colour paradox shows more ambiguity-averse individuals.

Another study by Bassi, Colacito and Fulghieri (2013) investigates the effect of weather and mood on risk-taking behaviour in financial decision making, with the use of experiments. They concentrate on how weather affects the individual's risk-taking behaviour. The results show that temperature and sunshine are positively related with risk-taking behaviour. To avoid any bias, Bassi et al. control for objective and subjective measures of the weather. Besides, they also show that a lower temperature and less sunshine lead to more risk-averse behaviour.

2.4 Hypotheses

Based on the existing related literature, several expectations are formed. First of all, I focus in this research on the two important behavioural aspects of ambiguity-aversion and a-insensitivity mentioned by Abdellaoui et al. (2011) and Dimmock et al. (2016). Dimmock et al. mention that a-insensitive people are ambiguity-averse for high likelihoods and ambiguity-seeking for low likelihoods, because they do not make a sufficient distinction between different likelihood levels. For instance, Dimmock et al. find that the presence of a-insensitivity makes it less likely to take part in ambiguous events, such as the stock market. Besides, Epstein and Schneider (2007) provide evidence that ambiguity-averse individuals are also not likely to take part in the stock market and are therefore not likely to make decisions under ambiguity. Furthermore, several papers show that the individual's emotional state influences decision making under ambiguity. Other literature also provides evidence, that weather affects the individual's emotional state. For instance, Persinger (1975) shows that individuals feel more happy, when there is more sunshine. Cunningham (1979) provides evidence that temperature is positively correlated with happiness. Besides, Saunders (1993), and Hirshleifer and Shumway (2003) find that temperature affects the stock returns, whereby stock returns seem to be positively correlated with the temperature.

When looking at the existing literature on the effect of mood on ambiguity attitudes, the findings show that sadness causes individuals to behave more ambiguity-neutral (Baillon, Koellinger, & Treffers, 2016). By contrast, Baillon et al. also find that individuals who feel fear and joy, make less payoff-maximizing decisions. Besides, it is shown that a higher temperature and more sunshine lead to more risk-seeking behaviour (Bassi, Colacito, & Fulghieri, 2013). Bassi et al. also find that a lower temperature and less amount of sunshine lead to more risk-averse behaviour. Based on the findings from the exisiting literature, I assume that a higher temperature and more sunshine lead to a higher level of happiness. On the other hand, I assume that a higher amount of precipitation, a higher amount of snowfall and a higher speed of the wind lead to a higher level of sadness.

Based on the reviewed existing literature about the effect of weather on mood and ambiguity attitudes, I state several expectations:

- H_1: The height of the temperature negatively affects ambiguity-aversion.
- H_2: The height of the average daily wind speed positively affects ambiguity-aversion.
- H_3: The amount of precipitation positively affects ambiguity-neutral behaviour.
- H_4: Weather conditions affect a-insensitivity.
- H_5: The effects of weather conditions on ambiguity attitudes differ among state regions in the United States of America.

3. Data

In this chapter, the data are described that will be used to investigate the effect of weather on ambiguity attitudes. First of all, the theory for the measurement of ambiguity attitudes is provided. Then, the dataset from the RAND American Life Panel (ALP 2012) will be described in detail, which includes a survey on ambiguity attitudes in the United States of America. Thereafter, I describe how I merge the dataset from the RAND ALP with the dataset from the National Centers for Environmental Information (NCEI 2016), which includes information on the weather in the United States of America during the period of survey. Finally, the descriptives are shown for the dataset of the NCEI.

3.1 Theory on the measure of ambiguity attitudes

Ellsberg's paradox (1961) is mainly used to investigate the three ambiguity attitudes; ambiguity-averse, ambiguity-neutral and ambiguity-seeking. Dimmock et al. (2013) and Dimmock et al. (2016) provide a way of quantitatively measuring ambiguity attitudes with the use of matching probabilities and Ellsberg's paradox. Again, an individual is confronted with a decision between a known Box K and an ambiguous Box U. Box K contains 50 purple balls and 50 orange balls. By contrast, Box U contains 100 balls for which the distribution between the purple and orange colour is unknown to the individual. The individual is now asked to make a choice between 'Box K' and 'Box U', and what winning colour is preferred. Different from the basic Ellsberg paradox, is that the individual is now also able to choose for 'indifferent' between Box K and Box U, which would imply that the individual is ambiguity-neutral. Therefore, it is possible to determine whether the individual behaves ambiguity-averse, ambiguity-neutral or ambiguity-seeking. At the end, the individual is able to win a certain amount of money, when the preferred winning colour is drawn from the chosen box.

A bisection method is used to compute matching probabilities (Dimmock, Kouwenberg, & Wakker, 2016). The first round of the procedure starts with an a-neutral (ambiguity-neutral) probability of $p = 0.5$, which is the subjective probability that is used by an ambiguity-neutral individual due to symmetry (Dimmock, Kouwenberg, & Wakker, 2016). If the individual chooses 'Box K', the individual shows ambiguity-aversion in the first round. In that case, Box K is made less attractive in the second round, in which the number of balls with the preferred colour is reduced to 25 and the number of balls with the non-preferred colour is increased to

75. That is, the winning probability is now 25% instead of 50%. If the individual chooses ‘Box K’ again in the second round, the number of balls with the preferred colour is reduced to 12 and the number of balls with the non-preferred colour increased to 88. On the other hand, if the individual chooses ‘Box U’ in the first round, the individual shows ambiguity-seeking behaviour. In that case, Box K is made more attractive in the second round, in which the number of balls with the preferred colour is increased to 75 and the number of balls with the non-preferred colour is reduced to 25. When the individual chooses ‘Box U’ again in the second round, the number of balls with the preferred colour in Box K is increased to 88 and the number of balls with the non-preferred colour is reduced to 12.

Overall, this whole process continues for four rounds until the number of balls with the preferred colour is determined that makes the individual indifferent (Dimmock, Kouwenberg, & Wakker, 2016), and with a change in the winning probability of Box K determined by half of the difference between the lowest and highest value of the Box K probability each time. However, the process will stop earlier when the individual chooses ‘indifferent’, since the lowest and highest value of the Box K probability are then the same. When a maximum of four rounds is reached, the matching probability is computed by taking the average probability between the lowest and highest value of the Box K probability. This results in the final matching probability ($m(0.5) = \frac{X}{100}$) for the a-neutral probability of $p = 0.5$, which is written as q^{50}. For instance, a matching probability of 0.3 implies that the individual is indifferent between a gamble on the preferred winning colour from the known Box K with a winning probability of 30% and a gamble on the preferred winning colour from the unknown Box U.

Besides the three ambiguity categories, Abdellaoui et al. (2011) and Dimmock et al. (2016) also state two decision making global indices; ambiguity-aversion and a-insensitivity. Existing literature shows that individuals are ambiguity-seeking for low likelihoods and ambiguity-averse for high likelihoods (Trautmann & Van de Kuilen, 2016). This implies that people do not discriminate enough between different likelihood levels, because it seems that they attach subjective probabilities to different likelihood levels as they are 50-50 (Dimmock, Kouwenberg, & Wakker, 2016). For that reason, Dimmock et al. (2016) also provide a way of measuring matching probabilities for low and high likelihoods. For low likelihoods, they use an a-neutral probability of 10% ($p = 0.1$) and for high likelihoods, they use an a-neutral probability of 90% ($p = 0.9$).

The measurement of the matching probability for low likelihoods (10%) is different from the measurement for intermediary likelihoods (50%), in that the distribution of coloured balls differs. An individual is again asked to choose between a known Box K and an unknown Box U. Box K now contains 10 different colours with each colour having 10 balls. Box U contains 100 balls for which the distribution between the 10 colours is unknown to the individual. Then, the whole process is the same as for intermediary likelihoods and will go on for four rounds until the number of balls with the preferred winning colour is determined that makes the individual indifferent (X). The winning probability for Box K is determined in the same way as for intermediary likelihoods and the questions will stop when the individual chooses 'indifferent', or when a maximum of four rounds is reached. Then, the matching probability is calculated by measuring the average probability between the lowest and highest value of the Box K probability. This results in the final matching probability ($m(0.1) = \frac{X}{100}$) for the a-neutral probability of $p = 0.1$, also written as q^{10}.

The measurement of the matching probability for high likelihoods (90%) also differs from the measurement of intermediary likelihoods (50%). The individual still needs to make a decision between a known Box K and an ambiguous Box U. Box K contains 10 different colours with each having 10 balls. Box U contains 100 balls for which the distribution between the 10 colours is unknown to the individual. Now, winning an amount of money works in the opposite way as in the previous case, in that the preferred winning colour must not be drawn from the chosen box. This process will go on for five rounds, until the number of balls with the other colours is determined that makes the individual indifferent (X). The winning probability for Box K is calculated in the same way as in the previous situations and the questions will stop when the individual chooses 'indifferent', or when a maximum of five rounds is reached. Then, the matching probability is calculated by measuring the average probability between the lowest and highest value of the Box K probability. This results in the final matching probability ($m(0.9) = \frac{X}{100}$) for the a-neutral probability of $p = 0.9$, written as q^{90}.

Once the matching probabilities of the three local measures (q^{10}, q^{50} and q^{90}) are computed, it is possible to determine the two global indices and three local measures for the ambiguity attitudes. First of all, Dimmock et al. (2016) use the following formula for the global index of ambiguity-aversion for intermediary likelihoods, based on Abdellaoui (2011):

$$b = 2 * AA_{0.5}$$

$$b = 2 * \big(0.5 - m(0.5)\big)$$

Ambiguity-aversion implies that the measure above is positive, ambiguity-neutral implies that the measure above is equal to zero, and ambiguity-seeking implies that the measure above is negative. The outcome corresponds to the elevation of the weighting function, for which a higher outcome thus indicates a higher level of ambiguity-aversion.

Next, the global index for a-insensitivity is determined. Therefore, the ambiguity attitudes for low and high likelihoods are calculated first with the following two formulas (Dimmock, Kouwenberg, & Wakker, 2016):

$$AA(0.1) = 0.1 - m(0.1)$$

$$AA(0.9) = 0.9 - m(0.9)$$

Also for these measures, ambiguity-aversion implies that the measures are positive, ambiguity-neutral implies that the measures are equal to zero, and ambiguity-seeking implies that the measures are negative. An ideal example of individuals who are a-insensitive, is when they are ambiguity-seeking for low likelihoods and ambiguity-averse for high likelihoods (Dimmock, Kouwenberg, & Wakker, 2016). That is, the value for $AA(0.1)$ must be negative and the value for $AA(0.9)$ must be positive. Dimmock et al. (2016) use the following formula, to measure the global index for a-insensitivity:

$$a = 1 - s$$

Where a is the index of a-insensitivity and s is the slope of the best-fitting line between the a-neutral probability p and the matching probability $m(p)$ (Dimmock, Kouwenberg, & Wakker, 2016). The slope captures how a-insensitive individuals are, since it gives an indication of how the matching probability changes when the likelihood level increases. Compared to b, the value of a corresponds to the angle of the curve. The slope is calculated with the following formula:

$$s = \frac{m(0.9) - m(0.1)}{0.9 - 0.1}$$

After substitution of s, the formula for the a-insensitivity index is:

$$a = 1 - \frac{m(0.9) - m(0.1)}{0.9 - 0.1}$$

Where a higher outcome of a indicates that the individual is more a-insensitive, whereas a lower outcome indicates that the individual is less a-insensitive and discriminates more between the likelihood levels (Dimmock, Kouwenberg, & Wakker, 2016).

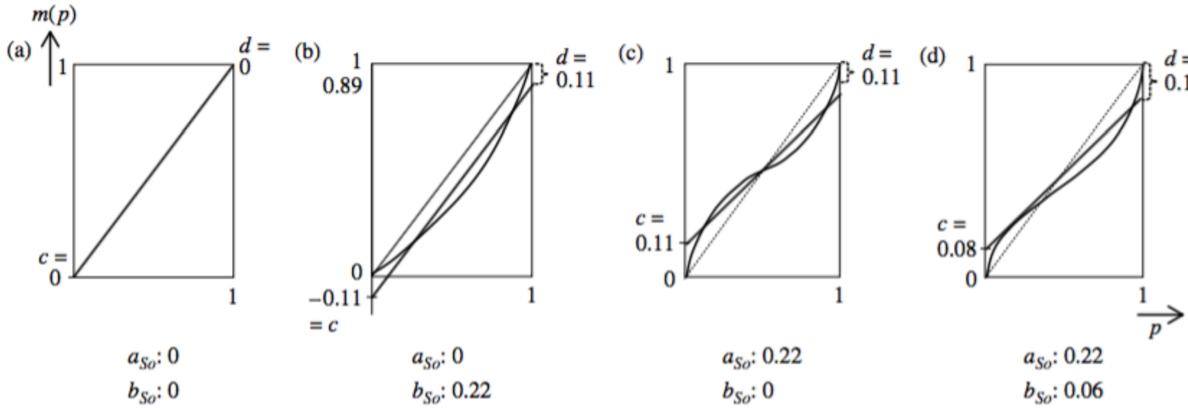

Figure 1: Graphs with different combinations of the a-insensitivity index (a) *and the ambiguity-aversion index* (b)*, retrieved from Dimmock et al. (2016)*

Figure 1 (p.18) shows four graphs with different combinations of the a-insensitivity index (a) and the ambiguity-aversion index (b). All graphs display the matching probability ($m(p)$) on the y-axis and the a-neutral probability (p) on the x-axis. For simplicity, I analyse the bold curves to look more specifically at the matching probabilities and their progress. The first graph indicates that the individual is ambiguity-neutral since b equals 0, which means that the a-neutral probabilities are equal to the matching probabilities. Besides, a equals 0 which implies that the individual is not a-insensitive. The second graph indicates that the individual is ambiguity-averse due to the fact that b equals 0.22. This means that the a-neutral probabilities are larger than the matching probabilities. Again, a is 0 which indicates that the individual is not a-insensitive. The third graph shows an inversed S-shape around the linear neutral-probability line for an ambiguity-neutral individual, because a equals 0.22 and b equals 0. Now, the a-neutral probabilities are smaller than the matching probabilities for low likelihoods (ambiguity-seeking), whereas the a-neutral probabilities are larger than the matching probabilities for high likelihoods (ambiguity-averse). The third graph also indicates that a higher value of a corresponds to an a-insensitivity line that is more flat, for which the individuals do not discriminate enough between different likelihood levels and the matching probabilities are transformed to 50-50. The fourth graph indicates that the individual is a-insensitive (a equals 0.22), but also ambiguity-averse (b equals 0.06). Due to ambiguity-aversion, the line has become lower and more flat than in the third graph.

3.2 ALP data on ambiguity attitudes

For measuring ambiguity attitudes, a dataset from the RAND American Life Panel (ALP 2012) is used. The ALP has come into existence in 2003 and is a regular, nationally representative panel. Nowadays, the ALP consists of about 6,000 individuals from the United States of America, who are 18 years and older. There have been over 440 different surveys in the field, which have led to some rich datasets. In this research, a dataset with a survey on the well-being of individuals from the United States of America is used. The survey was undertaken in the period from 20-03-2012 until 16-04-2012. The well-being survey is called Netspar Uncertainty, and includes a lot of different questions about how individuals make certain decisions with reference to saving and insurance. More importantly, another part of the questions is about decision making under uncertainty, which is used in this research to measure ambiguity attitudes. The survey on ambiguity attitudes includes a sample of 3,290 observations. It is a rich dataset, which includes many demographics and control questions.

Before the general descriptives are reported, it is first important to check the time respondents needed to fill in the survey. There are two reasons for this. First of all, a respondent could have used too much time, which could influence the seriousness of decision making under ambiguity. Besides, it is important that the respondent has started and finished the survey on the same day, since this makes it possible to link the daily weather information to the decision making under ambiguity on that same day. The ALP dataset includes the date and time of starting and finishing the survey. So, all individuals that have not finished the survey on the day they started are omitted from the analysis. This corresponds to 184 respondents. Besides, 38 individuals who have not completed the part on decision making under ambiguity are also omitted from the dataset. Therefore, there are 222 respondents omitted from the dataset in total.

3.2.1 Descriptives ALP data

Table 1 (p.22) shows that it is a rich dataset with a lot of control variables. First of all, the descriptives show that nearly 40% of the respondents who have completed the survey are male with an average age of 47.57 years old. Moreover, 60,6% of the 3,068 respondents is married or has a living partner, 2,5% is divorced, 14,8% is divorced, 2,8% is widowed and 19,3% has never been married. With 91%, a lot of people were born in the United States, whereas 97,6% is an United States citizen. In addition, the dataset also includes information about the state where they were born. Another important demographic is the height of the family income. Respondents were asked to which category the total family income of all household members (who live in the same house) belongs during the past 12 months. Of course, this highly depends on the number of household members which takes an average value of 1.20. Respondents were able to choose between 14 categories, that were stated from low to high. The mean of 10.29 indicates that the average total family income is between $35,000 and $39,999. The last category corresponds to an amount of $75,000 or more, and automatically gives the respondents in that category an additional question. This is a more detailed question with reference to the last category of the total family income. In this question, respondents could choose 4 categories, stated from low to high. The mean takes a value of 1.93, which corresponds to an average total family income of between $125,000 and $199,000.

Furthermore, there were questions about the job situation and it follows that 62,4% is employed. The dataset contains detailed information on this employment status, whether individuals are; retired, disabled, temporarily working, unemployed or another status. Besides, individuals also needed to report the type of work, which indicates that there is a great diversity of different jobs among the respondents. Another important demographic is education, which has a mean of 11.25 and a standard deviation of 2.20. Individuals needed to report their highest education level stated from low (5^{th} or 6^{th} grade) to high (Doctorate degree). The mean corresponds to a bachelor's degree, but the standard deviation shows that the education levels vary a lot. For further estimation, the level of education is divided into; low education (no high school diploma), medium education (high school diploma and no college degree) and high education (at least a college degree).

Respondents were also asked to state, as what ethnicity they consider themselves. The descriptives show that 78,5% of the 3,068 respondents primarily consider themselves as white or Caucasian. In addition, individuals were asked if they consider themselves as Hispanic or Latino, for which 15,9% of the 3,067 individuals does. Then, the following questions were more about financial decision making, such as; retirement, financial knowledge and economic trust. First, respondents were asked to state the time period that is most important to them, for planning their household saving. The five options were again stated from low (the next few months) to high (longer than ten years). The mean for this question is 2.84 (the next few years) and the standard deviation is 1.45. Secondly, three questions were included about a retirement plan by the employer. The first question asked whether the respondent has any employer-provided retirement accounts. Nearly half (49,7%) of the 3,067 respondents (1,523) has an employer-provided retirement plan, whereas still 2,9% does not know whether the employer provides such a plan. Next to this question, individuals were asked if they are able to choose how the money is invested. It stands out that 56,2% of the respondents is able to choose how all of the money is invested. However, many individuals (7,4%) do not know whether they have a possibility to decide on this. In addition, the third question asked whether they know what share of the money is invested in stock or stock mutual funds, if there is any employer-provided retirement account. For this question, 12,1% of the respondents reported that nothing is invested in stock. On the other hand, 18,4% reported that all of the money is invested in stock.

The next set of questions gives an indication of the financial and economic knowledge of each respondent. First of all, the individual's financial knowledge was tested by asking what the value of $100 on a savings account with an interest rate of 2% would be after 5 years. The descriptives show that 84,9% gave the right answer, which indicates that not all individuals have the knowledge how to compute this. Then, a situation was described in which the interest rate is 1% per year and the inflation rate is 2% per year. Respondents needed to report if after one year, they would be able to buy more, the same, or less than today. For this question, 75,4% gave the right answer. The last question on financial knowledge, includes a statement where respondents needed to choose between 'true', 'false' or 'don't know'.

Another set is about trust in financial decision making. The first question asked if most people can be trusted or not in general. The answers are on a Likert scale from 0 to 6, where 'Most people can be trusted' takes value 0. The answers were quite diverse and only 2,4% reports that most people can be trusted. On the other hand, 22,8% states that you can't be too careful. It was also allowed to report 'I don't know', which takes value 6. The second trust question indicates how worried respondents are of fraud, if they were to invest money in the stock market. The answers are on a Likert scale from 0 to 5, where 'Very high' takes value 1. The descriptives show a mean of 2.88 and a standard deviation of 1.08, which indicates that the answers were quite normally distributed. Most people (38%) chose 'Moderate'. It clearly follows that some individuals do not have a lot of trust in the stock market with reference to fraud, since 70,6% reports at 'Moderate', 'High' and 'Very high'. The last question asked what the chance is that an insurance company will refuse to pay a claim, when you already have bought a health insurance. On the same Likert scale as the second question, the majority (52,8%) reported 'Low' and 'Very Low'. Only the second question about trust regarding fraud in the stock market is used for analysis, since this captures decision making under ambiguity.

Table 1: Descriptive statistics for the control variables

Independent control variable	**Descriptive**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**	**Observations**
Male	Gender (Male=1 in %)	39,9	0.49	1	2	3,067
Age	Age	47.57	13.50	18	70	3,068
MarriedLivingPartner	Married / Living Partner (Yes=1 in %)	60,6	0.49	0	1	3,068
Seperated	Seperated (Yes=1 in %)	2,5	0.16	0	1	3,068
Divorced	Divorced (Yes=1 in %)	14,8	0.36	0	1	3,068
Widowed	Widowed (Yes=1 in%)	2,8	0.17	0	1	3,068
NeverMarried	Never Married (Yes=1 in %)	19,3	0.39	0	1	3,068
BornInUS	Born in US (Yes=1 in %)	91,0	0.29	1	2	3,068
USCitizen	US Citizen (Yes=1 in %)	97,6	0.15	1	2	3,068
FamilyIncome	Family Income	10.29	3.75	1	14	3,059
HigherFamilyIncome	Higher Family Income	1.93	0.99	1	4	1,020
NumberOfHouseholdMembers	Household Members	1.20	1.52	0	10	3,066
Employed	Employed (Yes=1 in %)	62,4	0.48	0	1	3,068
Education	Education	11.25	2.20	3	16	3,067
LowEducation	Low Education (Yes=1 in %)	5,1	0.22	0	1	3,067
MediumEducation	Medium Education (Yes=1 in %)	42,7	0.49	0	1	3,067
HighEducation	High Education (Yes=1 in %)	52,2	0.50	0	1	3,067
EthnicityWhite	White / Caucasian (Yes=1 in %)	78,5	0.41	0	1	3,068
EthnicityHispanicLatino	Hispanic / Latino (Yes=1 in %)	15,9	0.37	1	2	3,067
SavingTime	Saving Time	2.84	1.45	1	5	3,066
RetirementAtEmployer	Retirement at Employer (Yes=1 in %)	49,7	0.55	1	3	3,067
RetirementChoiceAtEmployer	Retirement Choice at Employer	1.74	0.97	1	4	1,522
EmployerRetirementInvested	Share Employer Retirement Invested	3.85	1.68	1	6	1,522
KnowledgeSaving	Knowledge Saving (Right in %)	84,9	0.73	1	4	3,067
KnowledgeInflation	Knowledge Inflation (Right in %)	75,4	0.68	1	4	3,067
SaferReturn	Statement Safer Return	1.94	0.79	1	3	3,068
TrustInPeople	Trust in People	3.20	1.40	0	6	3,068
TrustInStockMarket	Trust in Investment Stock Market	2.88	1.08	1	5	3,068
TrustInHealthInsurance	Trust in Health Insurance	3.43	1.04	1	5	3,066
OrderOfQuestions	Order of Questions	1.49	0.50	1	2	3,068
PleasantInterview	Pleasant Interview	1.81	0.87	1	5	3,058
ClearQuestions	Clear Questions	3.41	0.75	1	5	3,068

At the end, two control questions about the survey were asked with answers on a Likert scale from 0 to 5. The descriptives show that 82,7% thought that the survey was 'interesting' or 'very interesting', and 98,4% of the 3,068 respondents thought that the questions were at least 'more or less clear'. This indicates that the survey was filled in seriously and that respondents gave truthful answers. Finally, there was an equal chance for the respondents in what order they needed to answer questions about ambiguity-aversion or risk-aversion.

3.2.2 Measure of ambiguity attitudes in the ALP data

Based on the theory from Ellsberg (1961), Abdellaoui et al. (2011), Dimmock et al. (2016) and Dimmock et al. (2013), the ambiguity attitudes will now be calculated using the questions about decision making under ambiguity in the ALP survey. As described in the first paragraph on the theory for computing ambiguity attitudes, there are three different questions on ambiguous decision making in the ALP dataset. The first question for an intermediary likelihood uses an a-neutral probability of 50%, the second question for a low likelihood uses an a-neutral probability of 10%, and the third question for a high likelihood uses an a-neutral probability of 90%. For answering the questions from the ALP survey, respondents were able to win a real reward of $15, for which a total amount of $22,620 was paid to 1,508 respondents.

Since there are many possibilities for the combinations of options in each question, it is first important to determine what the matching probability would be for each combination. This is based on Dimmock et al. (2013) and makes it possible to link the matching probabilities to the different combinations of answers given by the respondents in the ALP survey. Table 2 until Table 7 (p.68-p.72) show respectively an overview of all possible combinations and matching probabilities for question 1, 2 and 3. After all the matching probabilities were computed, the answers were linked to the matching probabilities. Yet, the ambiguity attitudes are determined for each individual based on the explained formulas in the first paragraph. The three formulas for each ambiguity attitude are applied to each individual in the dataset.

Table 8: Descriptives of results ambiguity attitudes in the ALP data

Ambiguity attitude index	Mean	Standard deviation	Minimum	Maximum	Observations
$AA(0.1) = 0.1 - m(0.1)$	-0.13	0.20	-0.75	0.09	3,068
$AA(0.5) = 0.5 - m(0.5)$	0.02	0.21	-0.44	0.47	3,068
$AA(0.9) = 0.9 - m(0.9)$	0.19	0.26	-0.09	0.85	3,068

Table 8 (p.23) shows that the majority is ambiguity-seeking for low likelihoods (10%) and ambiguity-averse for high likelihoods (90%), due to the values of the means. Besides, the mean for the intermediary likelihoods (50%) is nearly equal to zero with a value of 0.02. Furthermore, the standard deviation is almost the same for each likelihood. Finally, it is quite logical that a higher likelihood level leads to a higher value of the minimum and maximum. Based on the descriptives in Table 8 (p.23), it is now possible to determine whether the individuals are ambiguity-averse, ambiguity-neutral or ambiguity-seeking.

Table 9: Results ambiguity attitudes in the ALP data

Ambiguity attitude under a-neutral probability p	**Low likelihood Question 2 (10%)**	**Intermediary Likelihood Question 1 (50%)**	**High Likelihood Question 3 (90%)**
Ambiguity-averse (in %)	12,3	**52,4**	**56,1**
Ambiguity-neutral (in %)	23,8	12,1	15,8
Ambiguity-seeking (in %)	**63,9**	35,6	28,1

Consistent with the means of the ambiguity attitudes in Table 9 (p.24), individuals who participated in the ALP survey are ambiguity-seeking for a low likelihood (10%) in question 2 and ambiguity-averse for a high likelihood (90%) in question 3 and for an intermediary likelihood (50%) in question 1. So, a higher fraction of the respondents is more ambiguity-averse for high likelihoods (56,1%) than for low likelihoods (12,3%). Based on Dimmock et al. (2016), I use a χ^2 test to determine if ambiguity-aversion is more likely for low likelihoods than for high likelihoods. The results show that individuals are more ambiguity-averse for high likelihoods than for low likelihoods, which is consistent with Trautmann and Van de Kuilen (2016), and Dimmock et al. (2016). In addition to the three local measures for ambiguity attitudes, Abdellaoui (2011) and Dimmock et al. (2016) also mention two global indices for a-insensitivity and ambiguity-aversion shown in table 10 (p.24)

Table 10: Results global indices of a-insensitivity and ambiguity-aversion in the ALP data

Global indices for ambiguity attitudes	**Mean**	**Standard deviation**	**Minimum**	**Maximum**	**Observations**
s (slope)	0.39	0.37	-0.22	1.99	3,068
a (a-insensitivity index)	0.61	0.37	-0.99	1.22	3,068
b (ambiguity-aversion index)	0.05	0.42	-0.88	0.94	3,068

The mean of the a-insensitivity index and the slope give a good indication of how a-insensitive individuals are on average, which can be interpret as follows. If the a-neutral probability increases with 1%, the matching probability will increase with 0.39%. Secondly, the a-insensitivity index a has a mean of 0.61 which indicates that respondents do not discriminate enough between the different likelihood levels. The ambiguity-aversion index b takes a mean of 0.05, which indicates that part of the respondents is ambiguity-averse.

Table 11: Correlations between the ambiguity attitudes and global indices

Ambiguity Attitude	$AA(0.1)$	$AA(0.5)$	$AA(0.9)$	a	b
$AA(0.1)$	1	0.41*	0.19*	0.52*	0.41*
$AA(0.5)$	0.41*	1	0.33*	-0.01	1.00*
$AA(0.9)$	0.19*	0.33*	1	-0.75*	0.33*
a	0.52*	-0.01	-0.75*	1	-0.01
b	0.41*	1.00*	0.33*	-0.01	1

**. The correlation is significant at the 0.01 level (2-tailed)*

Table 11 (p.25) shows that all three ambiguity attitudes are positively correlated with each other and are all significant at a 1%-level. Therefore, it is obvious that all three ambiguity attitude measures influence each other through the decision making of individuals. Also, both ambiguity attitudes for low and high likelihoods are correlated with the a-insensitivity index and ambiguity-aversion index. When looking at the correlation between the a-insensitivity index and ambiguity-aversion index, it follows that the magnitude is quite small and not significant with a value of -0.01. Dimmock et al. (2016) also find a small and non-significant effect for a Dutch survey on ambiguity (LISS panel). Therefore, it seems that both measures do not influence each other and that they can be seen as two different aspects of behaviour.

3.3 NCEI data on daily weather information

Weather data is obtained from the National Centers for Environmental Information (NCEI 2016). The NCEI provides rich historical data on oceanic, atmospheric and geophysical information. The ALP survey was in the field in the United States of America from 20-03-2012 until 16-04-2012, for which the historical data is present at the NCEI. The daily weather information is collected for each state. Since each state covers such a big area, it implies that the weather conditions could also vary a lot within a state. Moreover, the ALP data only contains information about the state where the individual lives at the moment of filling in the survey, but not the city itself. So, I assume that the capital city of each state is most representative for the historical daily weather conditions of each state. Besides, I assume that most respondents who completed the survey live in or near a capital city. Table 12 (p.73) shows a list of all states and the corresponding capital cities. The next step is to merge the NCEI dataset including weather information with the ALP dataset including decision making under ambiguity. Since the ALP dataset contains detailed information on the date and time of filling in the survey, and in which state the respondent lives at the moment of filling in the survey, it is possible to merge both datasets.

3.3.1 Descriptives NCEI data

Table 13 (p.27) shows the descriptive statistics of the weather conditions for each respondent at the moment of filling in the survey. The variables for precipitation, snowfall and snowdepth were all measured in inches, but I converted them to milimetres (1 inch = 25,4 mm). Besides, the maximum and minimum temperature, and the temperature at the time of observation were measured in Fahrenheit °F, but I converted them to Celsius ℃ ($= \frac{°F - 32}{1.8000}$). Since there is no information about the time of observation, the average is taken from the maximum and minimum temperature. One could imagine that the minimum temperature will not be found at the middle of the day, whereas the maximum temperature does most of the time. For that reason, also the average temperature is computed. Finally, the variable for the average daily wind speed was measured in miles per hour, but I converted it to kilometers per hour (1 mile per hour = 1.609344 kilometers per hour).

The survey was in the field during spring, wherein the weather conditions can still vary a lot. This also stands out from the descriptives, since it indicates that it was still snowing in some states, while the temperature was much higher in other status. Furthermore, the descriptives show that there is no information available on cloudiness and there is only few information available on the daily sunshine. However, the data contains ten different kinds of dummy variables for particular weather conditions, which varies from rain or snow to a more extreme weather condition, such as a thunderstorm or a tornado.

Table 13: Descriptive statistics for the weather data during the ALP survey

Independent weather variable	Descriptive	Mean	Standard deviation	Minimum	Maximum	Observations
Precipitation	Precipication in mm	2.81	7.10	0	87.12	3,068
Snowfall	Snowfall in mm	0.10	1.84	0	68.58	3,038
Snowdepth	Snowdepth in mm	15.86	155.74	0	1625.6	3,038
MaximumTemperature	Maximum temperature in °C	18.95	7.60	0.6	33.3	3,066
MinimumTemperature	Minimum temperature in °C	6.58	6.52	-9.4	21.7	3,066
ObservationTemperature	Temperature at time of observation in °C	10.13	7.73	-9.4	32.2	2,517
AverageTemperature	Average temperature in °C	12.77	6.70	-3.3	25.3	3,066
AverageDailyWindSpeed	Average daily wind speed in km/h	11.99	6.24	0	36.73	3,032
DailySunPercentage	Daily sun in %	56,7	36.8	1,0	96,0	48
DailySunTotal	Daily sun total	431.75	276.35	8	724	48
DummyFreezingNormal	Dummy freezing normal (Yes=1 in %)	34,4	0.48	0	1	3,047
DummyFreezingHeavy	Dummy freezing heavy (Yes=1 in %)	1,8	0.13	0	1	2,996
DummyThunder	Dummy thunder (Yes=1 in %)	6,3	0.24	0	1	3,066
DummyHail	Dummy hail (Yes=1 in %)	0,3	0.05	0	1	2,696
DummyTornado	Dummy tornado (Yes=1 in %)	0,0	0.00	0	0	537
DummyWindHeavyDamaging	Dummy heavy damaging wind (Yes=1 in %)	0,9	0.09	0	1	2,347
DummyMist	Dummy mist (Yes=1 in %)	40,1	0.49	0	1	2,796
DummyDrizzle	Dummy drizzle (Yes=1 in %)	3,5	0.18	0	1	1,984
DummyRain	Dummy rain (Yes=1 in %)	40,2	0.49	0	1	2,796
DummySnow	Dummy snow (Yes=1 in %)	2,7	0.16	0	1	1,660

4. Empirical strategy

In this chapter, the empirical strategy is described to test the hypotheses and to answer the main research question with the use of the ambiguity data from the ALP and the weather data from the NCEI. The methodology of estimating the effect of weather on ambiguity attitudes will be explained in detail.

4.1 The main empirical specifications

As was described in the previous chapter, there are two global indices and three local measures for the different ambiguity attitudes; the ambiguity-aversion index, the a-insensitivity index, the ambiguity attitude for low likelihoods, the ambiguity attitude for intermediary likelihoods and the ambiguity attitude for high likelihoods. This research begins with an estimation of the effect of weather on ambiguity attitudes with an Ordinary Least Squares (OLS) model. Since the ambiguity-aversion index is measured with the use of the ambiguity attitude for intermediary likelihoods, there will be four main empirical specifications in which each ambiguity attitude measure functions as the dependent variable. Since this research investigates the causal effect of weather on ambiguity attitudes, the main weather independent variables will be included in the regression. In a second and third step, several important economic and demographic variables will be included to control for the effects. The variables for daily sun will not be included, because there are too few observations. I assume that individuals fill in the survey during daylight hours. Therefore, the maximum temperature will be estimated in the first place since that corresponds the most with the temperature during the time of filling in the survey. However, the effect of the minimum temperature and average temperature on ambiguity attitudes function as a robustness check in a fourth and fifth step, to determine whether the results hold.

The main empirical specification for the four ambiguity attitude measures:

$$\begin{aligned}
Y_i = {} & \beta_0 + \beta_1 Precipitation_i + \beta_2 Snowfall_i + \beta_3 MaximumTemperature_i + \\
& \beta_4 AverageDailyWindSpeed_i + \beta_5 Age_i + \beta_6 Male_i + \beta_7 MarriedLivingPartner_i + \beta_8 FamilyIncome_i + \\
& \beta_9 NumberOfHouseholdMembers_i + \beta_{10} Employed_i + \beta_{11} HighEducation_i + \beta_{12} EthnicityWhite_i + \\
& \beta_{13} EthnicityHispanicLatino_i + \beta_{14} TrustInStockMarket_i + \beta_{15} OrderOfQuestions_i + \varepsilon_i,
\end{aligned}$$

with $Y_i \in \{a_i, b_i, AA(0.1)_i, AA(0.9)_i\}$. At the end, the variable $MaximumTemperature_i$ will also be substituted for the variables $AverageTemperature_i$ and $MinimumTemperature_i$.

4.2 The Gauss-Markov conditions

When using an OLS model to estimate unknown parameters in the regression model, the Gauss-Markov conditions need to be satisfied. If these are satisfied, OLS is the best linear unbiased estimator (BLUE) (Verbeek, 2012). This implies that it can be assumed, that the used estimator does not differ from the real effect of β. That is, $E\{b\} = \beta$. Therefore, four conditions need to be checked for the independent variables and the error term; homoskedasticity, normality, no multicollinearity and exogeneity. It is also important that the model is linear regarding the used parameters and that a random sample is used that follows the population model.

4.2.1 Homoskedasticity

The first condition of homoskedasticity implies that the variance of the error term is always constant and independent of the values of the explanatory variables (Verbeek, 2012). That is, $Var(\varepsilon|x_1, x_2) = Var(u) = \sigma^2$. If the variance is not constant and depends on the values of the explanatory variables, then the model suffers from heteroskedasticity. In such a case, the OLS estimators will still be unbiased. However, the standard errors will be invalid and the OLS regression model will not be the best. It is possible to test the different regression models for heteroskedasticity by using the Breush-Pagan test, which is actually a Lagrange Multiplier test (Verbeek, 2012). If the null hypothesis of homoskedasticity is rejected, the regression models should use White standard errors to have valid standard errors (White, 1980). When testing the regression models, it seems that heteroskedasticity is a problem and that the standard errors are invalid. This also follows from Figure 2 (p.29).

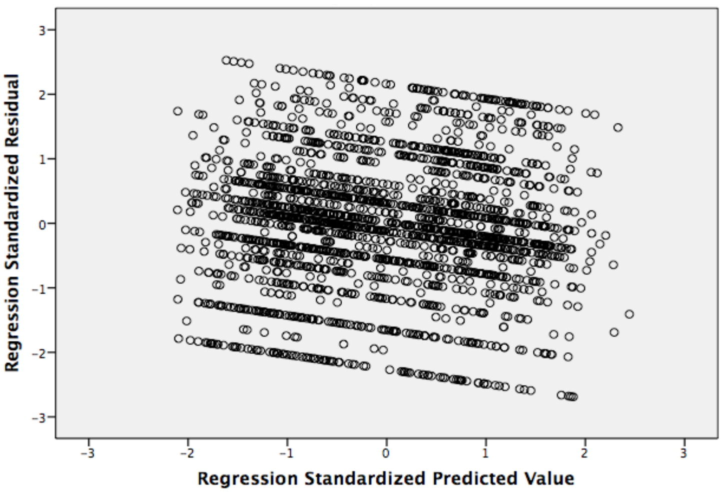

Figure 2: Scatter plot of the standardized residuals vs. standardized predicted values of the ambiguity attitude for low likelihoods ($AA(0.1)$)

Figure 2 (p.29) shows that there is decreasing pattern in the residuals of the error term, where most residuals are around zero and the variance of the residuals is not constant. Therefore, this is consistent with the Breusch-Pagan test. However, the residuals are randomly distributed around zero which implies that endogeneity seems not present (see paragraph 4.2.4, p.31). For that reason, White standard errors will be used to have a valid standard errors (White, 1980).

4.2.2 Normality

The second condition is about normality, which means that the error term follows a normal distribution. The expected value of the error term is then equal to zero ($E\{\varepsilon_i\} = 0$) and therefore, the predicted regression line is valid on average (Verbeek, 2012). If the error term is not normally distributed, the OLS estimator follows an asymptotic normal distribution. Since the sample in this research consists of 3,068 individuals, normality seems not a problem. The Central Limit Theorem namely states that the distribution of the error term in large samples is always about to be normal (Field, 2009). Then, the t-statistics and F-statistics will respectively follow a t-distribution and F-distribution. To test whether the error term is normally distributed, the residuals are obtained for each ambiguity attitude index after including White standard errors. Figure 3 (p.30) shows the distribution of the residuals for the ambiguity attitude index for intermediary likelihoods, using the main empirical specification of $AA(0.5)_i$.

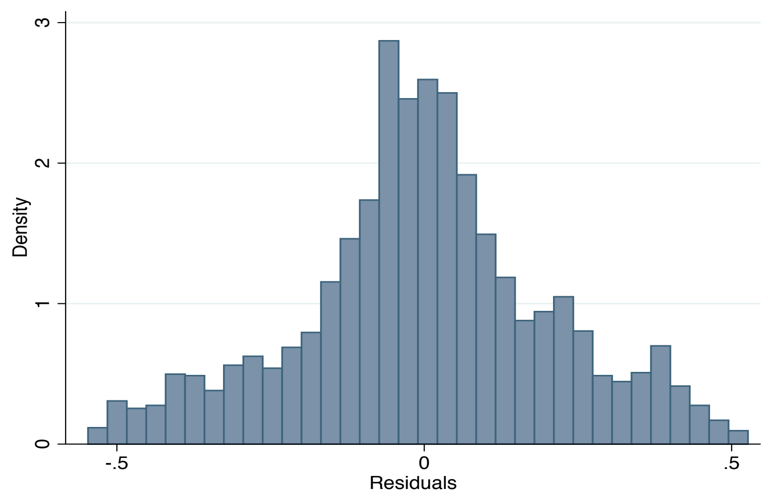

Figure 3: Distribution of the residuals for the ambiguity attitude index for intermediary likelihoods

It follows that the error term is approximately normally distributed, with most of the residuals around zero. This also holds for the other empirical specifications of ambiguity attitudes, when plotting their residuals against the density. For that reason, it is assumed that the condition of normality holds for the OLS regression models.

4.2.3 No multicollinearity

The third condition of no multicollinearity implies whether there is a perfect linear relation between the independent variables, which are included in the regression models for the ambiguity attitudes (Verbeek, 2012). To test if there is multicollinearity present, the correlations between the independent variables in the regression models are analysed first. Table 14 (p.74-p.75) shows that the correlations between the independent variables are in general not very high. Only some variables show a high and significant correlation, which could lead to inaccurate estimates. Besides, the correlations indicate that there is no perfect linear collinearity present between the independent variables. Furthermore, including too many dummy variables could also lead to multicollinearity, because these variables only take two values of outcome (Verbeek, 2012). If there is multicollinearity present, the sample in this research does not capture enough information about the variables.

To control for multicollinearity, the regression models for each ambiguity attitude are extended over three steps of regression. In a first step of regression, only the independent weather variables are included in the regression model. In a second step of regression, the demographic and economic variables are added to the regression model but some dummy variables are still left out. In a third step of regression, all relevant independent variables are added to the regression model. This allows to compare the regression steps with each other and to check if multicollinearity could be a problem for the estimation. If the estimated parameters differ a lot in significance before adding different explanatory variables to the regression model, multicollinearity could be problematic in the first place.

4.2.4 Exogeneity

The last Gauss-Markov condition is about exogeneity, which assumes the zero conditional mean of $E(\varepsilon_i|x_i) = 0$. That is, the explanatory variables need to be uncorrelated with the error term (Verbeek, 2012). If this is not the case, the model is incorrect and misspecified. One could also say that there is an omitted variable bias, which means that there are more variables that need to be included in the regression, to control for the effect. A possible solution for endogeneity is to use an IV 2SLS regression model, which uses a relevant and valid instrument to control for endogeneity using two stages (Verbeek, 2012). It is possible to check whether the variables are endogenous, by using a Ramsey RESET test. If the null hypothesis of no misspecification is rejected, there is evidence for endogeneity in the model. The results from the Ramsey RESET test on the regression models in this research show that endogeneity seems not a problem. Therefore, using OLS will be better since IV 2SLS is inefficient then (Verbeek, 2012). At the end, I also check whether the complete models are significant.

4.3 Ordered multinomial logit models

The three local ambiguity attitude measures that were determined in the third chapter (Table 9 (p.24)), display whether the individual is ambiguity-averse, ambiguity-neutral or ambiguity-seeking. In addition to the basic OLS regression models, multinomial logit models are used. I use multinomial logit models, because it allows me to calculate the probability of each specific categorical ambiguity level (ambiguity-averse, ambiguity-neutral and ambiguity-seeking) of the ambiguity attitudes for different likelihood levels. So, I create three categorical dependent variables; the ambiguity attitude for low likelihoods ($CategoricalAA(0.1)_i$), the ambiguity attitude for intermediary likelihoods ($CategoricalAA(0.5)_i$), and the ambiguity attitude for high likelihoods ($CategoricalAA(0.9)_i$). The categorical variables equal; 1 if the individual is ambiguity-averse, 2 if the individual is ambiguity-neutral and 3 if the individual is ambiguity-seeking. Table 15 (p.32) shows a summary of the values for the three local ambiguity attitude measures. Since a higher value of the dependent variable indicates a higher level of ambiguity-seeking behaviour, it implies that the values of the dependent variables take a natural order. Therefore, ordered multinomial logit models are allowed for estimating the effect of weather on the ambiguity attitudes for the three different likelihood levels.

Table 15: Summary values of the categorical variables for the three local ambiguity measures

Categorical ambiguity attitudes under a-neutral probability p	$CategoricalAA(0.1)_i$	$CategoricalAA(0.5)_i$	$CategoricalAA(0.9)_i$
Ambiguity-averse	1	1	1
Ambiguity-neutral	2	2	2
Ambiguity-seeking	3	3	3

Again, there will be three steps of regression for each dependent variable, in which all the explanatory variables depend on each other since it is a nonlinear probability model. The independent variables that will be included in each step, are the same as that were used in the three steps of OLS regressions. At the end, average marginal effects will be obtained from the models. This allows me to interpret the magnitude, sign and significance of the effect each explanatory variable has, on the probability of being ambiguity-averse, ambiguity-neutral or ambiguity-seeking for the three different likelihood levels. This is not possible without obtaining average marginal effects from the ordered multinomial logit models.

4.4 State regions

In the ALP survey, individuals needed to report their state of residence for which they could choose between 52 states. However, the United States of America is a big country wherein the weather conditions could differ a lot between the states. One could imagine that the temperature of a state in the northern region could differ a lot from the temperature of a state in the sourthern region. So, it is interesting to determine if there is a difference in the effect of weather on ambiguity attitudes between different state regions in the United States of America. Based on the United States Census Bureau, the United States are subdivided into four different state regions (United States Census Bureau, 2015), where the numbers correspond to the states listed in Table 12 (p.73):

- Northeast region: 7, 9, 21, 29, 30, 32, 38, 39, 45
- Midwest region: 13, 14, 15, 16, 22, 23, 25, 27, 34, 35, 41, 49
- South region: 2, 4, 8, 9, 10, 17, 18, 20, 24, 33, 36, 40, 42, 43, 46, 48, 51, 52
- West region: 1, 3, 5, 6, 11, 12, 26, 28, 31, 37, 44, 47, 50

For every region, the main OLS models of this research for the effect of weather on ambiguity attitudes are estimated individually. This allows to compare the results for the four regions and to determine if the effects of the weather conditions are larger for a certain region. To do this, the β's of the independent weather variables for the different state regions are compared with each other in sign, magnitude and significance. Regarding the independent weather variables, the variable for the maximum temperature will not be substitited for the variables of the minimum and average temperature. To conclude whether the effect is stronger for a certain state region, the β for a weather variable of one state region must have a larger effect than the β of the same weather variable of another state region (Field, 2009). It is also important to analyse the confidence intervals of the β's that are compared. Namely, if there are overlapping confidence intervals, the effect of the explanatory variable does not statistically differ from the effects of that same variable for the other state regions (Field, 2009).

4.5 Weather dummy variables

Besides the general independent weather variables, the NCEI dataset also includes ten weather dummy variables for if a certain weather condition is present or not. This is due to the fact that some weather conditions are not able to be quantified. Table 13 (p.27) shows the descriptives of these weather dummy variables. By also testing dummy variables with the use of OLS, it is possible to look more specifically into the effect of a certain weather condition on the four different ambiguity attitude measures besides the general weather independent variables. Including several weather dummy variables allows me to explore nonlinearities and to determine whether the ambiguity attitude is affected by the presence of a certain weather condition or not. Adding more dummy variables also requires a large number of observations. However, this will not be a problem for this research due to the total number of observations.

It follows from Verbeek (2012) that including too many dummy variables could lead to multicollinearity. For that reason, the correlations between the dummy weather variables are analyzed first. Table 16 (p.76) shows that nearly all correlations are not very high and often not significant. The dummy variable for whether an individual suffered from a tornado or not is removed, because of multicollinearity due to zero observations. Only the correlation between the dummy variables for mist and freezing normal is quite high and significant. For that reason, I use different steps of regression again, wherein the same independent variables are added each step as in the OLS models. In a first step, the OLS model only includes the weather dummy variables. In a second step, some economic and demographic variables are added to the model. In a third step, all relevant independent variables are added to the regression model. This results in the following empirical specification:

$$Y_i = \beta_0 + \beta_1 DummyFreezingNormal_i + \beta_2 DummyFreezingHeavy_i + \beta_3 DummyThunder_i + \beta_4 DummyHail_i + \beta_5 DummyWindHeavyDamaging_i + \beta_6 DummyMist_i + \beta_7 DummyDrizzle_i + \beta_8 DummyRain_i + \beta_9 DummySnow_i + \beta_{10} Age_i + \beta_{11} Male_i + \beta_{12} MarriedLivingPartner_i + \beta_{13} FamilyIncome_i + \beta_{14} NumberOfHouseholdMembers_i + \beta_{15} Employed_i + \beta_{16} TrustInStockMarket_i + \beta_{17} HighEducation_i + \beta_{18} EthnicityWhite_i + \beta_{19} EthnicityHispanicLatino_i + \beta_{20} OrderOfQuestions_i + \varepsilon_i,$$

with $Y_i \in \{a_i, b_i, AA(0.1)_i, AA(0.9)_i\}$. Due to a high and significant correlation between the dummy variables for mist and freezing normal, it is also necessary to check whether the results change when omitting one of them from the regression model. To avoid multicollinearity, an additional fourth step is used to exclude the dummy variable for freezing normal. It is also important to determine whether the other three Gauss-Markov assumptions hold. First of all, the Breusch-Pagan test indicates that there is evidence for heteroskedasticity in the models. So, I again use White standard errors to obtain valid standard errors. Secondly, the residual distributions for the ambiguity attitudes for different likelihood levels show that normality is satisfied.

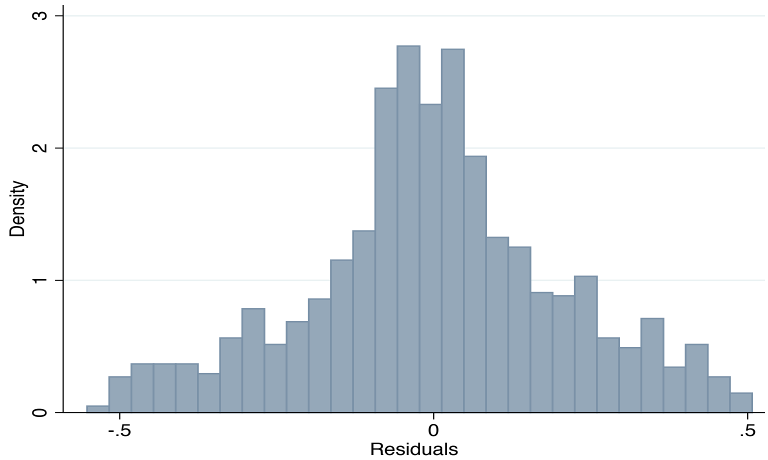

Figure 4: Distribution of the residuals for the ambiguity attitude index for intermediary likelihoods

Figure 4 (p.35) for instance shows, that the residuals of the ambiguity attitude for intermediary likelihoods are normally distributed. The last condition of exogeneity is tested with the use of the Ramsey RESET test. It follows that there is no evidence for endogeneity in the regression models, which means that using OLS is more efficient than using IV 2SLS.

5. Results

5.1 <u>OLS models for main weather independent variables</u>

First of all, Table 17 until Table 20 display the results of the four OLS models on the ambiguity aversion index, the a-insensitivity index and the ambiguity attitudes for low and high likelihoods. The tables indicate that multicollinearity seems not a problem, since the coefficients barely or do not change in magnitude, sign and significance when adding control variables to the regressions. Only *FamilyIncome* changes in significance after a second step, but does not change in magnitude and sign. So, this variable also captures another effect in the second regression, which is removed by adding several more control variables after that step. This holds for the results of the other ambiguity attitude measures. Furthermore, substituting the maximum temperature for the minimum and average temperature also barely changes or does not change the results at all. Therefore, the final results are obtained from the complete model using the maximum temperature under the third regressions.

When I add control variables to the regressions in a second step, the models become significant. This follows from the probability values of the models, for which the complete models of the four ambiguity attitude measures under a third, fourth and fifth step are significant at a 1%-level. Furthermore, the R^2 is quite low for the complete models of all four ambiguity attitude measures. Therefore, the OLS models explain a quite low percentage of the data variation. Besides, the results show R^2 increases the most after a second step, which is probably caused by adding the variable *OrderOfQuestions*. This variable is always significant for all four ambiguity attitude measures and therefore causes the OLS models to better fit the data of this research.

Table 17 (p.37) shows the results of the OLS models on the ambiguity-aversion index. The results show that *AverageDailyWindSpeed* is significant, whereas the other main independent weather variables are not significant. An increase of one km/h in the average daily wind speed increases the ambiguity-aversion index with 0.002, ceteris paribus. This effect is significant at a 10%-level. The results of the control variables indicate that male individuals are significantly less ambiguity-averse than female individuals. Namely, being a male decreases the ambiguity-aversion index with 0.062, compared to being a female. Also, being highly educated increases the ambiguity-aversion index with 0.044, compared to not being highly educated, ceteris paribus. The results also show that being white decreases the ambiguity-aversion index with 0.039, compared to not being white, ceteris paribus. This effect is significant at a 10%-level. Finally, the variable *OrderOfQuestions* shows an interesting result. If the individual needed to answer questions about ambiguity-aversion first, it decreases the ambiguity-aversion index with 0.148, compared to answering questions about risk-aversion first, ceteris paribus. Overall, the OLS model explains 4,3% of the data variation.

Table 17: OLS regressions on the ambiguity-aversion index

b	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Precipitation	-0.000	-0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Snowfall	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
MaximumTemperature	0.000	0.000	0.001		
	(0.001)	(0.001)	(0.001)		
AverageDailyWindSpeed	0.002*	0.002*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.001	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Male		-0.063***	-0.062***	-0.062***	-0.062***
		(0.016)	(0.016)	(0.016)	(0.016)
MarriedLivingPartner		-0.006	0.000	-0.000	-0.000
		(0.018)	(0.018)	(0.018)	(0.018)
FamilyIncome		0.005*	0.004	0.004	0.004
		(0.003)	(0.003)	(0.003)	(0.003)
NumberOfHouseholdMembers		0.007	0.007	0.007	0.007
		(0.006)	(0.006)	(0.006)	(0.006)
Employed		-0.008	-0.011	-0.011	-0.011
		(0.018)	(0.017)	(0.017)	(0.017)
TrustInStockMarket		-0.007	-0.007	-0.007	-0.007
		(0.008)	(0.008)	(0.008)	(0.008)
HighEducation			0.044***	0.045***	0.045***
			(0.017)	(0.017)	(0.017)
EthnicityWhite			-0.039*	-0.040*	-0.040*
			(0.021)	(0.021)	(0.021)
EthnicityHispanicLatino			0.006	0.007	0.008
			(0.024)	(0.024)	(0.024)
OrderOfQuestions			-0.148***	-0.148***	-0.148***
			(0.015)	(0.015)	(0.015)
AverageTemperature				0.001	
				(0.001)	
MinimumTemperature					0.001
					(0.001)
Constant	0.017	0.136**	0.349***	0.345***	0.346***
	(0.029)	(0.059)	(0.072)	(0.071)	(0.069)
N	3002	2991	2990	2990	2990
R^2	0.001	0.009	0.043	0.044	0.044
Probability > F	0.381	0.004	0.000	0.000	0.000

*Standard errors in parentheses, * p < .1, ** p < .05, *** p < .01*

Table 18 (p.39) shows the results of the OLS models on the a-insensitivity index. When analysing the results of the main weather independent variables, it now follows that all weather explanatory variables are not significant in the complete model. By contrast, I find several significant results for the control variables. Besides a different effect in gender on the ambiguity-aversion index, there is also a different effect in gender on the a-insensitivity index. The results display that being a male increases the a-insensitivity index with 0.051, compared to being a female, ceteris paribus. Secondly, one category higher in the level of trust in the stock market decreases the a-insensitivity index with 0.016, ceteris paribus. A possible reason for this could be, that individuals who have a higher level of trust in the stock market, have more knowledge about decision making under ambiguity. Consistent with a different effect in race on the ambiguity-aversion index, this also holds for the effect on the a-insensitivity index. Being white namely decreases the a-insensitivity index with 0.060, compared to not being white, ceteris paribus. Besides an effect of the variable *OrderOfQuestions* on the ambiguity-aversion index, answering questions about ambiguity-aversion first increases the a-insensitivity index with 0.045, compared to answering questions about risk-aversion first, ceteris paribus. Overall, the OLS model on the a-insensitivity index explains 2,4% of the data variation, which is even smaller than the OLS model on the ambiguity-aversion index explains.

Overall and consistent with the OLS models on the a-insensitivity index, Table 19 (p.40) does not show significant results for the effect of the weather independent variables on the ambiguity attitude for low likelihoods. However, only some control variables are significant. First of all, an increase in the individual's age with one year, decreases the ambiguity index for low likelihoods with 0.001, ceteris paribus. Furthermore, being highly educated increases the ambiguity index for low likelihoods with 0.020, compared to not being highly educated, ceteris paribus. Also, being white decreases the ambiguity index for low likelihoods with 0.039, compared to not being white, ceteris paribus. At the end, I again control the OLS model for the order of the questions, whether the individual needed to answer questions about ambiguity-aversion or risk-aversion first. Consistent with the OLS models on the ambiguity-aversion index and a-insensitivity index, the results clearly show that the order of the questions affects the ambiguity index for low likelihoods. When answering questions about ambiguity-aversion first, the ambiguity index for low likelihoods decreases with 0.022, compared to answering questions about risk-aversion first, ceteris paribus. Finally, Table 19 (p.40) displays that the OLS model on the ambiguity attitude for low likelihoods explains 1,9% of the data variation.

Table 18: OLS regressions on the a-insensitivity index

a	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Precipitation	0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Snowfall	0.000	0.000	0.001	0.001	0.001
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
MaximumTemperature	0.000	-0.000	0.000		
	(0.001)	(0.001)	(0.001)		
AverageDailyWindSpeed	-0.002^{*}	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.000	0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Male		0.051^{***}	0.051^{***}	0.051^{***}	0.051^{***}
		(0.014)	(0.014)	(0.014)	(0.014)
MarriedLivingPartner		0.005	0.008	0.008	0.008
		(0.015)	(0.015)	(0.015)	(0.016)
FamilyIncome		-0.005^{**}	-0.003	-0.003	-0.003
		(0.002)	(0.002)	(0.002)	(0.002)
NumberOfHouseholdMembers		0.009^{*}	0.007	0.007	0.007
		(0.005)	(0.005)	(0.005)	(0.005)
Employed		0.003	0.006	0.006	0.006
		(0.015)	(0.015)	(0.015)	(0.015)
TrustInStockMarket		-0.019^{***}	-0.016^{**}	-0.016^{**}	-0.016^{**}
		(0.007)	(0.007)	(0.007)	(0.007)
HighEducation			-0.019	-0.019	-0.019
			(0.015)	(0.015)	(0.015)
EthnicityWhite			-0.060^{***}	-0.060^{***}	-0.060^{***}
			(0.018)	(0.018)	(0.018)
EthnicityHispanicLatino			0.007	0.007	0.007
			(0.021)	(0.021)	(0.021)
OrderOfQuestions			0.045^{***}	0.045^{***}	0.045^{***}
			(0.013)	(0.013)	(0.013)
AverageTemperature				0.000	
				(0.001)	
MinimumTemperature					0.000
					(0.001)
Constant	0.624^{***}	0.626^{***}	0.564^{***}	0.562^{***}	0.563^{***}
	(0.025)	(0.052)	(0.063)	(0.062)	(0.060)
N	3002	2991	2990	2990	2990
R^2	0.001	0.015	0.024	0.024	0.024
Probability > F	0.525	0.000	0.000	0.000	0.000

Standard errors in parentheses, * p < .1, ** p < .05, *** p < .01

Table 19: OLS regressions on the ambiguity attitude for low likelihoods

$\boldsymbol{AA(0.1)}$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Precipitation	0.000	0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Snowfall	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MaximumTemperature	0.000	0.000	0.001		
	(0.001)	(0.001)	(0.001)		
AverageDailyWindSpeed	0.000	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
Male		-0.009	-0.009	-0.009	-0.009
		(0.008)	(0.008)	(0.008)	(0.008)
MarriedLivingPartner		-0.005	-0.001	-0.001	-0.001
		(0.008)	(0.009)	(0.009)	(0.009)
FamilyIncome		-0.000	-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
NumberOfHouseholdMembers		0.004	0.003	0.003	0.003
		(0.003)	(0.003)	(0.003)	(0.003)
Employed		-0.009	-0.009	-0.009	-0.009
		(0.008)	(0.008)	(0.008)	(0.008)
TrustInStockMarket		-0.004	-0.003	-0.003	-0.003
		(0.004)	(0.004)	(0.004)	(0.004)
HighEducation			0.020^{**}	0.020^{**}	0.020^{**}
			(0.008)	(0.008)	(0.008)
EthnicityWhite			-0.039^{***}	-0.039^{***}	-0.038^{***}
			(0.009)	(0.009)	(0.009)
EthnicityHispanicLatino			-0.003	-0.003	-0.004
			(0.011)	(0.011)	(0.011)
OrderOfQuestions			-0.022^{***}	-0.022^{***}	-0.022^{***}
			(0.007)	(0.007)	(0.007)
AverageTemperature				0.000	
				(0.001)	
MinimumTemperature					0.000
					(0.001)
Constant	-0.141^{***}	-0.064^{**}	-0.022	-0.017	-0.011
	(0.014)	(0.027)	(0.032)	(0.031)	(0.030)
N	3002	2991	2990	2990	2990
R^2	0.000	0.008	0.019	0.019	0.019
Probability > F	0.901	0.003	0.000	0.000	0.000

Standard errors in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$

Consistent with the OLS model on the ambiguity-aversion index, Table 20 (p.42) displays that the average daily wind speed in km/h is the same in sign, significance and magnitude in the complete model, whereas the other main independent weather are not significant. The results show that an increase of one km/h in the average daily wind speed increases the ambiguity index for high likelihoods with 0.002, ceteris paribus. Again, there are some control variables significant. First of all, an increase of one year in the individual's age leads to a decrease of 0.001 in the ambiguity index for high likelihoods, ceteris paribus. Secondly, the results for *Male* are the same in significance and sign for the OLS model on the ambiguity-aversion index. Namely, being a male decreases the ambiguity index for high likelihoods with 0.050, compared to being a female, ceteris paribus. Moreover, the results indicate that one category higher in the level of trust in the stock market increases the ambiguity index for high likelihoods with 0.010, ceteris paribus. This effect is significant at a 10%-level. The findings also show that being highly educated increases the ambiguity index for high likelihoods with 0.036, compared to not being highly educated, ceteris paribus. At the end, it is consistent with the other three ambiguity attitude measures that the order of the questions has a significant impact. The results show that an individual who needed to answer questions about ambiguity-aversion first has a lower ambiguity index for high likelihoods with 0.058, than an individual who needed to answer questions about risk-aversion first, ceteris paribus. Overall, the OLS model on the ambiguity attitude for high likelihoods explains 3,5% of the data variation.

Table 20: OLS regressions on the ambiguity attitude for high likelihoods

$AA(0.9)$	(1)	(2)	(3)	(4)	(5)
Precipitation	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Snowfall	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MaximumTemperature	0.000	0.000	0.000		
	(0.001)	(0.001)	(0.001)		
AverageDailyWindSpeed	0.002**	0.002**	0.002**	0.002**	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.001**	-0.001**	-0.001**	-0.001**
		(0.000)	(0.000)	(0.000)	(0.000)
Male		-0.050***	-0.050***	-0.050***	-0.050***
		(0.010)	(0.010)	(0.010)	(0.010)
MarriedLivingPartner		-0.009	-0.008	-0.007	-0.007
		(0.011)	(0.011)	(0.011)	(0.011)
FamilyIncome		0.003*	0.002	0.002	0.002
		(0.002)	(0.002)	(0.002)	(0.002)
NumberOfHouseholdMembers		-0.003	-0.002	-0.002	-0.002
		(0.003)	(0.003)	(0.003)	(0.003)
Employed		-0.011	-0.014	-0.014	-0.014
		(0.011)	(0.011)	(0.011)	(0.011)
TrustInStockMarket		0.012**	0.010*	0.010*	0.010*
		(0.005)	(0.005)	(0.005)	(0.005)
HighEducation			0.036***	0.036***	0.036***
			(0.010)	(0.010)	(0.010)
EthnicityWhite			0.009	0.010	0.010
			(0.013)	(0.013)	(0.013)
EthnicityHispanicLatino			-0.008	-0.009	-0.009
			(0.014)	(0.014)	(0.014)
OrderOfQuestions			-0.058***	-0.058***	-0.058***
			(0.009)	(0.009)	(0.009)
AverageTemperature				0.000	
				(0.001)	
MinimumTemperature					-0.000
					(0.001)
Constant	0.160***	0.235***	0.328***	0.333***	0.338***
	(0.018)	(0.036)	(0.043)	(0.043)	(0.041)
N	3002	2991	2990	2990	2990
R^2	0.002	0.018	0.035	0.035	0.035
Probability > F	0.187	0.000	0.000	0.000	0.000

*Standard errors in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$*

5.2 Ordered multinomial logit models for ambiguity attitudes

In the ordered multinomial logit models, only the maximum temperature is used. The previous results of the OLS models namely indicate that the effects barely change or do not change at all, when substituting the maximum temperature for the minimum temperature or average temperature. Furthermore, there is no need to take the Gauss-Markov assumptions in consideration, because the explanatory variables depend on each other in the ordered multinomial logit models. Table 21 until Table 23 display the results of the ordered multinomial logit models for the ambiguity attitudes for low, intermediary and high likelihoods. For each table, the first three columns show the basic results that can be interpret in terms of sign and significance, whereas the last three columns show the average marginal effects that can be interpret in terms of magnitude, sign and significance.

Table 21 (p.44) shows the results of the ordered multinomial logit model on the ambiguity attitude for low likelihoods. The average marginal effects show that all four weather independent variables are not significant. This is consistent with the results of the OLS model on the ambiguity attitude for low likelihoods. However, the results of the control variables in the ordered multinomial logit model indicates that they are different from the results of the OLS model. The variables *FamilyIncome*, *NumberOfHouseholdMembers* and *TrustInStockMarket* are now all significant. On average, one category higher in the family income height increases the probability of being ambiguity-seeking for low likelihoods with 0.9 percentage points, ceteris paribus. Besides, on average, an increase of one in the number of household members decreases the probability of being ambiguity-seeking for low-likelihoods with 1 percentage point, ceteris paribus. This effect is significant at a 10%-level. Furthermore, on average, one category higher in the level of trust in the stock market decreases the probability of being ambiguity-averse for low likelihoods with 1.2 percentage points, ceteris paribus. The results of the variables *EthnicityWhite*, and *OrderOfQuestions* are consistent with the results of the OLS model. On average, being white decreases the probability of being ambiguity-averse with 4.7 percentage points, compared to not being white, ceteris paribus. Finally, on average, answering questions about ambiguity-aversion first, decreases the probability of being ambiguity-averse for low likelihoods with 4.5 percentage points, compared to answering questions about risk aversion first, ceteris paribus. By contrast, on average, answering questions about ambiguity-aversion first increases the probability of being ambiguity-seeking with 9.5 percentage points, compared to answering questions about risk-aversion first, ceteris paribus.

Table 21: Ordered multinomial logit models and average marginal effects on the ambiguity attitude for low likelihoods

$\boldsymbol{CategoricalAA(0.1)}$	**(1)**	**(2)**	**(3)**	**Ambiguity aversion**	**Ambiguity neutral**	**Ambiguity seeking**
Precipitation	0.003	0.005	0.005	-0.001	-0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Snowfall	0.052	0.055	0.052	-0.006	-0.006	0.012
	(0.045)	(0.047)	(0.046)	(0.005)	(0.005)	(0.010)
MaximumTemperature	-0.003	-0.002	-0.004	0.000	0.000	-0.001
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
AverageDailyWindSpeed	0.002	-0.004	-0.005	0.000	0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
Age		-0.000	-0.002	0.000	0.000	-0.000
		(0.003)	(0.003)	(0.000)	(0.000)	(0.001)
Male		0.050	0.042	-0.004	-0.005	0.009
		(0.078)	(0.078)	(0.008)	(0.009)	(0.017)
MarriedLivingPartner		0.142^{*}	0.113	-0.012	-0.013	0.025
		(0.083)	(0.084)	(0.009)	(0.010)	(0.019)
FamilyIncome		0.051^{***}	0.042^{***}	-0.004^{***}	-0.005^{***}	0.009^{***}
		(0.012)	(0.013)	(0.001)	(0.001)	(0.003)
NumberOfHouseholdMembers		-0.063^{**}	-0.045^{*}	0.005^{*}	0.005^{*}	-0.010^{*}
		(0.026)	(0.027)	(0.003)	(0.003)	(0.006)
Employed		-0.034	-0.039	0.004	0.005	-0.009
		(0.086)	(0.086)	(0.009)	(0.010)	(0.019)
TrustInStockMarket		0.136^{***}	0.109^{***}	-0.012^{***}	-0.013^{***}	0.024^{***}
		(0.037)	(0.038)	(0.004)	(0.004)	(0.008)
HighEducation			0.034	-0.004	-0.004	0.008
			(0.082)	(0.009)	(0.010)	(0.018)
EthnicityWhite			0.408^{***}	-0.047^{***}	-0.047^{***}	0.094^{***}
			(0.096)	(0.012)	(0.011)	(0.023)
EthnicityHispanicLatino			0.072	-0.008	-0.008	0.016
			(0.110)	(0.004)	(0.004)	(0.008)
OrderOfQuestions			0.425^{***}	-0.045^{***}	-0.050^{***}	0.095^{***}
			(0.076)	(0.008)	(0.009)	(0.017)
Cut1						
Constant	-1.987^{***}	-1.100^{***}	-0.331			
	(0.149)	(0.284)	(0.341)			
Cut2						
Constant	-0.596^{***}	0.313	1.099^{***}			
	(0.143)	(0.283)	(0.341)			
N	3002	2991	2990	2990	2990	2990

Standard errors in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$

Table 22: Ordered multinomial logit models and average marginal effects on the ambiguity attitude for intermediary likelihoods

Ordered multinomial logit models				Average marginal effects		
$CategoricalAA(0.5)$	**(1)**	**(2)**	**(3)**	**Ambiguity aversion**	**Ambiguity neutral**	**Ambiguity seeking**
Precipitation	0.003	0.003	0.001	-0.000	0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.001)	(0.000)	(0.001)
Snowfall	0.010	0.010	0.013	-0.003	0.000	0.003
	(0.017)	(0.017)	(0.017)	(0.004)	(0.000)	(0.004)
MaximumTemperature	0.001	0.000	-0.000	0.000	-0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.001)	(0.000)	(0.001)
AverageDailyWindSpeed	-0.012**	-0.011*	-0.010*	0.002*	-0.000	-0.002*
	(0.006)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Age		0.003	0.003	-0.001	0.000	0.001
		(0.003)	(0.003)	(0.001)	(0.000)	(0.001)
Male		0.257***	0.260***	-0.062***	0.005***	0.057***
		(0.073)	(0.074)	(0.018)	(0.002)	(0.016)
MarriedLivingPartner		0.040	0.030	-0.007	0.001	0.007
		(0.079)	(0.081)	(0.019)	(0.002)	(0.018)
FamilyIncome		-0.022*	-0.016	0.004	-0.000	-0.004
		(0.011)	(0.012)	(0.003)	(0.000)	(0.003)
NumberOfHouseholdMembers		-0.014	-0.023	0.006	-0.000	-0.005
		(0.025)	(0.026)	(0.006)	(0.000)	(0.006)
Employed		0.012	0.027	-0.007	0.001	0.006
		(0.081)	(0.082)	(0.020)	(0.002)	(0.018)
TrustInStockMarket		-0.021	-0.015	0.004	-0.000	-0.003
		(0.034)	(0.036)	(0.009)	(0.001)	(0.008)
HighEducation			-0.203***	0.049***	-0.004**	-0.045***
			(0.078)	(0.019)	(0.001)	(0.017)
EthnicityWhite			-0.067	0.016	-0.001	-0.015
			(0.093)	(0.022)	(0.002)	(0.021)
EthnicityHispanicLatino			-0.002	0.000	-0.000	-0.000
			(0.107)	(0.025)	(0.002)	(0.024)
OrderOfQuestions			0.718***	-0.175***	0.014***	0.161***
			(0.072)	(0.017)	(0.002)	(0.016)
Cut1						
Constant	-0.022	0.244	1.261***			
	(0.137)	(0.270)	(0.329)			
Cut2						
Constant	0.475***	0.743***	1.777***			
	(0.137)	(0.271)	(0.329)			
N	3002	2991	2990	2990	2990	2990

*Standard errors in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$*

Table 22 (p.45) displays the results of the ordered multinomial logit model on the ambiguity attitude for intermediary likelihoods, which also captures the ambiguity-aversion index since $b = 2 * (0.5 - m(0.5))$. An analysis on the main independent weather variables indicates the same results as under the OLS model on the ambiguity-aversion index. The variable *AverageDailyWindSpeed* is also significant and decreases the probability of being ambiguity-seeking for intermediary likelihoods, ceteris paribus. This effect is significant at a 10%-level. When looking more specifically at the average marginal effects for the variable *AverageDailyWindSpeed*, the results show that a change in the probabilities for both being ambiguity-averse and ambiguity-seeking for intermediary likelihoods are significant at a 10%-level, whereas a change in the probability of being ambiguity-neutral for intermediary likelihoods is not significant. On average, an increase of one km/h in the average daily wind speed increases the probability of being ambiguity-averse for intermediary likelihoods with 0.2 percentage points, ceteris paribus. By contrast, on average, an increase of one km/h in the average daily wind speed decreases the probability of being ambiguity-seeking for intermediary likelihoods with 0.2 percentage points, ceteris paribus.

Several control variables are also significant. Comparing these results of the ordered multinomial logit model with the results of the OLS model on the ambiguity attitude for intermediary likelihoods, indicates that the results for the variables *Male*, *OrderOfQuestions* and *HighEducation* are consistent with the results of the OLS model. First of all, on average, being a male increases the probability of being ambiguity-seeking for intermediary likelihoods with 5.7 percentage points, compared to being a female, ceteris paribus. Moreover, answering questions about ambiguity-aversion first, increases the probability of being ambiguity-seeking for intermediary likelihoods, compared to answering questions about risk-aversion first, ceteris paribus. Considering the average marginal effects shows that on average, if the individual needed to answer questions about ambiguity-aversion first, the probability of being ambiguity-seeking for intermediary likelihoods increases with 16.1 percentage points, compared to answering questions about risk-aversion first, ceteris paribus. Finally, on average, being highly educated decreases the probability of being ambiguity-seeking for intermediary likelihoods with 4.5 percentage points, compared to not being highly educated, ceteris paribus.

Table 23 (p.48) shows that the results of the ordered multinomial logit model for the effect of the main weather independent variables on the ambiguity attitude for high likelihoods are consistent with the results of the OLS model. On average, an increase of one km/h in the average daily wind speed increases the probability of being ambiguity-averse for high likelihoods with 0.3 percentage points, ceteris paribus. On the contrary side, on average, an increase of one km/h in the average daily wind speed decreases the probability of being ambiguity-seeking for high likelihoods with 0.2 percentage points, ceteris paribus. Both average marginal effects are significant at a 10%-level. The other weather independent variables are not significant.

The results of the control variables show that the significant variables in the OLS model are still significant in the ordered multinomial logit models. On average, an increase of one year in the individual's age decreases the probability of being ambiguity-averse for high likelihoods with 0.2 percentage points, ceteris paribus. Moreover, on average, being a male increases the probability of being ambiguity-seeking for high likelihoods with 6.6 percentage points, compared to being a female, ceteris paribus. The findings also indicate that on average, one category higher in the level of trust in the financial stock market decreases the probability of being ambiguity-seeking for high likelihoods with 3.3 percentage points, ceteris paribus. Besides, on average, being highly educated increases the probability of being ambiguity-averse for high likelihoods with 7.1 percentage points, compared to not being highly educated, ceteris paribus. Also consistent with the findings of the OLS model, the result of the variable *OrderOfQuestions* in the ordered multinomial logit model indicates a positive effect on the probability of being ambiguity-seeking for high likelihoods, ceteris paribus.

In addition, the variables *FamilyIncome*, *Employed* and *EthnicityWhite* are now also significant. On average, one category higher in the family income height increases the probability of being ambiguity-averse for high likelihoods with 0.6 percentage points, ceteris paribus. Also, the results show a negative effect of being white on the probability of being ambiguity-seeking for high likelihoods, compared to not being white, ceteris paribus. Finally, on average, being employed increases the probability of being ambiguity-seeking for high likelihoods with 2.9 percentage points, compared to not being employed, ceteris paribus.

Table 23: Ordered multinomial logit model and average marginal effects on the ambiguity attitude for high likelihoods

Ordered multinomial logit models				Average marginal effects		
$\boldsymbol{CategoricalAA(0.9)}$	**(1)**	**(2)**	**(3)**	**Ambiguity aversion**	**Ambiguity neutral**	**Ambiguity seeking**
Precipitation	0.003	0.002	0.001	-0.000	0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.001)	(0.000)	(0.001)
Snowfall	0.008	0.008	0.010	-0.002	0.000	0.002
	(0.021)	(0.021)	(0.021)	(0.005)	(0.001)	(0.004)
MaximumTemperature	0.000	-0.002	-0.002	0.000	-0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.001)	(0.000)	(0.001)
AverageDailyWindSpeed	-0.016^{***}	-0.013^{**}	-0.011^{*}	0.003^{*}	-0.000^{*}	-0.002^{*}
	(0.006)	(0.006)	(0.006)	(0.001)	(0.000)	(0.001)
Age		0.010^{***}	0.011^{***}	-0.002^{***}	0.000^{***}	0.002^{***}
		(0.003)	(0.003)	(0.001)	(0.000)	(0.001)
Male		0.342^{***}	0.348^{***}	-0.081^{***}	0.015^{***}	0.066^{***}
		(0.075)	(0.076)	(0.018)	(0.004)	(0.014)
MarriedLivingPartner		0.034	0.028	-0.007	0.001	0.005
		(0.080)	(0.081)	(0.019)	(0.003)	(0.016)
FamilyIncome		-0.039^{***}	-0.027^{**}	0.006^{**}	-0.001^{**}	-0.005^{**}
		(0.011)	(0.012)	(0.003)	(0.000)	(0.002)
NumberOfHouseholdMembers		0.017	0.001	-0.000	0.000	0.000
		(0.025)	(0.026)	(0.006)	(0.001)	(0.005)
Employed		0.124	0.149^{*}	-0.035^{*}	0.006^{*}	0.029^{*}
		(0.082)	(0.083)	(0.019)	(0.003)	(0.016)
TrustInStockMarket		-0.191^{***}	-0.169^{***}	0.040^{***}	-0.007^{***}	-0.033^{***}
		(0.035)	(0.036)	(0.008)	(0.001)	(0.007)
HighEducation			-0.300^{***}	0.071^{***}	-0.012^{***}	-0.058^{***}
			(0.078)	(0.018)	(0.003)	(0.015)
EthnicityWhite			-0.217^{**}	0.051^{**}	-0.008^{**}	-0.043^{**}
			(0.092)	(0.022)	(0.003)	(0.019)
EthnicityHispanicLatino			0.007	-0.002	0.000	0.001
			(0.105)	(0.025)	(0.004)	(0.020)
OrderOfQuestions			0.521^{***}	-0.123^{***}	0.022^{***}	0.101^{***}
			(0.073)	(0.017)	(0.003)	(0.014)
Cut1						
Constant	0.068	0.267	0.966^{***}			
	(0.137)	(0.271)	(0.325)			
Cut2						
Constant	0.763^{***}	0.979^{***}	1.693^{***}			
	(0.138)	(0.271)	(0.326)			
N	3002	2991	2990	2990	2990	2990

Standard errors in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$

5.3 OLS models for state regions

To determine the difference between the four state regions regarding the effect of the main weather independent variables on the four different ambiguity attitude measures, only the main weather independent variables are analysed. Whereas the results of the OLS models for all four ambiguity attitude measures do not show any significant results for the variables *Precipitation* and *MaximumTemperature*, Table 24 (p.50) shows the opposite for the ambiguity-aversion index. The findings namely indicate that these variables are significant in the south region, while they are not significant in the other state regions. First of all, an increase of one milimetre in the amount of precipitation in the south region increases the ambiguity-aversion index with 0.006, ceteris paribus. This effect is significant at a 10%-level. In addition, an increase of one degrees Celsius in the maximum temperature in the south region leads to a decrease of 0.006 in the ambiguity-aversion index, ceteris paribus. The last result for the west region indicates, that an increase of one km/h in the average daily wind speed in the west region increases the ambiguity-aversion index with 0.004, ceteris paribus. This effect is significant at a 10% level. Moreover, this is consistent with the results of the OLS model on the ambiguity-aversion index. For the other state regions, the variable *AverageDailyWindSpeed* is not significant.

Whether these effects are also statistically larger, thus depends on the confidence intervals of the variables in all four state regions. First, the confidence intervals of the variables *Precipitation* and *MaximumTemperature* for the south region overlap the confidence intervals of that same variables for the other state regions. This means that there is no evidence that the effects are different in the south region than in the other regions. Secondly, the confidence interval of the variable *AverageDailyWindSpeed* of the west region also overlaps the confidence intervals of that same variable of the other state regions. So, the effect of an increase of one km/h in the average daily wind speed in the west region is not statistically different from the effects in the other regions. Overall, evidence shows that there is a difference in significance between the state regions for the effects of these variables on the ambiguity-aversion index.

Table 25 (p.51) displays only one significant effect for the main weather independent variables. An increase of one millimetre in the amount of precipitation in the south region increases the a-insensitivity index with 0.005, ceteris paribus. This effect is significant at a 10%-level. When comparing the confidence intervals, it stands out that they overlap each other. So, the effect of an increase in the amount of precipitation on the a-insensitivity index in the south region is not statistically different from the effects in other state regions, but only differs in significance.

Table 24: OLS regressions on the ambiguity-aversion index for state regions

b	**Northeast region**	**Midwest region**	**South region**	**West region**
Precipitation	-0.005	-0.001	0.006*	0.001
	[-0.022,0.012]	[-0.006,0.003]	[-0.000,0.012]	[-0.002,0.003]
Snowfall	-0.020	0.000	0.000	-0.001
	[-0.065,0.025]	[0.000,0.000]	[0.000,0.000]	[-0.008,0.005]
MaximumTemperature	-0.003	-0.001	-0.006**	0.003
	[-0.007,0.002]	[-0.005,0.004]	[-0.012,-0.001]	[-0.003,0.008]
AverageDailyWindSpeed	-0.003	0.001	0.000	0.004*
	[-0.010,0.004]	[-0.003,0.006]	[-0.005,0.006]	[-0.000,0.009]
Age	-0.003*	-0.001	0.000	-0.000
	[-0.005,0.000]	[-0.004,0.001]	[-0.002,0.003]	[-0.003,0.002]
Male	-0.114***	-0.068**	-0.023	-0.065**
	[-0.182,-0.047]	[-0.129,-0.007]	[-0.078,0.032]	[-0.122,-0.008]
MarriedLivingPartner	-0.017	0.007	0.021	-0.003
	[-0.098,0.065]	[-0.064,0.079]	[-0.041,0.082]	[-0.063,0.058]
FamilyIncome	0.001	-0.004	-0.001	0.011**
	[-0.011,0.013]	[-0.016,0.009]	[-0.011,0.008]	[0.002,0.021]
NumberOfHouseholdMembers	0.007	0.009	0.013	-0.000
	[-0.016,0.031]	[-0.015,0.033]	[-0.008,0.034]	[-0.020,0.020]
Employed	-0.016	0.019	-0.001	-0.043
	[-0.091,0.060]	[-0.049,0.087]	[-0.062,0.059]	[-0.108,0.021]
HighEducation	0.046	0.037	0.078***	0.036
	[-0.027,0.120]	[-0.025,0.099]	[0.019,0.137]	[-0.028,0.100]
EthnicityWhite	-0.007	-0.030	-0.062*	-0.076**
	[-0.091,0.077]	[-0.161,0.101]	[-0.134,0.011]	[-0.147,-0.005]
EthnicityHispanicLatino	-0.033	-0.068	-0.019	0.038
	[-0.139,0.072]	[-0.359,0.222]	[-0.093,0.054]	[-0.041,0.117]
TrustInStockMarket	-0.014	-0.029*	0.002	0.009
	[-0.048,0.019]	[-0.062,0.005]	[-0.024,0.029]	[-0.020,0.038]
OrderOfQuestions	-0.153***	-0.095***	-0.185***	-0.158***
	[-0.219,-0.087]	[-0.155,-0.036]	[-0.239,-0.131]	[-0.214,-0.102]
Constant	0.732***	0.628*	0.526***	0.160
	[0.427,1.037]	[-0.004,1.261]	[0.239,0.814]	[-0.095,0.416]
N	659	659	958	849
R^2	0.061	0.036	0.063	0.066
Probability > F	0.000	0.080	0.000	0.000

*95% confidence intervals in brackets, * p < .1, ** p < .05, *** p < .01*

Table 25: OLS regressions on the a-insensitivity index for state regions

a	Northeast region	Midwest region	South region	West region
Precipitation	0.003	-0.000	0.005*	0.000
	[-0.012,0.018]	[-0.004,0.004]	[-0.000,0.010]	[-0.002,0.003]
Snowfall	0.016	0.000	0.000	0.001
	[-0.055,0.087]	[0.000,0.000]	[0.000,0.000]	[-0.006,0.009]
MaximumTemperature	-0.000	-0.000	0.001	0.001
	[-0.004,0.004]	[-0.005,0.004]	[-0.004,0.006]	[-0.004,0.005]
AverageDailyWindSpeed	-0.001	-0.003	0.001	-0.003
	[-0.008,0.005]	[-0.007,0.001]	[-0.004,0.006]	[-0.007,0.001]
Age	0.000	0.001	-0.001	0.001
	[-0.002,0.003]	[-0.001,0.003]	[-0.003,0.001]	[-0.001,0.003]
Male	0.100***	0.034	0.085***	-0.006
	[0.038,0.162]	[-0.026,0.095]	[0.035,0.135]	[-0.057,0.045]
MarriedLivingPartner	0.044	0.004	-0.003	0.002
	[-0.025,0.113]	[-0.062,0.070]	[-0.058,0.051]	[-0.053,0.057]
FamilyIncome	-0.002	-0.002	0.002	-0.006
	[-0.011,0.008]	[-0.013,0.009]	[-0.006,0.010]	[-0.014,0.002]
NumberOfHouseholdMembers	-0.008	0.017	-0.002	0.016**
	[-0.028,0.012]	[-0.004,0.038]	[-0.020,0.016]	[0.000,0.033]
Employed	0.029	0.034	-0.022	0.004
	[-0.036,0.095]	[-0.031,0.100]	[-0.076,0.032]	[-0.053,0.060]
HighEducation	0.003	-0.018	-0.038	-0.041
	[-0.064,0.070]	[-0.081,0.044]	[-0.088,0.012]	[-0.095,0.012]
EthnicityWhite	-0.101***	-0.090*	-0.056*	-0.042
	[-0.175,-0.028]	[-0.195,0.015]	[-0.122,0.010]	[-0.103,0.019]
EthnicityHispanicLatino	-0.063	-0.011	-0.022	0.055
	[-0.150,0.024]	[-0.235,0.213]	[-0.087,0.043]	[-0.015,0.125]
TrustInStockMarket	-0.006	-0.014	-0.018	-0.023*
	[-0.036,0.024]	[-0.044,0.016]	[-0.042,0.006]	[-0.048,0.003]
OrderOfQuestions	-0.007	0.062**	0.069***	0.047*
	[-0.065,0.051]	[0.005,0.119]	[0.022,0.116]	[-0.002,0.096]
Constant	0.653***	0.590**	0.560***	0.571***
	[0.391,0.916]	[0.093,1.086]	[0.313,0.808]	[0.339,0.803]
N	659	659	958	849
R^2	0.039	0.027	0.042	0.035
Probability > F	0.032	0.181	0.000	0.002

*95% confidence intervals in brackets, * p < .1, ** p < .05, *** p < .01*

Table 26 (p.53) shows the results of the OLS model on the ambiguity attitude for low likelihoods, for all four state regions. The results show that there is a significant effect for the variable *Snowfall* in the northeast region. An increase of one milimetre in the amount of snowfall in the northeast region increases the ambiguity index for low likelihoods with 0.020, ceteris paribus. The other state regions show smaller effects of snowfall on the ambiguity index for low likelihoods and which are all not significant. When comparing the confidence interval of the variable *Snowfall* for the northeast region with the confidence intervals of that same variable for the other regions, it stands out that they do not overlap each other. Thus besides the fact that there is a difference in significance for snowfall between the four state regions, there is also evidence that the effect of an increase in the amount of snowfall on the ambiguity index for low likelihoods is larger for the northeast region than for the other regions. The other main weather independent variables are all not significant.

Table 27 (p.54) shows the results of the OLS model on the ambiguity attitude for high likelihoods, for all four state regions. The results display significant effects for the variables *Precipitation* and *AverageDailyWindSpeed*. First of all, an increase of one millimetre in the amount of precipitation in the south region decreases the ambiguity index for high likelihoods with 0.003, ceteris paribus. Secondly, an increase of one km/h in the average daily wind speed in the west region increases the ambiguity index for high likelihoods with 0.003, ceteris paribus. This effect is significant at a 10%-level. Therefore, there is again evidence that there is a difference in significance for both variables between the four state regions. If the effects of the weather conditions also statistically differ, depends on the confidence intervals for both variables. The results indicate that the confidence intervals of the variables *Precipitation* and *AverageDailyWindSpeed* for respectively the south region and west region, overlap the confidence intervals of these same variables for the other state regions. This means that the effects of precipitation and the average daily wind speed on the ambiguity index for high likelihoods are not statistically different in the other state regions.

Table 26: OLS regressions on the ambiguity attitude for low likelihoods for state regions

$AA(0.1)$	**Northeast region**	**Midwest region**	**South region**	**West region**
Precipitation	-0.001	0.000	0.001	0.000
	[-0.009,0.008]	[-0.002,0.002]	[-0.002,0.004]	[-0.001,0.002]
Snowfall	0.020***	0.000	0.000	-0.001
	[0.013,0.028]	[0.000,0.000]	[0.000,0.000]	[-0.005,0.003]
MaximumTemperature	0.000	0.001	-0.001	0.001
	[-0.002,0.002]	[-0.001,0.003]	[-0.004,0.002]	[-0.002,0.003]
AverageDailyWindSpeed	-0.000	-0.000	-0.000	0.000
	[-0.003,0.003]	[-0.002,0.002]	[-0.003,0.003]	[-0.002,0.002]
Age	-0.001*	-0.001	-0.000	-0.001
	[-0.002,0.000]	[-0.002,0.001]	[-0.002,0.001]	[-0.002,0.000]
Male	-0.013	-0.022	0.018	-0.016
	[-0.045,0.019]	[-0.052,0.008]	[-0.010,0.046]	[-0.043,0.011]
MarriedLivingPartner	0.022	0.009	-0.010	-0.019
	[-0.017,0.061]	[-0.025,0.042]	[-0.043,0.022]	[-0.047,0.010]
FamilyIncome	-0.002	-0.001	0.001	0.000
	[-0.007,0.004]	[-0.007,0.005]	[-0.004,0.005]	[-0.004,0.005]
NumberOfHouseholdMembers	-0.002	0.007	0.001	0.008*
	[-0.012,0.008]	[-0.003,0.018]	[-0.009,0.011]	[-0.001,0.017]
Employed	-0.010	-0.002	-0.006	-0.013
	[-0.044,0.024]	[-0.036,0.033]	[-0.036,0.025]	[-0.044,0.017]
HighEducation	0.037**	0.020	0.018	0.009
	[0.002,0.073]	[-0.013,0.053]	[-0.011,0.046]	[-0.022,0.041]
EthnicityWhite	-0.051***	-0.038	-0.027	-0.062***
	[-0.089,-0.014]	[-0.091,0.015]	[-0.063,0.009]	[-0.092,-0.031]
EthnicityHispanicLatino	-0.026	-0.052*	-0.035**	0.028
	[-0.071,0.019]	[-0.112,0.008]	[-0.069,-0.000]	[-0.008,0.065]
TrustInStockMarket	-0.012	-0.008	-0.000	0.005
	[-0.028,0.003]	[-0.025,0.009]	[-0.014,0.013]	[-0.009,0.018]
OrderOfQuestions	-0.037**	-0.008	-0.014	-0.036***
	[-0.068,-0.006]	[-0.038,0.021]	[-0.041,0.014]	[-0.062,-0.009]
Constant	0.121*	0.084	-0.007	-0.059
	[-0.011,0.253]	[-0.070,0.237]	[-0.147,0.133]	[-0.172,0.054]
N	659	659	958	849
R^2	0.053	0.021	0.015	0.042
Probability > F	0.000	0.072	0.327	0.000

*95% confidence intervals in brackets, * p < .1, ** p < .05, *** p < .01*

Table 27: OLS regressions on the ambiguity attitude for high likelihoods for state regions

$AA(0.9)$	**Northeast region**	**Midwest region**	**South region**	**West region**
Precipitation	-0.003	0.000	-0.003**	-0.000
	[-0.011,0.005]	[-0.003,0.003]	[-0.006,-0.000]	[-0.002,0.002]
Snowfall	0.007	0.000	0.000	-0.002
	[-0.046,0.061]	[0.000,0.000]	[0.000,0.000]	[-0.008,0.004]
MaximumTemperature	0.000	0.001	-0.002	0.000
	[-0.002,0.003]	[-0.002,0.004]	[-0.005,0.002]	[-0.003,0.003]
AverageDailyWindSpeed	0.001	0.002	-0.001	0.003*
	[-0.004,0.005]	[-0.001,0.005]	[-0.005,0.002]	[-0.000,0.006]
Age	-0.001*	-0.001	0.001	-0.001*
	[-0.003,0.000]	[-0.003,0.000]	[-0.001,0.002]	[-0.003,0.000]
Male	-0.093***	-0.050**	-0.051***	-0.011
	[-0.135,-0.052]	[-0.091,-0.009]	[-0.085,-0.016]	[-0.048,0.025]
MarriedLivingPartner	-0.013	0.005	-0.008	-0.020
	[-0.059,0.032]	[-0.042,0.052]	[-0.044,0.029]	[-0.059,0.019]
FamilyIncome	-0.001	0.001	-0.001	0.005
	[-0.007,0.006]	[-0.008,0.009]	[-0.007,0.004]	[-0.001,0.011]
NumberOfHouseholdMembers	0.004	-0.006	0.002	-0.005
	[-0.009,0.017]	[-0.021,0.009]	[-0.010,0.015]	[-0.017,0.007]
Employed	-0.034	-0.029	0.012	-0.017
	[-0.078,0.010]	[-0.074,0.016]	[-0.024,0.049]	[-0.057,0.023]
HighEducation	0.035	0.035	0.048***	0.043**
	[-0.010,0.080]	[-0.007,0.077]	[0.014,0.083]	[0.006,0.080]
EthnicityWhite	0.030	0.036	0.018	-0.028
	[-0.021,0.081]	[-0.036,0.107]	[-0.026,0.061]	[-0.073,0.017]
EthnicityHispanicLatino	0.025	-0.044	-0.017	-0.016
	[-0.037,0.087]	[-0.215,0.127]	[-0.063,0.029]	[-0.063,0.032]
TrustInStockMarket	-0.007	0.004	0.014*	0.023**
	[-0.029,0.014]	[-0.018,0.026]	[-0.002,0.031]	[0.004,0.043]
OrderOfQuestions	-0.031	-0.058***	-0.069***	-0.074***
	[-0.071,0.009]	[-0.098,-0.019]	[-0.101,-0.036]	[-0.108,-0.039]
Constant	0.397***	0.415**	0.346***	0.286***
	[0.221,0.574]	[0.036,0.793]	[0.170,0.521]	[0.130,0.442]
N	659	659	958	849
R^2	0.046	0.039	0.048	0.054
Probability > F	0.006	0.015	0.000	0.000

*95% confidence intervals in brackets, * $p < .1$, ** $p < .05$, *** $p < .01$*

5.4 OLS models for weather dummy variables

Table 28 until Table 31 (p.77-p.80) show the results of the OLS models on the four ambiguity attitude measures, with the use of weather dummy variables. The control variables are only interpreted in significance, since the effects of the control variables on the four ambiguity attitude measures are already analysed under the OLS models including the main weather independent variables. Moreover, it is expected that the control variables under the OLS models with the main weather independent variables better reflect the effects on the four ambiguity attitude measures. This is due to the fact that multicollinearity is less likely to appear, when there are less dummy variables added to the regressions (Verbeek, 2012).

First of all, the results indicate that multicollinearity seems not be a problem for all four ambiguity attitude measures after omitting the variable *DummyFreezingNormal* and including more control variables. When I omit the variable *DummyFreezingNormal* from the regression, the variable *DummyMist* changes a lot in magnitude and sign due to the high correlation between these two variables. Besides, other effects barely change or do not change at all in magnitude, sign and significance due to the omitted variable *DummyFreezingNormal*. For that reason, I obtain final results from the fourth step since this step of regression better controls for multicollinearity. Moreover, all models become significant after adding more control variables to the regressions. It follows from the probability values that the complete models are significant at a 1%-level, in explaining the effects on the four ambiguity attitude measures. Finally, consistent with the OLS models using the main weather independent variables, the R^2 seems to be highly influenced when the variable *OrderOfQuestions* is added to the model. So, the results indicate that this variable has a high impact on explaining the data variation.

First of all, Table 28 (p.77) shows the results of the OLS model on the ambiguity-aversion index using weather dummy variables. The findings indicate two significant effects for the weather dummy variables on the ambiguity-aversion index. The first result shows that the presence of hail increases the ambiguity-aversion index with 0.251, compared to the absence of hail, ceteris paribus. This effect is significant at a 10%-level. The second result shows that the presence of snow decreases the ambiguity-aversion index with 0.116, compared to the absence of snow, ceteris paribus. This effect is significant at a 10%-level. It stands out that the other weather dummy variables do not have a significant effect on the ambiguity-aversion index. For the control variables, *Age*, *Male* and *OrderOfQuestions* all have a negative and significant effect on the ambiguity-aversion index, ceteris paribus. At the end, the R^2 indicates that the OLS model on the ambiguity-aversion index fits the data with a percentage of 5,0%.

Table 29 (p.78) displays the findings for the OLS model on the a-insensitivity index, using weather dummy variables. The results show that only the variable *DummyDrizzle* has a significant effect on the a-insensitivity index, ceteris paribus. Namely, the presence of drizzle increases the a-insensitivity index with 0.127, compared to the absence of drizzle, ceteris paribus. Besides, the control variables *Male*, *FamilyIncome*, *TrustInStockMarket* and *EthnicityWhite* all have a significant effect on the a-insensitivity index, ceteris paribus. At the end, with a percentage of 4,1%, the R^2 is even lower for the OLS model on the a-insensitivity index than for the OLS model on the ambiguity-aversion index. The results indicate that the OLS model on the a-insensitivity index explains 4,1% of the data variation.

Table 30 (p.79) shows that *DummyDrizzle* and *DummySnow* both have a significant effect on the ambiguity index for low likelihoods, ceteris paribus. When there is drizzle present, it leads to an increase in the ambiguity index for low likelihoods with 0.083, compared to the absence of drizzle, ceteris paribus. Besides, the presence of snow decreases the ambiguity index for low likelihoods with 0.082, compared to the absence of snow, ceteris paribus. This effect is significant at a 10%-level. The results show that the control variables *Age*, *Male*, *TrustInStockMarket* and *OrderOfQuestions* have a significant effect on the ambiguity index for low likelihoods, ceteris paribus. Consistent with the OLS models using the main weather independent variables, the R^2 is quite low. The results show that the OLS model on the ambiguity attitude for low likelihoods explains 3,3% of the data variation.

Finally, Table 31 (p.80) displays the results of the OLS model on the ambiguity attitude for high likelihoods, using weather dummy variables. Consistent with the OLS model on the ambiguity attitude for low likelihoods using weather dummy variables, there is a negative effect of the variable *DummySnow*. Namely, the presence of snow decreases the ambiguity index for high likelihoods with 0.075, compared to the absence of snow, ceteris paribus. The other weather dummy variables are all not significant. A further analysis on the control variables indicates that *Age*, *Male*, *EthnicityWhite* and *OrderOfQuestions* all have a significant and negative effect on the ambiguity index for high likelihoods, ceteris paribus. At the end, the R^2 indicates that the OLS model on the ambiguity attitude for high likelihoods explains 5,5% of the data variation.

6. Discussion

The results are now summarized and discussed in light of the existing literature, by considering the five hypotheses that I stated. First of all, the first hypothesis is considered, that the height of the temperature negatively affects ambiguity-aversion. The results of the OLS model for the effect of main weather independent variables on the ambiguity-aversion index display that there is no supporting evidence for the first hypothesis. It stands out that temperature is not significant, which also follows from the results of the OLS models for the effect of main weather independent variables on the ambiguity attitudes for low and high likelihoods. This finding also holds for the results of the ordered multinomial logit model and the average marginal effects for the effect of main weather independent variables on the ambiguity attitude for intermediary likelihoods (corresponds to the ambiguity-aversion index), which indicate that temperature is also not significant. When looking more specifically at the average marginal effects for the ambiguity attitudes for low and high likelihoods, the results also show that temperature is not significant. Saunders (1993), Kamstra et al. (2000), and Hirshleifer and Shumway (2003) find that a higher temperature leads to higher stock returns, whereas Cao and Wei (2005) show a negative effect of temperature on stock returns. Besides, Bassi et al. (2013) show that a higher temperature leads to more risk-taking behaviour. For that reason, the results of this research do not complement the existing literature with an effect of temperature on ambiguity-aversion.

The second hypothesis implies that the height of the average daily wind speed positively affects ambiguity-aversion. The results of the OLS model for the effect of main weather independent variables on the ambiguity-aversion index show that the average daily wind speed in km/h is significant. This indicates that there is supporting evidence for the second hypothesis. It also stands out that the average daily wind speed in km/h is significant for the OLS model for the effect of main weather independent variables on the ambiguity attitude for high likelihoods, whereas the effects on the a-insensitivity index and ambiguity attitude for low likelihoods are both not significant. This also holds for the results of the ordered multinomial logit model and their average marginal effects. These results namely show that an increase in the average daily wind speed in km/h makes individuals more ambiguity-averse for intermediary likelihoods and high likelihoods.

At first sight, the effect of an increase of one km/h in the average daily wind speed on the ambiguity-aversion index looks quite small. So, I will analyse the general average daily wind speed values more specifically. The descriptives show that the mean of the average daily wind speed in km/h is 11.99, with a minimum value of 6.24 and a maximum value of 36.73. The marginal effect of the average daily wind speed in km/h on the ambiguity-aversion index equals 0.002. Therefore, a minimum average daily wind speed in km/h corresponds to an ambiguity-aversion index of 0.012 ($= 6.24 * 0.002$) ceteris paribus, while a maximum average daily wind speed in km/h corresponds to an ambiguity-aversion index of 0.073 ($= 36.73 * 0.002$) ceteris paribus. This proves that the effect on ambiguity-aversion is not so small though.

The third hypothesis states that the amount of precipitation positively affects ambiguity-neutral behaviour. The results of the OLS models for the effect of main weather independent variables on the four ambiguity attitude measures do not specifically display whether ambiguity-neutral behaviour is affected by precipitation, since the dependent variables are not categorical. For that reason, I consider the results of the ordered multinomial logit models and their average marginal effects for the effect of main weather independent variables on the ambiguity attitudes for low, intermediary and high likelihoods. It stands out that precipitation is not significant for all three ambiguity attitudes, which means that this is not in line with the third hypothesis.

The first three hypotheses correspond to ambiguity-averse behaviour, for which I had more specific expectations based on the existing literature. However, since little is known about the effect of emotional states on a-insensitivity, the fourth hypothesis is somewhat more general and therefore states that weather conditions affect a-insensitivity. The results of the OLS model for the effect of main weather independent variables on the a-insensitivity index indicates that all weather conditions are not significant. I also explored nonlinearities using weather dummy variables that are not quantified. The results of the OLS model for the effect of weather dummy variables on the a-insensitivity index show that the presence of drizzle makes individuals more a-insensitive. The other weather dummy variables are not significant.

Finally, the fifth hypothesis implies that the effects of weather conditions on ambiguity attitudes differ among state regions in the United States of America. Therefore, I used OLS models for the effect of main weather independent variables on the four ambiguity attitude measures, for the four state regions. The results indicate that there is a difference in significance between the effects of main weather independent variables in the state regions, on all four ambiguity attitude measures. However, the confidence intervals of the estimated results only indicate that the effect of an increase of one millimetre in the amount of snowfall in the northeast region on the ambiguity attitude for low likelihoods, is statistically larger than in the other regions. Overall, many effects of weather conditions differ in significance between the four state regions, but only one effect is statistically different. The results are therefore in line with the fifth hypothesis.

Besides the main weather independent variables and weather dummy variables, I also added several control variables to the OLS models and ordered multinomial logit models, to control for the effects of weather variables. The results of the control variables show some interesting results. First of all, the results of the OLS models for the effect of main weather independent variables and weather dummy variables on the a-insensitivity index display that one category higher in the level of trust in the financial stock market makes individuals less a-insensitive. So, they discriminate more between the different likelihood levels. This indicates that such individuals have a better financial knowledge about the stock market and thus have a higher financial literacy. This is consistent with the findings of Dimmock et al. (2016), who also show a negative effect of financial literacy on the a-insensitivity index for a Dutch panel.

Secondly, the results of the OLS models and ordered multinomial logit models all show that the order of the questions, whether individuals needed to answer questions about ambiguity-aversion or risk-aversion first, is very important for measuring ambiguity attitudes. Namely, if the individuals needed to answer questions about ambiguity-aversion first, the ambiguity-aversion index is lower whereas the a-insensitivity index is higher. These results also hold for males, who are less ambiguity-averse and more a-insensitive than females. Besides, individuals are less ambiguity-averse for low and high likelihoods, when they needed to answer questions about ambiguity-aversion first. For that reason, it could be important for future research to only include questions about ambiguity-aversion or about risk-aversion, since they seem to influence each other. The results also indicate that the R^2 is affected by the order of the questions and cause the OLS models to explain a higher percentage of the data variation. Overall, the R^2 is quite low for the OLS models using main weather independent variables and weather dummy variables on all four ambiguity-attitude measures. Even though the results show valid and significant effects, the estimates could be less precise than with a higher R^2.

A possible reason for this low R^2 could stem from the fact that I assumed, that the effect of weather on ambiguity attitudes is caused by the individual's emotional state. Therefore, I stated several assumptions for the link between weather and emotional states, based on the existing literature. I suggest to ask individuals in what mood they are, at the moment of filling in the survey. This makes it possible to link the weather conditions to the individual's emotional state, and to determine the effect on ambiguity attitudes. Furthermore, it would increase the accuracy of estimation if individuals state their city of residence in addition to their state of residence. I namely assumed, that the respondents live in or close to the capital city of their state. Most states cover such a big area, which could lead to high variations in weather within a state. By contrast, people could also be used to the weather conditions in their state and are therefore less likely to be affected by a change in the weather conditions, regarding their ambiguity attitudes. Furthermore, I was not able to investigate if the amount of sunshine has an impact on ambiguity attitudes, due to a lack of observations on the amount of sunshine. However, Persinger (1975) shows that individuals are less happy, when there is less sunshine. Besides, Bassi et al. (2013) show that a higher amount of sunshine leads to more risk-taking behaviour. These findings indicate that the amount of sunshine could be important for measuring ambiguity attitudes.

Overall, I only did the analysis for the United States of America. It would be interesting to check whether the results hold for other countries. Also, the survey period in this research was from 20-03-2012 until 16-04-2012, which corresponds to spring season wherein the amount of sunshine is likely to be higher than in winter season. Moreover, other weather conditions are also likely to differ a lot between these two periods. Therefore, it could be interesting to investigate whether the results of this study hold for other seasons. Even though the weather varies a lot in the survey period of this research, and even though there is detailed information on all states present, the results could differ between seasons. I suggest to obtain panel data by conducting a two-period survey during summer season and winter season, by taking in account the limitations of this research. I would choose these seasons, since they are likely to have most contradicting characteristics of all four seasons. Moreover, I would only include questions about ambiguity-aversion based on the results on the question order. With such a panel study, the same individuals could be followed over the two seasons, for which it is likely that a lot of control variables are time-invariant whereas the weather variables are time-variant. A fixed effects model would omit all time-invariant variables and estimate the within variation. However, a disadvantage of this method is that it would not estimate the effects of the time-invariant variables. By contrast, a random effects model would estimate both the within and between variation, which would be more efficient. By comparing the results of both models and by using a Hausman specification test, it is possible to choose between these two models.

7. Conclusion

Since there was only little evidence for the effect of weather on ambiguity attitudes via emotional states, I tried to fill that gap by focusing on the two global indices and two local measures for the ambiguity-attitudes; the ambiguity-aversion index, the a-insensitivity index, the ambiguity attitude for low likelihoods and the ambiguity attitude for high likelihoods. This research provides new evidence and contributes to the existing literature on ambiguity attitudes. Therefore, I combined data on decision making under ambiguity from the ALP with data on the weather conditions from the NCEI, for the United States of America. Based on Dimmock et al. (2016), I computed matching probabilities from the ALP dataset to measure the ambiguity attitudes. With the use of OLS models and ordered multinomial logit models including main weather independent variables and weather dummy variables, I did an analysis on the United States of America to determine whether there is an effect of weather on ambiguity attitudes.

The results show that the average daily wind speed postively affects ambiguity-averse behaviour. In addition, evidence indicates that the average daily wind speed makes individuals more ambiguity-averse for high likelihoods. However, the results also show that precipitation, snowfall and temperature are not significant for all four ambiguity attitude measures. I also explored nonlinear effects with the use of weather dummy variables. Evidence shows that the presence of drizzle makes individuals more a-insensitive, and thus causes individuals to discriminate less between different likelihood levels. The other weather dummy variables do not have a significant effect on a-insensitivity.

Since the states cover a quite big area and weather conditions can vary a lot between different states, I subdivided the United States of America into four different regions; the northeast region, the midwest region, the south region and the west region. When looking more specifically at these four state regions of the United States of America regarding the four ambiguity attitude measures, evidence shows that there is a difference in significance between the four state regions for several weather effects. However, the results indicate that only one effect is statistically larger. The results namely show that an increase in the amount of snowfall in the northeast region, makes individuals more ambiguity-averse for low likelihoods. This effect is statistically larger than the effects of the amount of snowfall in other state regions.

I also used several control variables, for which the results show some interesting findings. First of all, evidence shows that it is more likely that individuals in the ALP dataset are more ambiguity-averse for high likelihoods than for low likelihoods. Futhermore, having more trust in the financial stock market, which corresponds to decision making under ambiguity, makes individuals less a-insensitive. It thus seems that individuals with a higher level of trust in the stock market, also have a better financial knowledge and thus a higher financial literacy. Therefore, they discriminate more between different likelihood levels. The results also show that males are less ambiguity-averse and more a-insensitive than females. This also holds for the order of the questions in the survey. Individuals who needed to answer questions about ambiguity-aversion first instead of risk-aversion, are less ambiguity-averse and more a-insensitive. Evidence therefore indicates, that it is very important when measuring ambiguity attitudes or risk attitudes with the use of a survey, to only include questions about ambiguity-aversion or about risk-aversion since the results show that they influence each other.

Overall, these results could give a better understanding of the economic behaviour of individuals and therefore a better explanation for decisions that are made under ambiguity. For instance, for decision making on the financial stock market or the intertemporal decision making on the individual's retirement. Whereas the results show that weather can affect the individual's ambiguity attitudes, the results also suggest that more specific research could be done on the role of the emotional aspect and the relation to weather conditions. This could provide a better insight into the effect of weather on decision making behaviour under different ambiguous events via the individual's emotional state, such as the heights of the investments that are undertaken by individuals. Even though I find little evidence for an effect of weather on ambiguity attitudes, future research is required to draw better conclusions on this topic and for which this research could function as a basis.

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Appendix A: Tables data

Table 2: Winning probabilities for question 1: Intermediary likelihood of 50%

Options Four Rounds	**P in % (Probability Winning Colour Box K)**	**1-P in % (Probability Winning Colour Box K)**	**1 (Box K)**	**2 (Box U)**	**3 (Indifferent)**
A	50	50	Option B	Option E	End
B	25	75	Option C	Option G	End
C	12	88	Option D	Option I	End
D	6	94	End	End	End
E	75	25	Option H	Option F	End
F	88	12	End	End	End
G	38	62	Option J	Option K	End
H	62	38	Option M	Option L	End
I	18	82	End	End	End
J	32	68	End	End	End
K	44	56	End	End	End
L	68	32	End	End	End
M	56	44	End	End	End

Table 3: Possibilities and matching probabilities for question 1: Intermediary likelihood of 50%

Possibilities Rounds Question 1	**Round 1**	**Round 2**	**Round 3**	**Round 4**	**Matching Probability m(0.5) in %**
BoxK-BoxK-BoxK-BoxK	1	1	1	1	3,0
BoxK-BoxU-BoxK-Indifferent	1	2	1	3	32,0
BoxU-BoxK-BoxK-BoxU	2	1	1	2	59,0
BoxK-BoxK-BoxK-Indifferent	1	1	1	3	6,0
BoxK-BoxU-BoxK-BoxU	1	2	1	2	35,0
BoxU-BoxK-Indifferent	2	1	3		62,0
BoxK-BoxK-BoxK-BoxU	1	1	1	2	9,0
BoxK-BoxU-Indifferent	1	2	3		38,0
BoxU-BoxK-BoxU-BoxK	2	1	2	1	65,0
BoxK-BoxK-Indifferent	1	1	3		12,0
BoxK-BoxU-BoxU-BoxK	1	2	2	1	41,0
BoxU-BoxK-BoxU-Indifferent	2	1	2	3	68,0
BoxK-BoxK-BoxU-BoxK	1	1	2	1	15,0
BoxK-BoxU-BoxU-Indifferent	1	2	2	3	44,0
BoxU-BoxK-BoxU-BoxU	2	1	2	2	71,5
BoxK-BoxK-BoxU-Indifferent	1	1	2	3	18,0
BoxK-BoxU-BoxU-BoxU	1	2	2	2	47,0
BoxU-Indifferent	2	3			75,0
BoxK-BoxK-BoxU-BoxU	1	1	2	2	21,5
Indifferent	3				50,0
BoxU-BoxU-BoxK	2	2	1		81,5
BoxK-Indifferent	1	3			25,0
BoxU-BoxK-BoxK-BoxK	2	1	1	1	53,0
BoxU-BoxU-Indifferent	2	2	3		88,0
BoxK-BoxU-BoxK-BoxK	1	2	1	1	28,5
BoxU-BoxK-BoxK-Indifferent	2	1	1	3	56,0
BoxU-BoxU-BoxU	2	2	2		94,0

Table 4: Winning probabilities for question 2: Low likelihood of 10%

Options Four Rounds	P in % (Probability Winning Colour Box K)	1-P in % (Probability Other Colours Box K)	1 (Box K)	2 (Box U)	3 (Indifferent)
A	10	90	Option B	Option E	End
B	5	95	Option C	Option D	End
C	3	97	End	End	End
D	8	92	End	End	End
E	20	80	Option I	Option F	End
F	40	60	Option G	Option H	End
G	30	70	End	End	End
H	70	30	End	End	End
I	15	85	End	End	End

Table 5: Possibilities and matching probabilities for question 2: Low likelihood of 10%

Possibilities Rounds Question 2	Round 1	Round 2	Round 3	Round 4	Matching probability m(0.1) in %
BoxK-BoxK-BoxK	1	1	1		1,5
Indifferent	3				10,0
BoxU-BoxU-BoxK-Indifferent	2	2	1	3	30,0
BoxK-BoxK-Indifferent	1	1	3		3,0
BoxU-BoxK-BoxK	2	1	1		12,5
BoxU-BoxU-BoxK-BoxU	2	2	1	2	35,0
BoxK-BoxK-BoxU	1	1	2		4,0
BoxU-BoxK-Indifferent	2	1	3		15,0
BoxU-BoxU-Indifferent	2	2	3		40,0
BoxK-Indifferent	1	3			5,0
BoxU-BoxK-BoxU	2	1	2		17,5
BoxU-BoxU-BoxU-BoxK	2	2	2	1	55,0
BoxK-BoxU-BoxK	1	2	1		6,5
BoxU-Indifferent	2	3			20,0
BoxU-BoxU-BoxU-Indifferent	2	2	2	3	70,0
BoxK-BoxU-Indifferent	1	2	3		8,0
BoxU-BoxU-BoxK-BoxK	2	2	1	1	25,0
BoxU-BoxU-BoxU-BoxU	2	2	2	2	85,0
BoxK-BoxU-BoxU	1	2	2		9,0

Table 6: Winning probabilities for question 3: High likelihood of 90%

Options Five Rounds	P in % (Probability Other Colours Box K)	1-P in % (Probability Winning Colour Box K)	1 (Box K)	2 (Box U)	3 (Indifferent)
A	90	10	Option B	Option K	End
B	45	55	Option C	Option E	End
C	22	78	Option D	Option I	End
D	11	89	End	End	End
E	68	32	Option F	Option H	End
F	56	44	End	End	End
G	74	26	End	End	End
H	80	20	Option G	Option J	End
I	34	66	End	End	End
J	85	15	End	End	End
K	95	5	Option L	Option M	End
L	92	8	End	End	End
M	98	2	End	End	End

Table 7: Possibilities and matching probabilities for question 3: High likelihood of 90%

Possibilities Rounds Question 3	**Round 1**	**Round 2**	**Round 3**	**Round 4**	**Round 5**	**Matching Probability m(0.9) in %**
BoxK-BoxK-BoxK-BoxK	1	1	1	1		5,5
BoxK-BoxU-BoxK-Indifferent	1	2	1	3		56,0
BoxK-BoxU-BoxU-BoxU-BoxU	1	2	2	2	2	87,5
BoxK-BoxK-BoxK-Indifferent	1	1	1	3		11,0
BoxK-BoxU-BoxK-BoxU	1	2	1	2		62,0
Indifferent	3					90,0
BoxK-BoxK-BoxK-BoxU	1	1	1	2		16,5
BoxK-BoxU-Indifferent	1	2	3			68,0
BoxU-BoxK-BoxK	2	1	1			91,0
BoxK-BoxK-Indifferent	1	1	3			22,0
BoxK-BoxU-BoxU-BoxK-BoxK	1	2	2	1	1	71,0
BoxU-BoxK-Indifferent	2	1	3			92,0
BoxK-BoxK-BoxU-BoxK	1	1	2	1		28,0
BoxK-BoxU-BoxU-BoxK-Indifferent	1	2	2	1	3	74,0
BoxU-BoxK-BoxU	2	1	2			93,5
BoxK-BoxK-Box-UIndifferent	1	1	2	3		34,0
BoxK-BoxU-BoxU-BoxK-BoxU	1	2	2	1	2	77,0
BoxU-Indifferent	2	3				95,0
BoxK-BoxK-BoxU-BoxU	1	1	2	2		39,5
BoxK-BoxU-BoxU-Indifferent	1	2	2	3		80,0
BoxU-BoxU-BoxK	2	2	1			96,5
BoxK-Indifferent	1	3				45,0
BoxK-BoxU-BoxU-BoxU-BoxK	1	2	2	2	1	82,5
BoxU-BoxU-Indifferent	2	2	3			98,0
BoxK-BoxU-BoxK-BoxK	1	2	1	1		50,5
BoxK-BoxU-BoxU-BoxU-Indifferent	1	2	2	2	3	85,0
BoxU-BoxU-BoxU	2	2	2			99,0

Table 12: List of states and capital cities

Number	State Residence	Capital City	Number	State Residence	Capital City
1	Alaska	Juneau	27	Nebraska	Lincoln
2	Alabama	Montgomery	28	Nevada	Carson City
3	Arizona	Phoenix	29	New Hampshire	Concord
4	Arkansas	Little Rock	30	New Jersey	Trenton
5	California	Sacramento	31	New Mexico	Santa Fe
6	Colorado	Denver	32	New York	Albany
7	Connecticut	Hartford	33	North Carolina	Raleigh
8	Delaware	Dover	34	North Dakota	Bismarck
9	Florida	Tallahassee	35	Ohio	Columbus
10	Georgia	Atlanta	36	Oklahoma	Oklahoma City
11	Hawaii	Honolulu	37	Oregon	Salem
12	Idaho	Boise	38	Pennsylvania	Harrisburg
13	Illinois	Springfield	39	Rhode Island	Providence
14	Indiana	Indianapolis	40	South Carolina	Columbia
15	Iowa	Des Moines	41	South Dakota	Pierre
16	Kansas	Topeka	42	Tennessee	Nashville
17	Kentucky	Frankfort	43	Texas	Austin
18	Louisiana	Baton Rouge	44	Utah	Salt Lake City
19	Maine	Augusta	45	Vermont	Montpelier
20	Maryland	Annapolis	46	Virginia	Richmond
21	Massachusetts	Boston	47	Washington	Olympia
22	Michigan	Lansing	48	West Virginia	Charleston
23	Minnesota	St. Paul	49	Wisconsin	Madison
24	Mississippi	Jackson	50	Wyoming	Cheyenne
25	Missouri	Jefferson City	51	Washington D.C.	Washington D.C.
26	Montana	Helena	52	Puerto Rico	San Juan

Table 14: Correlations between the independent variables from the regression models

Independent variable	Precipitation	Snowfall	MaximumTemperature	AverageDailyWindSpeed	DailySunPercentage	Age	Male	MarriedLivingPartner
Precipitation	1	0.06*	-0.14*	-0.03	-0.46*	-0.02	0.01	-0.01
Snowfall	0.06*	1	-0.10*	-0.00	-0.12	-0.02	0.01	-0.01
Maximum Temperature	-0.14*	-0.10*	1	-0.25*	-0.05	0.02	-0.01	0.04**
Average Daily Wind Speed	-0.03	-0.00	-0.25*	1	0.63*	0.02	0.00	0.05*
Daily Sun Percentage	-0.46*	-0.12	-0.05	0.63*	1	0.05	0.06	0.17
Age	-0.02	-0.02	0.02	0.02	0.05	1	-0.09*	0.07*
Male	0.01	0.01	-0.01	0.00	0.06	-0.09*	1	-0.09*
Married Living Partner	-0.01	-0.01	0.04**	0.05*	0.17	0.07*	-0.09*	1
Family Income	-0.04**	-0.01	-0.02	0.08*	0.39*	0.16*	-0.09*	0.38*
Number Of Household Members	0.03	-0.01	-0.01	-0.02	0.05	-0.38*	0.06*	0.02
Employed	-0.05*	0.00	0.00	0.02	0.02	-0.18*	-0.06*	0.04
High Education	0.00	-0.02	-0.06*	0.03	0.08	0.06*	-0.03	0.07*
Ethnicity White	-0.04**	0.02	0.06*	0.05*	0.10	0.21*	-0.05*	0.17*
Ethnicity Hispanic Latino	-0.03	0.01	-0.11*	0.16*	0.00	0.23*	-0.01	0.05*
Trust In Stock Market	-0.02	0.01	-0.08*	0.10*	0.28	0.09*	-0.10*	0.08*
Order Of Questions	0.03	-0.01	0.00	-0.02	-0.02	0.00	0.00	0.01

**. The correlation is significant at the 0.01 level (2-tailed)*

***. The correlation is significant at the 0.05 level (2-tailed)*

Independent variable	FamilyIncome	NumberOfHouseholdMembers	Employed	HighEducation	EthnicityWhite	EthnicityHispanicLatino	TrustInStockMarket	OrderOfQuestions
Precipitation	-0.04**	0.03	-0.05*	0.00	-0.04**	-0.03	-0.02	0.03
Snowfall	-0.01	-0.01	0.00	-0.02	0.02	0.01	0.01	-0.01
Maximum Temperature	-0.02	-0.01	0.00	-0.06*	0.06*	-0.11*	-0.08*	0.00
Average Daily Wind Speed	0.08*	-0.02	0.02	0.03	0.05*	0.16*	0.10*	-0.02
Daily Sun Percentage	0.39*	0.05	0.02	0.08	0.10	0.00	0.28	-0.02
Age	0.16*	-0.38*	-0.18*	0.06*	0.21*	0.23*	0.09*	0.00
Male	-0.09*	0.06*	-0.06*	-0.03	-0.05*	-0.01	-0.10*	0.00
Married Living Partner	0.38*	0.02	0.04	0.07*	0.17*	0.05*	0.08*	0.01
Family Income	1	-0.09*	0.33*	0.35*	0.24*	0.22*	0.27*	0.02
Number Of Household Members	-0.09*	1	0.00	-0.15*	-0.18*	-0.23*	-0.10*	-0.01
Employed	0.33*	0.00	1	0.16*	0.06*	0.02	0.07*	0.00
High Education	0.35*	-0.15*	0.16*	1	0.10*	0.13*	0.23*	0.02
Ethnicity White	0.24*	-0.18*	0.06*	0.10*	1	0.21*	0.19*	-0.01
Ethnicity Hispanic Latino	0.22*	-0.23*	0.02	0.13*	0.21*	1	0.23*	-0.01
Trust In Stock Market	0.27*	-0.10*	0.07*	0.23*	0.19*	0.23*	1	0.02
Order Of Questions	0.02	-0.01	0.00	0.02	-0.01	-0.01	0.02	1

**. The correlation is significant at the 0.01 level (2-tailed)*

***. The correlation is significant at the 0.05 level (2-tailed)*

Table 16: Correlations between the weather dummy variables from the regression models

Independent variable	Dummy Freezing Normal	Dummy Freezing Heavy	Dummy Thunder	Dummy Hail	Dummy Wind Heavy Damaging	Dummy Mist	Dummy Drizzle	Dummy Rain	Dummy Snow
Dummy Freezing Normal	1	0.17*	-0.08*	-0.01	-0.06*	0.69*	0.03	0.37*	0.11
Dummy Freezing Heavy	0.17*	1	0.22*	-0.01	-0.01	-0.06*	-0.03	0.04*	-0.02
Dummy Thunder	-0.08*	0.22*	1	0.16*	0.22*	0.00	0.09*	0.18*	0.01
Dummy Hail	-0.01	-0.01	0.16*	1	-0.01	-0.05*	-0.01	0.01	0.27*
Dummy Wind Heavy Damaging	-0.06*	-0.01	0.22*	-0.01	1	-0.07*	-0.02	0.00	-0.02
Dummy Mist	0.69*	-0.06*	0.00	-0.05*	-0.07*	1	0.11*	0.40*	0.14*
Dummy Drizzle	0.03	-0.03	0.09*	-0.01	-0.02	0.11*	1	0.21*	0.01
Dummy Rain	0.37*	-0.04*	0.18*	0.01	0.00	0.40*	0.21*	1	0.04
Dummy Snow	0.11	-0.02	0.01	0.27*	-0.02	0.14*	0.01	0.04	1

**. The correlation is significant at the 0.01 level (2-tailed)*

***. The correlation is significant at the 0.05 level (2-tailed)*

Appendix B: Tables results

Table 28: OLS regressions on the ambiguity-aversion index using weather dummy variables

b	(1)	(2)	(3)	(4)
DummyFreezingNormal	-0.042	-0.050	-0.039	
	(0.051)	(0.051)	(0.051)	
DummyFreezingHeavy	-0.136	-0.110	-0.139	-0.164
	(0.119)	(0.116)	(0.122)	(0.116)
DummyThunder	0.007	0.007	-0.001	0.008
	(0.052)	(0.051)	(0.051)	(0.051)
DummyHail	0.246^{*}	0.257^{*}	0.257^{**}	0.251^{*}
	(0.137)	(0.141)	(0.130)	(0.130)
DummyWindHeavyDamaging	-0.110	-0.119	-0.061	-0.068
	(0.095)	(0.092)	(0.094)	(0.094)
DummyMist	-0.003	0.002	0.003	-0.018
	(0.046)	(0.046)	(0.046)	(0.039)
DummyDrizzle	0.033	0.054	0.050	0.048
	(0.072)	(0.072)	(0.071)	(0.071)
DummyRain	-0.017	-0.017	-0.016	-0.019
	(0.030)	(0.030)	(0.030)	(0.030)
DummySnow	-0.091	-0.096	-0.114^{*}	-0.116^{*}
	(0.064)	(0.061)	(0.060)	(0.060)
Age		-0.002^{**}	-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)	(0.001)
Male		-0.071^{***}	-0.069^{***}	-0.068^{***}
		(0.026)	(0.025)	(0.025)
MarriedLivingPartner		0.008	0.001	0.001
		(0.030)	(0.029)	(0.029)
FamilyIncome		0.001	0.004	0.005
		(0.004)	(0.005)	(0.005)
NumberOfHouseholdMembers		-0.004	-0.004	-0.005
		(0.009)	(0.009)	(0.009)
Employed		-0.012	-0.016	-0.016
		(0.029)	(0.028)	(0.028)
TrustInStockMarket		-0.013	-0.012	-0.011
		(0.012)	(0.013)	(0.013)
HighEducation			-0.007	-0.008
			(0.027)	(0.027)
EthnicityWhite			-0.007	-0.006
			(0.038)	(0.037)
EthnicityHispanicLatino			-0.068	-0.070
			(0.057)	(0.056)
OrderOfQuestions			-0.151^{***}	-0.152^{***}
			(0.025)	(0.025)
Constant	0.064^{***}	0.310^{***}	0.640^{***}	0.639^{***}
	(0.016)	(0.089)	(0.127)	(0.127)
N	1161	1156	1155	1155
R^2	0.006	0.017	0.051	0.050
Probability > F	0.297	0.131	0.000	0.000

Standard errors in parentheses, * *p < .1,* ** *p < .05,* *** *p < .01*

Table 29: OLS regressions on the a-insensitivity index using weather dummy variables

a	**(1)**	**(2)**	**(3)**	**(4)**
DummyFreezingNormal	0.089**	0.085**	0.084**	
	(0.042)	(0.043)	(0.043)	
DummyFreezingHeavy	0.024	-0.001	-0.009	0.045
	(0.102)	(0.094)	(0.097)	(0.092)
DummyThunder	0.081*	0.068	0.076*	0.058
	(0.043)	(0.043)	(0.043)	(0.043)
DummyHail	-0.006	0.023	0.004	0.016
	(0.160)	(0.161)	(0.164)	(0.164)
DummyWindHeavyDamaging	-0.022	0.010	0.003	0.017
	(0.090)	(0.092)	(0.093)	(0.093)
DummyMist	-0.027	-0.025	-0.015	0.029
	(0.043)	(0.043)	(0.043)	(0.038)
DummyDrizzle	0.164***	0.143**	0.122**	0.127**
	(0.063)	(0.062)	(0.062)	(0.062)
DummyRain	-0.031	-0.033	-0.042	-0.037
	(0.026)	(0.026)	(0.026)	(0.026)
DummySnow	-0.032	-0.021	-0.013	-0.009
	(0.066)	(0.066)	(0.065)	(0.064)
Age		0.000	0.001	0.001
		(0.001)	(0.001)	(0.001)
Male		0.079***	0.080***	0.078***
		(0.023)	(0.023)	(0.023)
MarriedLivingPartner		0.008	0.017	0.016
		(0.025)	(0.025)	(0.025)
FamilyIncome		-0.007**	-0.007*	-0.007*
		(0.004)	(0.004)	(0.004)
NumberOfHouseholdMembers		-0.002	-0.004	-0.003
		(0.008)	(0.008)	(0.008)
Employed		0.006	0.008	0.010
		(0.025)	(0.025)	(0.025)
TrustInStockMarket		-0.025**	-0.021*	-0.022**
		(0.011)	(0.011)	(0.011)
HighEducation			0.015	0.017
			(0.025)	(0.025)
EthnicityWhite			-0.080***	-0.081***
			(0.031)	(0.031)
EthnicityHispanicLatino			-0.030	-0.027
			(0.043)	(0.044)
OrderOfQuestions			0.006	0.007
			(0.022)	(0.022)
Constant	0.586***	0.602***	0.656***	0.658***
	(0.014)	(0.077)	(0.106)	(0.107)
N	1161	1156	1155	1155
R^2	0.011	0.036	0.044	0.041
Probability > F	0.050	0.000	0.000	0.000

Standard errors in parentheses, * *p < .1,* ** *p < .05,* *** *p < .01*

Table 30: OLS regressions on the ambiguity attitude for low likelihoods using weather dummy variables

$AA(0.1)$	(1)	(2)	(3)	(4)
DummyFreezingNormal	0.017	0.012	0.012	
	(0.021)	(0.021)	(0.021)	
DummyFreezingHeavy	-0.047	-0.035	-0.040	-0.033
	(0.072)	(0.067)	(0.068)	(0.067)
DummyThunder	0.009	0.006	0.006	0.003
	(0.024)	(0.024)	(0.024)	(0.024)
DummyHail	0.027	0.034	0.029	0.031
	(0.145)	(0.140)	(0.141)	(0.140)
DummyWindHeavyDamaging	-0.013	-0.007	0.001	0.003
	(0.054)	(0.052)	(0.051)	(0.051)
DummyMist	-0.002	0.002	0.005	0.012
	(0.022)	(0.022)	(0.022)	(0.020)
DummyDrizzle	0.079***	0.089***	0.082***	0.083***
	(0.027)	(0.027)	(0.027)	(0.027)
DummyRain	-0.004	-0.004	-0.005	-0.005
	(0.014)	(0.014)	(0.014)	(0.014)
DummySnow	-0.080	-0.081*	-0.082*	-0.082*
	(0.049)	(0.048)	(0.049)	(0.048)
Age		-0.002***	-0.001***	-0.001***
		(0.000)	(0.001)	(0.001)
Male		-0.024*	-0.024**	-0.024**
		(0.012)	(0.012)	(0.012)
MarriedLivingPartner		0.016	0.018	0.018
		(0.014)	(0.014)	(0.014)
FamilyIncome		-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.002)
NumberOfHouseholdMembers		-0.004	-0.003	-0.003
		(0.004)	(0.004)	(0.004)
Employed		-0.020	-0.020	-0.020
		(0.014)	(0.014)	(0.014)
TrustInStockMarket		-0.012*	-0.012*	-0.013*
		(0.006)	(0.007)	(0.007)
HighEducation			0.016	0.016
			(0.014)	(0.014)
EthnicityWhite			-0.019	-0.019
			(0.017)	(0.017)
EthnicityHispanicLatino			0.004	0.005
			(0.025)	(0.025)
OrderOfQuestions			-0.029**	-0.028**
			(0.012)	(0.012)
Constant	-0.133***	0.038	0.077	0.077
	(0.008)	(0.039)	(0.055)	(0.055)
N	1161	1156	1155	1155
R^2	0.008	0.026	0.033	0.033
Probability > F	0.107	0.003	0.001	0.001

Standard errors in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$

Table 31: OLS regressions on the ambiguity attitude for high likelihoods using weather dummy variables

$AA(0.9)$	(1)	(2)	(3)	(4)
DummyFreezingNormal	-0.055**	-0.057**	-0.055**	
	(0.027)	(0.027)	(0.027)	
DummyFreezingHeavy	-0.066	-0.034	-0.033	-0.069
	(0.043)	(0.044)	(0.047)	(0.043)
DummyThunder	-0.056*	-0.049	-0.055*	-0.043
	(0.030)	(0.030)	(0.029)	(0.030)
DummyHail	0.032	0.016	0.026	0.018
	(0.083)	(0.085)	(0.088)	(0.089)
DummyWindHeavyDamaging	0.004	-0.015	-0.002	-0.011
	(0.066)	(0.066)	(0.068)	(0.068)
DummyMist	0.020	0.022	0.017	-0.012
	(0.027)	(0.027)	(0.028)	(0.025)
DummyDrizzle	-0.052	-0.025	-0.015	-0.018
	(0.042)	(0.042)	(0.043)	(0.044)
DummyRain	0.021	0.023	0.028	0.025
	(0.019)	(0.018)	(0.019)	(0.019)
DummySnow	-0.054	-0.065*	-0.072**	-0.075**
	(0.038)	(0.035)	(0.035)	(0.035)
Age		-0.002**	-0.002***	-0.002***
		(0.001)	(0.001)	(0.001)
Male		-0.087***	-0.088***	-0.087***
		(0.016)	(0.016)	(0.016)
MarriedLivingPartner		0.010	0.004	0.004
		(0.017)	(0.017)	(0.017)
FamilyIncome		0.004	0.004	0.004
		(0.003)	(0.003)	(0.003)
NumberOfHouseholdMembers		-0.002	-0.000	-0.001
		(0.006)	(0.006)	(0.006)
Employed		-0.025	-0.027	-0.028
		(0.018)	(0.018)	(0.018)
TrustInStockMarket		0.009	0.005	0.005
		(0.007)	(0.008)	(0.008)
HighEducation			0.004	0.002
			(0.017)	(0.017)
EthnicityWhite			0.045**	0.046**
			(0.021)	(0.021)
EthnicityHispanicLatino			0.028	0.026
			(0.031)	(0.031)
OrderOfQuestions			-0.033**	-0.034**
			(0.015)	(0.015)
Constant	0.199***	0.356***	0.352***	0.351***
	(0.010)	(0.054)	(0.074)	(0.075)
N	1161	1156	1155	1155
R^2	0.009	0.047	0.058	0.055
Probability > F	0.032	0.000	0.000	0.000

Standard errors in parentheses, * *p < .1,* ** *p < .05,* *** *p < .01*