ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor thesis Behaviour, Health, and Wellbeing

The relationship between motivated beliefs and information selection on climate change

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Name: Daan Priem
Student number: 533924dp
Supervisor: Victor Gonzalez Jimenez
Second assessor:

Abstract

Motivated beliefs, understood as the cognitive process of holding and maintaining specific beliefs that stem from personal motivations or desires rather than relying on objective evidence and logical reasoning, can affect climate change mitigation. A diversion in beliefs and given information creates a barrier to climate change adaptation. This thesis aims to investigate the relationship between having motivated beliefs about climate change and finding and interpreting climate change information. In a survey, respondents had to assign probabilities to different scenarios of global mean sea level rise. This probability assignment was performed before and after they had the option to access information about climate change. The probabilities were used to quantify the ambiguity aversion index and the likelihood insensitivity index. The results indicate that exposure to additional information about climate change causes a decrease in ambiguity aversion toward climate change for the respondents. The thesis provides no evidence for a relationship between exposure to additional information and the likelihood insensitivity of respondents.

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1. Introduction

On Nov. 4, 2020, the U.S. became the sole country in the world to withdraw from the Paris Agreement. Former President Trump decided to withdraw because of his belief that climate change was a fabrication, and he ignored any scientific evidence that contradicted his belief. Trump was selectively seeking and believing information that gave support to his beliefs. In addition, Trump also placed key individuals known to be climate change deniers in influential climate-related positions. (De Pryck & Gemenne, 2017; Selby, 2018). The withdrawal of the agreement affected not only the climate but also the political relations between major economies (Zhang et al., 2017).

Climate change is a global problem that requires cooperation from different entities to solve it. Without this cooperation, the efforts of some to mitigate climate change are nullified by the additional pollution of others (Young, 1990). When there are different beliefs about climate change, cooperation becomes more difficult. If a large country such as America withdraws from climate agreements due to a self-serving belief of its president, it creates many additional barriers to achieving global climate goals (Urpelainen & Van De Graaf, 2018).

When it comes to climate change, individuals have different beliefs about its impact, existence, and severity (Brownlee et al., 2013). It can be that this divergence in beliefs stems from self-serving beliefs. That is, individuals tend to ignore evidence that contradicts their beliefs (Druckman & McGrath, 2019). Climate change is a complex problem because it is influenced by many different disciplines such as economics, politics, and the environment. This also encourages the formation of motivated beliefs and creates a division in beliefs among individuals (Thunderbird School of Global Management, z.d.-c)

Information about events can improve decision-making. However, the processing of information can be done selectively as different sources of information have different attributes and carry different sorts of information (Shaw, 1982). The internet makes information on topics such as climate change readily available but some of this information may be unreliable. Therefore, it is becoming increasingly difficult to discern accurate from inaccurate information, and information can always be found that supports the point (Dunn, 2010). Motivated beliefs can have major consequences when individuals make decisions on impactful issues such as climate change. Climate change is a relevant and complex topic so, it is critical that the right information be used for decision-making and that motivated beliefs be suppressed. This is to counteract negative economic and climate impacts.

From a policy perspective is it also relevant to know whether motivated beliefs influence climate change. For example, a lot of climate policies for agriculture rely on voluntary adjustment and effort (Anwar et al., 2012). Careful thought and understanding must then be given to what drives individuals to change and influences their environmental behavior. Research has also shown that climate-change mitigation is mainly linked to concerns about climate change, which in turn is driven by beliefs, and adaptation is mainly linked to the potential local impacts of climate change (Haden et al., 2012). So, policies should take this into account.

This paper extends the literature by aiming to explore the relationship between motivated beliefs and information acquisition on climate change. This paper introduces a combination of existing literature on motivated beliefs, climate change, and information acquisition to use a survey experiment to measure motivated beliefs regarding climate change.

By conducting a survey experiment that tests the impact of motivated beliefs on information acquisition on climate change, this study has the potential to contribute to the development of strategies to address climate change denialism and promote pro-environmental behaviors. Additionally, this study could help with efforts to design effective climate change mitigation measures by informing.

The survey asked respondents to state their probabilistic beliefs about a climate-change-related event. That is, the average rise, in centimeters, of the global mean sea level. These probabilistic beliefs are used to measure ambiguity aversion and likelihood insensitivity. Ambiguity aversion describes individuals' tendency to overestimate the likelihood of negative events compared to their actual probabilities. Likelihood insensitivity, on the other hand, refers to the tendency to assign excessive importance to unlikely events while undervaluing likely events (Baillon, et al., 2018a). Understanding these concepts is crucial in explaining motivated beliefs because individuals may exhibit insufficient responsiveness to information either due to mistakenly believing that negative outcomes are unavoidable or lacking adequate sensitivity to incoming information (Al-Najjar & Weinstein, 2009). The complexity of climate change gives room for the formation of motivated beliefs. To implement effective climate policy, it is important to examine how individuals are adapting their behavior toward climate change. All in all, the research question that this thesis aims at answering is:

'' *What is the relationship between individuals' motivated beliefs about climate change and their selection and interpretation of information related to the issue?''*

The remaining sections of this paper are divided as follows. The second chapter describes the relevant literature to provide an overview of the concepts and theories used for the study. Chapter three will provide a detailed description of the experimental design used for the study. The results with tables of the regressions will be described in chapter four and the conclusion and discussion will follow in chapters five and six.

2. Literature review

The following chapter provides an overview of the literature used for the study. Literature on motivated beliefs, information selection, ambiguity attitudes, and climate change will be presented. The literature will also be provided on the link between climate change and several demographic factors.

2.1 *Motivated reasoning*

Individuals tend to reach conclusions they prefer or desire. They are constrained here only by their ability to generate logical and plausible justifications for these conclusions, this is known as motivated reasoning (Kunda, 1990). Motivated reasoners update their beliefs in a non-Bayesian way. Specifically, a trade-off takes place, so to speak, between holding an accurate attitude and believing information that is ''good'' for the belief. Motivated reasoners are more likely to act on the information that is seen as ''good'' for the belief (Thaler, 2021).

Individuals tend to agree with the conclusions that they prefer. This preference influences the search for evidence, arguments, and recollections. These processes create a biased belief (Charness & Dave, 2017). A particular strong belief or desire to maintain a positive self-image is a good motive for manipulating beliefs. For example, individuals do not want to be wrong about the beliefs they hold about themselves because of their ego (Castagnetti & Schmacker, 2022). The result is an overestimation of one's abilities and overconfidence.

Motivated beliefs, however, can also be beneficial. Indeed, overconfidence can have an important instrumental value for motivation for future goals or tasks (Bénabou & Tirole, 2002). Self-confidence in opportunities for success and qualities are important motivators for overcoming obstacles and achieving goals (Bénabou, 2015). Non-Bayesian behaviors are exhibited such as disregarding much information and evidence when they contradict a valuable belief for the individual, even when it is new information (Bénabou & Tirole, 2016).

2.2 *Information seeking*

Individuals are engaged daily in observing, listening, deciding, seeking, and sometimes ignoring information. This is also called "information behavior (Given et al., 2023). Using that information, individuals try to make decisions and create beliefs. The bulk of the information available and the behind-the-scenes activities of many companies make the landscape of getting the right information complex for consumers (Case & Given, 2016).

Digitalization increased the availability of information. It is becoming increasingly difficult to find out if the information is correct because of information overload (Cortellazzo et al., 2019). This bulk of information enhances the possibility to form motivated beliefs. If there is a lot of information available, there is a greater chance of finding information that encourages one's opinions, interests, and desires (Bromberg-Martin & Sharot, 2020).

Two aspects of beliefs that people use, because they are seen as valuable, are positive valence and certainty. People will tend to seek information that removes uncertainty or produces positive beliefs (Charpentier et al., 2018). However, people are more likely to update their beliefs when new information is obtained that provides support for the preferred belief (Drobner, 2022). In addition, positive beliefs are also known to be valued more than negative beliefs. This is also linked to previous research which has shown that people learn and adopt more from information that triggers positive beliefs than from information that triggers negative beliefs (Bromberg-Martin & Sharot, 2020).

2.3 *Ambiguity Attitudes & Likelihood Insensitivity*

Since the introduction of the Ellsberg paradox, more and more research has been conducted on ambiguity because Ellsberg showed that new models were needed. Gilboa (1987), Schmeidler (1989), and Fox & Weber (2002) have introduced such new models among others. This experiment by Ellsberg showed that individuals prefer the urn whose probabilities are known and constitute evidence for ambiguity aversion. Ambiguity aversion means that individuals tend to favor probabilities that are known over unknown probabilities. Ellsberg showed that the phenomena of ambiguity and ambiguity aversion violate the idea that people's uncertain beliefs can be accurately represented using subjective probabilities (Machina & Siniscalchi, 2014).

In addition to ambiguity aversion, ambiguity seeking also exists. This can include behavior that favors events with low probability. This explains why people gamble. It is also known as the long-shot effect (Tversky & Kahneman, 1992). Individuals' attitudes towards ambiguity are influenced by factors such as the probability of uncertain events, the context or domain in which the outcomes occur, and the specific source responsible for generating the uncertainty (Trautmann & Van De Kuilen, 2015). Likelihood insensitivity is another component of ambiguity attitudes that is behind the ambiguity seeking for unlikely events. Likelihood insensitivity refers to the tendency of individuals to assign too much weight to unlikely events while assigning too little weight to events of intermediate likelihood.

This means that events of moderate probabilities will move toward a balanced 50/50 ratio. This amounts to overweighting the movement from certainty to uncertainty. Likelihood insensitivity is a perceptual phenomenon (Abdellaoui et al., 2011).

Research by Dimmock et al. (2016) has shown how to measure ambiguity aversion and likelihood insensitivity from probabilistic beliefs. That method is partially followed in this study.

A significant part of the method used in the study comes from the source method. In this method, source functions are used to quantitatively measure ambiguity attitudes (Abdellaoui et al., 2011). These source functions arise from risky and ambiguous events. Let E represent an uncertain event.

$$W_{So}(P(E))U(\alpha) + (1 - W_{So}(P(E)))U(\beta)$$

Here U stands for utility for which U(0) = 0 and P stands for subjective probability measure. Ambiguity neutral means that the individual treats subjective probabilities as objective probabilities, in this case

$$W_{So}(P(E)=P(E)$$

(Abdellaoui et al., 2011).

This study will work under rank-dependent preferences (Quiggin, 1982).

Figure 1 shows different functions with different ambiguous attitudes. The x-axis shows the ambiguity neutral probability p which in this study would be the assigned probability of global mean sea level rise since 1993 for the different events. The y-axis shows the source function or weight given to a subjective probability, W_{so}: [0,1]. For Figure 1a, a linear matched probability function holds, and it represents an ambiguity-neutral attitude. A convex W_{So}, which has values of subjective probabilities below the 45-degree line, represents pessimism. This function gives too much weight to bad outcomes and too little weight to good outcomes. Figure 1b shows a convex function indicating an ambiguity-averse attitude. Figure 1c has a matched probability function with an inverse S-shape. Thus, there is both a convex part and a concave part. At the convex part, individuals are ambiguity averse and at the concave part, individuals are ambiguity-seeking. The concave part is close to 0 which means that individuals are ambiguous seeking for favored outcomes with small probability (Dimmock et al., 2016).

Figure 1d shows a combination of ambiguity likelihood insensitivity, ambiguity aversion, and ambiguity seeking.

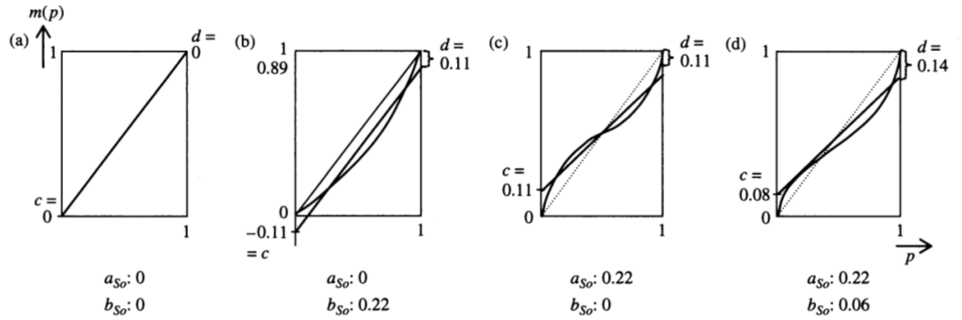

Figure 1: Quantitative Indexes of Ambiguity Aversion (b_{so}) and A-insensitivity (a_{so}) taken from Dimmock et al. (2016).

Because both likelihood insensitivity and ambiguity aversion are components of ambiguity attitudes, two types of indices are used for this study, which will be explained in more detail.

In the survey, respondents are presented with several bets to which they must give odds in the form of (E1, X1; E2, X2; E3, X3, ...). The events are in the form of a range in cm over global mean sea level rise since 1993 on average worldwide. The events can be interpreted as follows E_1 = negligible climate change in terms of sea level rise, E_2 = mild climate change in terms of sea level rise, and E_3 = acute climate change in terms of sea level rise. P (E_N) is noted as the subjects' probabilistic beliefs about climate change in terms of sea level rise.

Without insensitivity or pessimism, the decision-maker evaluates the bet as:

$$EU = P(E1)u(X1)+P(E2)u(x2)+P(E3)u(X3)+\ldots$$ (Diederich & Busemeyer, 2012).

Under RDU, the following applies:

$$RDU = w(P(E1))u(X1)+(w(P(E1)+P(E2))-w(P(E1))u(X2)+(1-(w(P(E1)+P(E2)))u(X3)+\ldots$$

Pessimism implies that w is convex so EU>RDU (Bleichrodt & Eeckhoudt, 2005).

In our case, likelihood insensitivity would imply that w has an inverse S-shape. So mild climate change is given too little weight. This can lead to overestimating negligible climate change and thus to inaction. it can also lead to inaction because it can be believed that the worse cannot be avoided. Pessimism or ambiguity aversion would imply that the beliefs about climate change being acute are higher than they should be. This can lead to two effects: too much action or inaction because it's believed that the worse cannot be avoided.

2.4 *Climate change*

Climate change is relentless and has been accelerating in various forms over the past few decades. As discussed earlier, climate change is a very complex problem that might create a snowball effect. For example, a rise in sea temperature causes more methane to be released, causing global warming to rise more rapidly (Letcher, 2021). This has major impacts on coastal areas, causing an increase in flooding and mixing of saltwater with freshwater rivers. There is concern that sea level rise is accelerating as can be seen in Figure 2, especially since 1900. The blue line shows what the sea level rise expectation was without 20th-century global warming. The red line was the historical expectation, and the black line shows the actual rise (Wuebbles et al., 2017). Research by Church and White (2011) has shown that the global mean sea level rise between 1901 and 1990 was 11 to 14 centimeters. Since 1993, the global mean sea level has risen exponentially by another 7 centimeters. Much of this sea level rise, after thorough research, can be attributed to human-caused climate change.

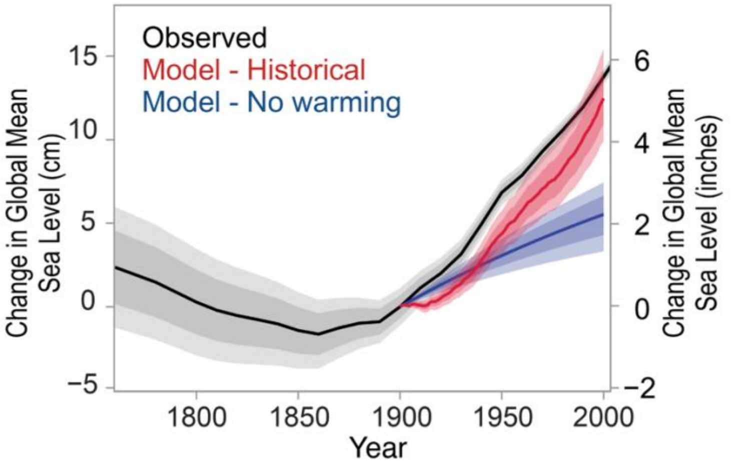

Figure 2: Change in Global Mean Sea Level (cm) on the left and (inches) on the right taken from Wuebbles et al. (2017).

Climate change affects not only nature but also the global economy. For example, inflationary pressures result from a decrease in the supply of goods, and production is increasingly affected by extreme weather conditions such as drought or sea level rise (Tol, 2018). These increasingly common extreme events also cause major financial losses. Physical assets may decline in value and income sources may disappear. Climate change also affects the ability of central banks to maintain monetary and financial stability (Batten, 2018).

Despite the scientific evidence about human-caused climate change, society has different beliefs about climate change and its causes. Individuals' beliefs about climate change also influence perceptions of risk and mitigation behavior (Whitmarsh, 2011). Research by Hoogendoorn et al. (2020) has shown that varying beliefs about climate change also affect perceptions of the consequences of climate change. Someone who believes that climate change is a more natural phenomenon will perceive the consequences of climate change as less severe compared to someone who believes that climate change is caused by humans. Because beliefs are difficult to change, it is important to understand how these beliefs are formed and in doing so, it is important to make people aware of human-caused climate change and its severity to encourage mitigation behaviors and take preventive measures that will help counter climate change.

There is evidence that beliefs about climate change affect the interpretation and estimation of extreme events (Carlton et al., 2016). Understanding the relationship between climate change, uncertainty, and extreme events is important for climate change communication (Goebbert et al., 2012). Good climate change communication provides a foundation for creating policies to mitigate climate change.

Findings indicate that socio-demographic factors such as gender, age, and educational level can influence uncertainty, attitude, and awareness of climate change issues. The younger generation is more aware of climate change and its consequences than the older generation. It is therefore important to raise awareness about the consequences of climate change among the older generation as well (Masud et al., 2017). Therefore, age was added to the model. Research has shown that education about climate change is an important factor that determines whether people care about the climate and are willing to do something about climate change. The better people understand the concept the more people are willing to do something about it (O'Connor et al., 1999). Therefore, education was added to the model. Research by Borghans et al. (2009) has shown that women are more risk-averse than men. Research has also shown that women on average are more concerned and aware of climate change than men (Semenza et al., 2008). Therefore, gender was added to the model.

2.5 *Hypotheses*

Based on the aforementioned literature, three hypotheses are proposed that will be tested in this study and will contribute to answering the main research question. Research by Baillon, et al. (2018a) has shown that likelihood insensitivity decreases as more information becomes available. In addition, more information causes individuals to engage in more ambiguity-seeking behavior.

H1: Respondents have a decreased ambiguity aversion and likelihood insensitivity toward climate change after being exposed to extra information.

The competence hypothesis states that knowledge about a topic such as climate change provides an incentive for ambiguity-seeking behavior (Heath & Tversky, 1991). Individuals who care about the climate often have a greater deal of knowledge (or the belief they do) about the climate. Individuals with more expertise tend to have a greater capacity for critical thinking and analytical reasoning. As a consequence, they are more open to arguments contrary to their beliefs which may result in more willingness to revise their beliefs when confronted with new evidence (Albarracin et al., 2014). Knowledge tends to have asymmetric effects on likelihood insensitivity (Maffioletti & Santoni, 2019). Likelihood insensitivity tends to decrease when individuals have more knowledge.

H2: Individuals who are known to care about climate change have a lower ambiguity aversion and likelihood insensitivity toward climate change relative to individuals drawn from a general population.

Research by Schubert et al. (2000) showed that how the information is framed can be important to the ambiguous attitude. In addition, it is context dependent whether women are more ambiguity averse than men. Women are generally more giving and concerned about climate (Semenza et al., 2008). Research studies have shown mixed findings regarding gender differences in ambiguity aversion specifically related to climate change matters. But women's higher level of concern about climate change could potentially be associated with a higher level of ambiguity aversion. Research by Von Gaudecker et al. (2022) was also characterized by a higher number of women in the ambiguity aversion group of research on the climate change section within the research. We will therefore test whether women here also have greater ambiguity aversion toward climate change than men. Research by Fehr-Duda et al. (2006) has shown that women are more likelihood insensitive than men. This is therefore expected in this study.

H3: Females have a higher ambiguity aversion and likelihood insensitivity toward climate change than men.

3. Experimental Design

The next chapter will describe the experiment of this study. The survey of the study will be described, as will the variables used in the study. Also discussed will be the indices that help investigate the hypotheses and ultimately answer the main research question.

3.1 *Experiment*

The experiment of this study has three parts. The first and second part of this study contains the same six subjective probability questions. The only difference between the two parts (within-subject) is respondents have the choice to access additional information. Respondents will be asked the same six questions to examine whether the choice of additional information and any interpretation of the information affected the probability estimate and thus the ambiguity attitude.
Each question in part one and part two of the study indicates what the respondent believes to be the probability that the described event occurred. The third part of the experiment consists of demographic questions about age, gender, and educational level. In each question, respondents had to give a percentage indication to the question ''What is the probability that global mean sea level has risen between ... and ... centimeters since 1993?'' In doing so, a different lower and upper bound was used for each question (see Appendix A for the survey). Respondents give a probability estimate between 0 and 100 percent.

To measure likelihood beliefs, respondents are informed only about specific probability intervals. Likelihood beliefs are then measured by looking at the symmetry of the midpoints of the intervals (Baillon et al., 2018b).

Ambiguity is not about a single event but is more a source of uncertainty. For that, there must be at least three equal exclusive events to measure ambiguity (Baillon et al., 2018b). Table I contains all mutually exclusive single events of both parts and their compositions. Each of these questions elicits a probability that will be called $M(E_i)$ in the study.

Table I: Single global mean sea level rise events for Two parts (Unit is centimeters)

	Event E_1	**Event E_2**	**Event E_3**	**Event E_4**	**Event E_5**	**Event E_6**
Part 1	(0, 5)	(5, 7)	(7, 12)	(0, 7)	(5, 12)	((0, 5) U (7, 12))
Part 2	(0, 5)	(5, 7)	(7, 12)	(0, 7)	(5, 12)	((0, 5) U (7, 12))

The segments of events four to six are composites of the segments of events one to three.

The additional information described the global mean sea level rise between 1901 and 1990. This averaged 11 to 14 centimeters. This information could give respondents a reference point to adjust their original estimates on the questions in the second part. The respondent had the choice of viewing this information or moving on immediately to part two.

Subjective probabilities of all 12 single events were measured using the indices that will be explained later in detail. The survey was created using the program Qualtrics. The survey will be in English, but the target audience is Dutch residents. First, respondents will be given a small introduction to the topic and some information about myself.

The target population of the study was two different groups. One group consisted of adults in the Netherlands known to care about the climate (environmental active). This group was approached by circulating the survey at the Erasmus Sustainability Hub during their activities. The other group consisted of random adults in the Netherlands (random). For this group, the survey was distributed on different social media channels such as WhatsApp, LinkedIn, and Instagram. Two sample groups were chosen to allow comparison between the groups and study the differences.

Respondents could complete the survey from May 28, 2023, to June 14, 2023. A total of 98 people completed the survey divided into two sample groups. The sample group with random individuals contained 58 respondents and the sample group with individuals known to care about the climate contained 40 respondents. Some respondents did not complete the survey in full or have given unrealistic values, so these respondents were removed from the data. In the end, 85 respondents respectively remained. All removed respondents came from the sample group with random individuals, which means that this group now consists of 45 respondents. The survey was used to answer the hypotheses and main research question of the study.

3.1 *Index Construction*

Pessimism, or a preference for avoiding ambiguity, is a motivational factor that is tied to a general inclination towards either disliking or liking uncertainty (Baillon et al., 2012).

In the case of ambiguity neutrality, the probability of the different events m(E1), m(E2), m(E3), m(E4), m(E5), and m(E6) should add up to 1. In the case of ambiguity aversion, the sum of m(E1) and its complements will fall below 1. The difference from 1 can be seen as the degree of aversion. We use the average difference of the six events and record it as follows. For the average single-event probability (Baillon et al., 2018b).

$$M_i = M(E_i),\ M_{ij} = M(E_{ij}),\ \overline{M_s} = (M_1 + M_2 + M_3) / 3$$

E_{ij} denotes the composition of E_i en E_j where i and j are not the same. E_i is the single event and E_{ij} is the composite event (Baillon et al., 2018b).

For the average component event probability, the function is as follows:

$$\overline{M_c} = (M_4 + M_5 + M_6) / 3$$

The ambiguity aversion index is as follows (Baillon et al., 2018b):

$$b = 1 - \overline{M_c} - \overline{M_s}$$

If b is negative, it resembles ambiguity-seeking behavior and if b is positive, it resembles ambiguity-aversive behavior. Ambiguity aversion indices capture individual deviations from the ambiguity-neutral probabilities of events.

Insensitivity, or ambiguity likelihood insensitivity is a cognitive element that exists independently of any preference and is unrelated to the aversion or seeking aspect (Kunreuther et al., 2001).

The likelihood insensitivity index describes how probabilities and event weights tend to converge towards an equal chance (50/50), with low probabilities being overestimated and high probabilities being underestimated. Consequently, there is a reduced difference between $\overline{M_c} - \overline{M_s}$ (Baillon et al., 2018b). $\overline{M_c} - \overline{M_s} = 0$ can arise in the most extreme cases when there is complete insensitivity and complete ambiguity (Cohen & Jaffray, 1980). The likelihood insensitivity index is as follows:

$$a = 3 \times (1/3 - (\overline{M_c} - \overline{M_s}))$$

If a is negative it resembles likelihood-sensitive behavior and if a is positive, it resembles likelihood-insensitive behavior (Baillon et al., 2018b).

3.2 *Specification of the variables*

Dependent variable:

Likelihood insensitivity Index

From the survey, each respondent provides estimates for six of the questions. There are two parts which mean that each respondent will therefore have two likelihood insensitivity indexes, with each index averaged to create a variable for likelihood insensitivity for each respondent. This is a continuous variable where the value of the index can be either positive or negative. A value of greater than 0 means prevailing insensitivity. The larger the index is, the more insensitive the respondent is. A value less than 0 means that sensitivity arises. An index with the value of 0 means ambiguity neutrality (Baillon, et al., 2018b).

Ambiguity aversion Index

From the survey, each respondent provides estimates for six of the questions. There are two parts which mean that each respondent will therefore have two ambiguity aversion indexes, with each index averaged to create a variable for ambiguity aversion for each respondent. This is also a continuous variable where the value can be either positive or negative. When the index has a value of 1, the respondent's ambiguity aversion is maximum. The matching probabilities of the events are then equal to 0. When the index has a value of -1, the ambiguity aversion is minimal. The matching probabilities of the events are then equal to 1. So, the larger the index, the more ambiguity averse the respondent is. When the index has a value of 0, there is ambiguity neutrality (Baillon, et al., 2018b).

Changes in index

Because the second set of questions included an option to see additional information about sea level rise, it is important to see if there is a difference between the indices due to the addition of the extra information.

Independent variables:

Group

Data will be analyzed from two different sample groups. The environmentally active group will consist of respondents known to care about climate. Using the Erasmus Sustainability Hub, respondents will be recruited for the survey. The random group will consist of random respondents where it is not known beforehand whether they care about the climate. The study needs to distinguish between these groups to see if the attitude towards climate before the experiment affects the allocation of opportunities at the different events. This is a dummy variable where the value is 0 when the respondent is in the environmentally active group and 1 when the respondent is in the random group.

Treatment

This variable indicates whether the respondent is already exposed to additional information or not. For the first 6 questions, the respondent has not yet been exposed to additional information and for the last 6 questions, the respondent does. It is a dummy variable with a value of 0 if the respondent is not yet exposed to additional information and a value of 1 if the respondent is exposed to additional information.

Access additional information

Respondents are given during the survey the option to see additional information for the last section of questions. This can be used to measure whether the additional information affects the allocation of opportunities for the different events. This is a dummy variable with the value 0 when the respondent chooses to access the extra information and 1 when the respondent chooses not to access the extra information.

Age

This is a continuous variable. The respondents were asked to fill in their ages. This study focuses only on adults so all responses with values below 18 for the variable age were removed from the sample. Furthermore, unrealistic values have been removed from the sample. In addition to the variable age, the variable age squared was also included in the data. It is frequently observed that incorporating the squared value of age can enhance the prediction of the impact of age on the dependent variables.

Gender

Respondents were asked which gender they identified themselves with. There was a choice between male, female, non-binary, and prefer not to say. All respondents chose the male or female option, which makes the variable gender a dummy variable where a male has the value of 0 and a female has the value of 1. Respondents were not obligated to report which gender they identified themselves with and had the choice to indicate that he or they preferred not to say. These values were reported as missing.

Education

The variable education consists of dummy variables. The survey asked respondents what their highest level of education was. The respondents had the choice between Primary education, Secondary education, MBO, HBO/WO, or other education. None of the respondents chose the option of Primary education or Secondary education. Hence, these options were not further included in the analyses. Hereafter, the variable education consisted of three dummy variables. Each respondent could choose only one option. When the respondent chooses one of the options, that value becomes 1 and the other options are given the value 0.

*Treatment*Group*

This is an interaction term between the variable’s treatment and group. It examines the effect of being exposed to additional information and belonging to the environmentally active group. This is a dummy variable that takes the value 0 when the respondent belongs to the environmentally active group and is exposed to additional information and 1 otherwise.

*Treatment*Access additional information*

This is an interaction term between the variable's treatment and access to additional information. It examines the effect of being exposed to additional information and choosing to access the additional information. This is a dummy variable that takes the value 0 when the respondent is exposed to additional information and chooses to access the additional information and 1 otherwise.

*Treatment*Gender*

This is an interaction term between the variable’s treatment and gender. It examines the effect of being exposed to additional information and being a female respondent. This is a dummy variable that takes the value 1 when the respondent is exposed to additional information and is a female and 0 otherwise.

4. Results

4.1 *Explanation of regressions*

To measure the impact of exposure to information (treatment) on the likelihood insensitivity and ambiguity aversion indices, an OLS regression was done. To measure the moderating effect of belonging to the environmentally active group (group) an OLS regression was done with an interaction term between treatment and group. To measure the moderating effect of accessing the additional information an OLS regression was done with an interaction term between treatment and accessing information. Lastly, to measure the moderating effect of gender an OLS regression was done with an interaction term between treatment and gender.

Likelihood insensitivity and ambiguity aversion were used as dependent variables in the different regressions. In addition, a distinction was made between regressions with and without control variables to check the robustness of the results. Two indices of ambiguity aversion and probability insensitivity are observed per respondent thus using clustered standard errors. The dataset contains two observations per respondent making the total number of observations 170. The first and second observations of matched probabilities (observations in parts one and two) are compared using t-tests with a Bonferroni correction because multiple comparisons are involved.

To examine whether the demographic variables also affected the indices across the different regressions in the study, these variables were also always included in the regressions as control variables. The variable education was divided into three dummy variables.

4.2 *Regression Results*

Several t-tests were conducted to examine whether the differences between responses before and after the choice of accessing information were significantly different from each other. When respondents chose to access additional information, the differences for all questions were significant at a 5% significance level ($P<0.05^*$). When respondents chose not to access additional information the differences for all questions were insignificant. Table II shows the overall mean probabilities of before and after exposure to additional information of the two sample groups for each question. A restriction was added here that only the respondents who also accessed the additional information were included because only there the difference was significant. As can be seen in the table, for all questions the average percentages increased after exposure and accessing additional information. This means that individuals thought events were more likely to happen after accessing additional information.

Table II: Average survey responses for individuals who accessed additional information.

	Before additional information	*After additional information*	
	Percentage/ Mean (SD)	**Percentage/ Mean (SD)**	**Difference**
Event [0,5] cm	60.81%	63.53%	2.72%
	(2.642)	(3.090)	
Event [5,7] cm	64.46%	69.71%	5.25%
	(2.130)	(2.665)	
Event [7,12] cm	63.53%	74.91%	11.38%
	(2.347)	(2.232)	
Event [0,7] cm	67.03%	71.71%	4.68%
	(2.493)	(2.638)	
Event [5,12] cm	64.88%	75.87%	10.99%
	(2.193)	(2.561)	
Event [0,5 or 7,12] cm	79.75%	89.68%	9.93%
	(2.220)	(1.665)	

Note: The table above shows averages of responses to the survey questions, respondents had to answer in percentages. *The point estimates between brackets are the Standard errors of the coefficients.*

To test the first hypothesis: ‘’Respondents have a decreased ambiguity aversion and likelihood insensitivity toward climate change after being exposed to extra information’’ we estimate a regression to investigate if additional information (treatment) influenced the ambiguity aversion index (later, we will do the same regression for the Likelihood insensitivity index).

This regression measures whether additional information affects the ambiguity aversion index. Here a distinction is made between the regression with and without control variables.

(1) *Ambiguity Aversion Index =* $\beta_0 + \beta_1 * \textit{Treatment} + \mu$

(1) *Ambiguity Aversion Index =* $\beta_0 + \beta_1 * \textit{Treatment} + \beta_2 * \textit{Age} + \beta_3 * \textit{Age}^2 + \beta_4 * \textit{MBO} + \beta_5 * \textit{HBO/WO} + \beta_6 * \textit{Other education} + \beta_7 * \textit{Gender} + \mu$

The first regression shows that the variable treatment and the constant are significant. When people have had access to additional information, respondents' ambiguity aversion index goes down by about 0.115 as opposed to when they have not yet had access to additional information. In the context of this study, this means that when individuals have more climate change information, their ambiguity aversion towards climate change decreases. The regression with control variables shows that the variable treatment is still significant as well as the variables MBO, HBO/WO, and other education. Almost all levels of significance are unaffected by controlling for the above control variables. It can also be seen that the coefficients of the variables do not differ much after adding the control variables which could mean that the control variables have a limited impact on the relationship between the ambiguity aversion index and treatment.

To test the second hypothesis: ''Individuals who are known to care about climate change have a lower ambiguity aversion and likelihood insensitivity toward climate change relative to individuals drawn from a general population'' we want to investigate the moderating effect of belonging to the environmentally active group (individuals known to care about the climate). We estimate a regression to investigate if the sample group in which the respondents are in, influences the ambiguity aversion index (later, we will do the same regression for the likelihood insensitivity index). Here again, a distinction was made between control and no control variables.

This regression measures whether ''group'' affects the ambiguity aversion index. Here a distinction is made between the regression with and without control variables.

(2) Ambiguity Aversion Index = $\beta_0 + \beta_1 *Treatment + \beta_2 *Group + \beta_3 *Treatment*Group + \mu$

(2) Ambiguity Aversion Index = $\beta_0 + \beta_1 * Treatment + \beta_2 *Group + \beta_3 *Treatment*Group + \beta_4 *Age + \beta_5 *Age^2 + \beta_6 * MBO + \beta_7 *HBO/WO + \beta_8 *Other\ education + \beta_9 *Gender + \mu$

To test whether information had an effect across groups a Wald test was conducted. The joint significance of the independent variables Group and Treatment*Group was tested. The test revealed that the coefficients of Group and Treatment*Group are not significant ($p>0.05$), suggesting that there is no strong evidence to support a significant relationship between Group and Treatment*Group and the ambiguity aversion index. We cannot say whether information had an effect across groups.

The second regression shows that Treatment is again significant and negative in both cases. This means that being exposed to information and being in the random group leads to a decrease in the ambiguity aversion index of 0.166 points. The Wald test was insignificant which means we cannot say whether this is also the case for the environmentally active group. Thus, no comparison can be made between the two groups. The variables MBO, HBO/WO, and other education are also significant. The relationship between group and ambiguity aversion is in both regressions insignificant (with other variables held constant). This means that we cannot say that there is a relationship between the sample group the respondents are in and the ambiguity aversion index.

This regression measures the moderating effect of accessing the additional information. For this, a regression was done with the variable's treatment, access to additional information (whether the respondent chose to see the information), and an interaction term examining the effect of being exposed to info and choosing to access the info.

(3) Ambiguity Aversion Index = $\beta_0 + \beta_1$ **Treatment +* β_2 **Accessinfo +* β_3**Treatment*Accessinfo +* μ

(3) ***Ambiguity Aversion Index =*** β_0 *+* β_1 ** Treatment +* β_2**Group +* β_3**Treatment*Group +* β_4**Age +* β_5**Age^2 +*β_6 ** MBO+*β_7 **HBO/WO +* β_8 **Other education +* β_9 **Gender +* μ

The third regression shows that treatment is again significant and negative in both cases. This means that being exposed to info and belonging to the group that did not access the additional information leads to a decrease in the ambiguity aversion index of 0.150 points. It cannot be determined whether accessing the additional information affected one group more than the other because only the variable treatment and educational variables are significant. The relationship between accessing additional information and ambiguity aversion is in both regressions insignificant (with other variables held constant). This means that we cannot say that there is a relationship between accessing additional information and the ambiguity aversion index.

The results of regressions one through three can be found in table III below.

Table III Results of regressions on the Ambiguity aversion index

Ambiguity aversion	(1)	(1)	(2)	(2)	(3)	(3)
Treatment	- 0.115*	- 0.115*	- 0.166***	- 0.166***	- 0.150***	- 0.150***
	(0.049)	(0.047)	(0.039)	(0.045)	(0.051)	(0.051)
Group	-	-	0.032	0.052	-	-
			(0.062)	(0.061)		
Treatment*Group	-	-	0.095	0.095	-	-
			(0.095)	(0.090)		
Age	-	-0.025	-	-0.025	-	-0.021
		(0.016)		(0.016)		(0.015)
Age^2	-	0.0002	-	0.0002	-	0.0002
		(0.0002)		(0.0002)		(0.0002)
MBO	-	0.840***	-	0.865***	-	0.718***
		(0.169)		(0.158)		(0.185)
HBO/WO	-	0.578***	-	0.629***	-	0.559***
		(0.044)		(0.059)		(0.049)

Other education	-	0.700***	-	0.702***	-	0.575***
		(0.051)		(0.064)		(0.119)
Gender	-	-0.081	-	-0.078	-	-0.080
		(0.047)		(0.046)		(0.047)
Access additional information	-	-	-	-	0.073	0.035
					(0.091)	(0.088)
Treatment*Access additional information	-	-	-	-	0.172	0.172
					(0.139)	(0.126)
Constant	0.320***	-0.399	-0.337***	-0.471	-0.335***	-0.442
R-squared	0.0316	0.1513	0.0516	0.1781	0.0810	0.1780
Observations	170	170	170	170	170	170
Prob > F	0.0205	0.0001	0.0001	0.0001	0.0052	0.0001

*Note: The table above presents regression from equations 1-3. *P < 0.05, **P < 0.01, ***P < 0.001. The point estimates between brackets are the Standard errors of the coefficients.*

Table IV describes the averages of the survey responses and the difference. This provides a clear picture of the differences in responses between the two sample groups. A distinction is made between the environmentally active group and the random group.

Table IV: Descriptive statistics

	Environmental active	Random	
	Percentage/ Mean(SD)	**Percentage/ Mean(SD)**	**Difference**
Event [0,5] cm	55.43% (17.523)	70,16% (22.921)	-14.73%
Event [5,7] cm	64.62% (14.461)	62.71% (21.643)	1.91%
Event [7,12] cm	67.21% (10.613)	54.09% (26.015)	13.12%
Event [0,7] cm	65.44% (15.154)	69.8% (27.119)	-4.36%
Event [5,12] cm	68.12% (13.222)	58.18% (24.204)	9.94%
Event [0,5 or 7,12] cm	80,35% (9.299)	76.67% (25.973)	3.68%
Access Additional information	**0.075% (0.267%)**	**0.31% (0.468)**	-0.235%
	92.50%	68.89%	
Yes	7.50%	31.11%	
No			
Event [0,5] cm	60.23% (17.923)	68.2% (29.924)	-7.97%
Event [5,7] cm	71.33% (14.969)	64.22% (28.386)	7.11%
Event [7,12] cm	76.81% (8.570)	65.13% (27.450)	11.68%

Event [0,7) cm	73.43% (15.826)	68.22% (28.656)	5.21%
Event [5,12] cm	79.44% (9.293)	64.71% (29.929)	14.73%
Event [0,5 or 7,12] cm	89.61% (7.564)	82.38% (25.205)	7.23%
Age	22.65 (1.748)	25.56 (11.220)	
Gender	**0.475%** **(0.507)**	**0.422%** **(0.499)**	
Male	52.50%	57.78%	
Female	47.50%	42.22%	
Non-binary			
Prefer not to say			
Primary education			
Secondary education			
MBO	2.50%	6.67%	
HBO/WO	97.50%	91.11%	
Other education		2.22%	

Note: The table above shows averages of responses to the survey questions, respondents had to answer in percentages. *The point estimates between brackets are the Standard errors of the coefficients.*

The total number of respondents is 85. With a distribution of 40 respondents for the environmentally active group and 45 respondents for the random group. In the environmentally active group, almost every respondent chose to access additional information (37 out of 40). In the random group, a majority chose to access the additional information (31 out of 45). The distribution between men and women is almost equal in both sample groups (19 versus 21 and 26 versus 19). Almost every respondent in both sample groups has an HBO/WO background (97,50% and 91,11%). It can be seen from table IV that always the largest average difference in probability can be seen in the questions where sea level rise is the largest such as question 11 (Event [5,12] cm, after exposure to additional information) where the difference is 14.73% on average.

To further test the hypotheses, regression models now follow with Likelihood insensitivity as the dependent variable.

This regression measures whether additional information affects the likelihood insensitivity index. Here a distinction is made between the regression with and without control variables.

(4) *Likelihood insensitivity Index =* $\beta_0 + \beta_1 * \textit{Treatment} + \mu$

(4) *Likelihood insensitivity Index =* $\beta_0 + \beta_1 * \textit{Treatment} + \beta_2 * \textit{Age} + \beta_3 * \textit{Age}^2 + \beta_4 * \textit{MBO} + \beta_5 * \textit{HBO/WO} + \beta_6 * \textit{Other education} + \beta_7 * \textit{Gender} + \mu$

The fourth regression shows that the variable treatment is not significant in either regression which means we cannot say whether the exposure to additional information influences the likelihood insensitivity index (with other variables held constant). It cannot be determined whether accessing the additional information affected one group more than the other because only the variable HBO/WO and the constant are significant in the regressions. The relationship between HBO/WO and the likelihood insensitivity index is significant (with other variables held constant).

This regression measures whether ''group'' affects the likelihood insensitivity index. Here a distinction is made between the regression with and without control variables.

(5) Likelihood insensitivity Index = $\beta_0 + \beta_1 *Treatment + \beta_2 *Group + \beta_3*Treatment*Group + \mu$

(5) ***Likelihood insensitivity Index =*** $\beta_0 + \beta_1 * Treatment + \beta_2*Group + \beta_3*Treatment*Group + \beta_4*Age + \beta_5*Age^2 + \beta_6 * MBO+\beta_7 *HBO/WO + \beta_8 *Other\ education + \beta_9 *Gender + \mu$

To test whether information had an effect across groups a Wald test was conducted. The joint significance of the independent variables Group and Treatment*Group was tested. The test revealed that the coefficients of Group and Treatment*Group are not significant ($p>0.05$), suggesting that there is no strong evidence to support a significant relationship between Group and Treatment*Group and the likelihood insensitivity index. We cannot say whether information had an effect across groups.

The fifth regression shows that the variable treatment (whether someone already had access to additional information) is insignificant (with other variables held constant). This means that we cannot say that there is a relationship between treatment and likelihood insensitivity. It cannot be determined whether accessing the additional information affected one group more than the other because the variable group and the interaction term of Treatment*Group are also insignificant. The insignificance of the variables also means that we cannot say that the sample group the respondents are in affects the likelihood insensitivity index.

This regression measures the moderating effect of accessing the additional information. For this, a regression was done with the variable's treatment, access to additional information (whether the respondent chose to see the information), and an interaction term examining the effect of being exposed to info and choosing to access the info.

(6) Likelihood insensitivity Index = $\beta_0 + \beta_1 *Treatment + \beta_2 *Accessinfo + \beta_3*Treatment*Accessinfo + \mu$

(6) Likelihood insensitivity Index = $\beta_0 + \beta_1 * Treatment + \beta_2 * Group + \beta_3 * Treatment * Group + \beta_4 * Age + \beta_5 * Age^2 + \beta_6 * MBO + \beta_7 * HBO/WO + \beta_8 * Other\ education + \beta_9 * Gender + \mu$

The sixth regression shows that treatment is again insignificant in both cases. This means that we cannot say that there is a relationship between treatment and likelihood insensitivity. The relationship between accessing additional information and likelihood insensitivity is in both regressions insignificant (with other variables held constant). This means that we cannot say that there is a relationship between accessing additional information and the likelihood insensitivity index. It cannot be determined whether accessing the additional information affected one group more than the other because only the variable HBO/WO is significant.

The results of regressions four through six can be found in table V below.

As can be seen in Table V, the variables treatment, group, and access to additional information are insignificant in each model. To that end, these models do not help to test the hypotheses on likelihood insensitivity.

Table V Results of regressions on the Likelihood insensitivity index

Likelihood insensitivity	(4)	(4)	(5)	(5)	(6)	(6)
Treatment	-0.036	-0.036	-0.075	-0.075	-0.062	-0.062
	(0.059)	(0.059)	(0.064)	(0.064)	(0.062)	(0.063)
Group	-	-	0.090	0.060	-	-
			(0.0812)	(0.086)		
Treatment*Group	-	-	0.074	0.074	-	-
			(0.114)	(0.114)		
Age	-	-0.026	-	-0.025	-	-0.024
		(0.018)		(0.018)		(0.019)
Age^2	-	0.0004	-	0.0003	-	0.0003
		(0.0002)		(0.0002)		(0.0002)
MBO	-	-0.034	-	-0.010	-	-0.089
		(0.059)		(0.063)		(0.129)
HBO/WO	-	-0.150***	-	-0.100	-	-0.159***
		(0.047)		(0.067)		(0.048)
Other education	-	0.239	-	0.241	-	0.183
		(0.246)		(0.254)		(0.257)
Gender	-	-0.039	-	-0.036	-	-0.038

		(0.061)		(0.061)		(0.061)
Access additional	-	-	-	-	0.048	-0.013
information					(0.117)	(0.138)
Treatment*Access	-	-	-	-	0.134	0.134
additional information					(0.167)	(0.163)
Constant	0.781***	1.324***	0.733	1.249***	0.771***	1.310***
R-squared	0.0022	0.0470	0.0322	0.0645	0.0214	0.0542
Observations	170	170	170	170	170	170
Prob > F	0.5451	0.0001	0.0941	0.0001	0.3756	0.0001

*Note: The table above presents regression from equations 4-6. *P < 0.05, **P < 0.01, ***P < 0.001. The point estimates between brackets are the Standard errors of the coefficients.*

To test the third hypothesis: ''Females have a higher ambiguity aversion and likelihood insensitivity toward climate change than men'' we must use regressions with ambiguity aversion and likelihood insensitivity as the dependent variables and age, age^2, MBO, HBO/WO, Other education, treatment*gender and gender as the independent and control variables.

These regressions look at the moderation effect of being a female in both samples. The interaction term treatment*gender examines the effect of being exposed to info and being a female respondent. It also examines whether gender influences ambiguity aversion and likelihood insensitivity. The formulae are as follows:

(7) Ambiguity aversion Index = $\beta_0 + \beta_1 * Treatment * Gender + \beta_2 * Gender + \beta_3 * Treatment + \mu$

(7) Ambiguity aversion Index = $\beta_0 + \beta_1 * Treatment * Gender + \beta_2 * Gender + \beta_3 * Treatment + \beta_4 * Age + \beta_5 * Age^2 + \beta_6 * MBO + \beta_7 * HBO/WO + \beta_8 * Other\ education + \mu$

(8) Likelihood insensitivity = $\beta_0 + \beta_1 * Treatment * Gender + \beta_2 * Gender + \beta_3 * Treatment + \mu$

(8) Likelihood insensitivity = $\beta_0 + \beta_1 * Treatment * Gender + \beta_2 * Gender + \beta_3 * Treatment + \beta_4 * Age + \beta_5 * Age^2 + \beta_6 * MBO + \beta_7 * HBO/WO + \beta_8 * Other\ education + \mu$

To test whether females are more responsive to additional information compared to males a Wald test was conducted. The joint significance of the independent variables Treatment*Gender and Treatment was tested. The test revealed that the coefficients of Treatment*Gender and Treatment are jointly significant at the 5% level (Wald $\chi^2 = 3.01$, df = 2, $p < 0.05$). This indicates that the set of variables considered has a statistically significant effect on the Ambiguity aversion index. It can be concluded that females are more responsive to additional information compared to males.

To test whether females are more responsive to additional information compared to males a Wald test was conducted. This time the likelihood insensitivity index is the dependent variable. The joint significance of the independent variables Treatment*Gender and Treatment was tested. The test revealed that the coefficients of Treatment*Gender and Treatment are not significant (p>0.05), suggesting that there is no strong evidence to support a significant relationship between Treatment*Gender and Treatment, and the likelihood insensitivity index. We cannot say whether females are more responsive to additional information compared to males.

The seventh regression shows that treatment is significant (with other variables held constant) when control variables are included in the regression. This means that being exposed to info and being a female leads to a decrease in the ambiguity aversion index of 0.140 points. It cannot be determined whether accessing the additional information affected one group more than the other because only the variable treatment and educational variables are significant. The variables gender and the interaction term are both insignificant (with other variables held constant). This means that we cannot say that there is a relationship between gender and the ambiguity aversion index.

The eighth regression shows that treatment is not significant, this means that we cannot say that there is a relationship between treatment and the likelihood insensitivity index. Both the variable gender and the interaction term between gender and treatment are insignificant so we cannot say whether there is a relationship between gender and the likelihood insensitivity index. It cannot be determined whether accessing the additional information affected one group more than the other because only the variable HBO/WO is significant.

The results of regressions seven and eight can be found in table VI below.

Table VI Results of regressions on ambiguity aversion and likelihood insensitivity

Ambiguity aversion	(7)	(7)	**Likelihood insensitivity**	(8)	(8)
Treatment	- 0.140	- 0.140*		-0.03	-0.03
	(0.073)	(0.069)		(0.087)	(0.087
Age	-	-0.025		-	-0.025
		(0.016)			(0.018)
Age^2	-	0.0002		-	0.0003

		(0.0002)		(0.0002)
MBO	-	0.840***	-	-0.034
		(0.172)		(0.059)
HBO/WO	-	0.578***	-	-0.150***
		(0.048)		(0.047)
Other education	-	0.700***	-	0.239
		(0.048)		(0.263)
Gender	-0.103	-0.081	-0.054	-0.032
	(0.060)	(0.058)	(0.080)	(0.083)
Treatment*Gender	0.054	0.054	-0.013	-0.013
	(0.096)	(0.093)	(0.116)	(0.116)
Constant	-0.274***	-0.387	0.805***	1.321***
R-squared	0.0469	0.1530	0.0085	0.0471
Observations	170	170	170	170
Prob > F	0.0736	0.0001	0.7480	0.0001

*Note: The table above presents regression from equations 7 and 8. *P < 0.05, **P < 0.01, ***P < 0.001. The point estimates between brackets are the Standard errors of the coefficients.*

5. Conclusion

The issue of climate change has emerged as a persistent and substantial challenge over an extended period. Climate change is a complex problem that provides itself across many disciplines such as economics, politics, and the environment. The magnitude of the impact varies among these disciplines. This is precisely what drives the formation of motivated beliefs and creates disagreement about the seriousness and veracity of climate change. A large amount of information available makes it difficult to discern accurately from inaccurate information. All of this complicates the mitigation of climate change. This paper examines the influence of information on ambiguity aversion and likelihood insensitivity (as measures of beliefs). Therefore, the main research question is:

'' *What is the relationship between individuals' motivated beliefs about climate change and their selection and interpretation of information related to the issue?''*

Two indices were used to measure ambiguity attitudes: ambiguity aversion and likelihood insensitivity. These variables were examined quantitatively. Ambiguity attitudes interact with motivated beliefs in the belief formation process. They can shape how individuals engage with and process ambiguous information. When there is conflicting or missing information, ambiguity arises which gives room to form beliefs about the probability of an uncertain event (Frisch & Baron, 1988; Trautmann & Van De Kuilen, 2015). OLS regressions were used to answer the main research question.

The results of the regressions with ambiguity aversion show that ambiguity aversion toward climate change decreases among respondents when they are exposed to additional information about climate change. The regressions with likelihood insensitivity did not result in significance. This leaves the influence of additional climate change information on the likelihood insensitivity toward climate change inconclusive among respondents. To explain ambiguous attitudes, both variables are needed. Therefore, the answer to the main question is twofold. On the one hand, we can say that additional information causes individuals to become less ambiguity averse toward climate change. This can be explained by the fact that when individuals are better informed, they engage in more ambiguity-seeking behavior. On the other hand, likelihood insensitivity measures the degree of ambiguity and in this study, the regressions are not significant which means that nothing can be said about the degree of ambiguity toward climate change. Thus, we cannot fully conclude the relationship between motivated beliefs toward climate change and the selection and interpretation of climate change information.

6. Discussion

There may have been response bias in completing the survey, which could have affected the results. It could be that the respondents did not fully understand the questions and just chose to give a random answer instead of a thoughtful one.
Further, the analyses of the study are discussed. The first hypothesis stated that respondents have a decreased ambiguity aversion and likelihood insensitivity toward climate change after being exposed to additional information. The results show that individuals who are exposed to additional climate change information, have a decreased ambiguity aversion towards climate change. This was expected. The results of the regressions with likelihood insensitivity were not significant and the relationship between likelihood insensitivity and additional climate change information remains inconclusive.

The results of the regressions on ambiguity aversion show that individuals who have an MBO, HBO/WO, or other educative backgrounds, have higher ambiguity aversion toward climate change than individuals who have not attended education. This can be explained by previous research that has shown that better education about climate change is an important factor in determining the extent to which individuals care about the climate (O'Connor et al., 1999). What is special is that the results show that when a respondent has an MBO background his or her ambiguity aversion index increases by more points than when the respondent has an HBO/WO, other educative, or no educative background. It was expected that respondents with an HBO/WO background would have the greatest increase in the ambiguity aversion index because the literature says more and better education causes individuals to care more about climate change and avoid uncertainties more. This will probably be because there are very few respondents with an MBO background and almost all respondents had an HBO/WO background so the results may be biased.

The results of the regressions on likelihood insensitivity show that individuals who have an HBO/WO background have less likelihood insensitivity toward climate change than individuals who did not. The results are only significant for the fourth and fifth regressions. The fact that only this variable is significant may be because 92.94% of the respondents have an HBO/WO background.

The second hypothesis stated that individuals who are known to care about climate change have a lower ambiguity aversion and likelihood insensitivity toward climate change relative to individuals drawn from a general population. Both the results for the regressions of group and its interaction term with treatment and the ambiguity aversion index and the likelihood insensitivity index are insignificant so that means we cannot say that respondents known to care about climate have a lower ambiguity aversion or likelihood insensitivity index. The relationship between the variables may be inaccurate due to sampling bias. This is because the respondents for the environmental active sample group were recruited only at activities of the Erasmus Sustainability Hub and thus are not representative of the entire population. There is more variation in individuals in the random sample group.

The third hypothesis stated that Females have a higher ambiguity aversion and likelihood insensitivity toward climate change than men. Both the results for the regressions of gender and its interaction term with treatment on the ambiguity aversion index and the likelihood insensitivity index are insignificant so that means we cannot say that females have a higher ambiguity aversion or likelihood insensitivity index than males. Previous research showed that women care more about the climate and are more concerned about it than men. Besides, women are more likelihood insensitive than men according to research. In addition, the variable age is also not significant in any of the regressions, which also contrasts with previous research. Previous research showed that the younger generation is more aware of climate change and its impact (Semenza et al., 2008).

There are also some limitations to this research. The biggest limitation of the study comes from the validity of the variables and the data of this study. There may be limitations regarding the representativeness of the data used in this study. Almost all survey respondents are students, making the data not representative of adults in the Netherlands. In addition, the random sample group consists mainly of friends, family, and acquaintances of the author. Therefore, the sample is unlikely to be representative of society in the Netherlands.

The R-squared statistics of all models are all far too low < 0.4. This means that the number of control variables in the models is probably too low. There are probably other variables that explain why additional information about climate change causes a higher ambiguity aversion index. If more control variables are added, the variation of the models can be predicted more precisely.

In conclusion, further research is needed to investigate the relationship between motivated beliefs about climate change and the selection and interpretation of information regarding the issue. More control variables are needed when further research is done. For further research, we can also look at better and larger sample groups that are more representative of society such as selecting more targeted respondents who care about the climate and urging random individuals. Furthermore, matching probabilities can easily be used in other settings (other than sea level rise) to measure motivated beliefs. Perhaps different results would then emerge.

7. References

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8. Appendix A

Survey Questions

Dear respondent,

Thank you for participating in this survey! This is a research project being conducted by a Dutch Economics and Business Economics student at Erasmus University Rotterdam.

Participation in this research study is entirely optional. You have the freedom to choose whether to take part. If you decide to participate in this research survey, you retain the right to withdraw your participation at any point in time.

The procedure involves filling in an online survey that will take approximately 5 - 7 minutes. Your response will be treated with strict confidentially and anonymity. The researcher will have no means of identifying you based on your participation. If you have any questions, please don't hesitate to contact 533924dp@eur.nl

Clicking on the ''agree'' button below indicates that:
- You have read the above information
- You voluntarily agree to participate

If you do not wish to participate in the research survey, please decline participation by clicking away from the survey.

Please answer each question carefully and honestly.

1. What is the probability that the global mean sea level has risen between 0 centimeters and 5 centimeters since 1993?

2. What is the probability that the global mean sea level has risen between 5 centimeters and 7 centimeters since 1993?

3. What is the probability that the global mean sea level has risen between 7 centimeters and 12 centimeters since 1993?

4. What is the probability that the global mean sea level has risen between 0 centimeters and 7 centimeters since 1993?

5. What is the probability that the global mean sea level has risen between 5 centimeters and 12 centimeters since 1993?

6. What is the probability that the global mean sea level has risen between 0 centimeters and 5 centimeters **or** 7 centimeters and 12 centimeters since 1993?

Additional information will be available for the following questions

Next, you can choose to access some information about global mean sea levels. If you want to access that information, click "Yes". If you do not wish to access that information, click "No".

Research indicates that the global mean sea level increased by 11 to 14 cm between 1901 and 1990 (Wuebbles et al., 2017)*.*

7. What is the probability that the global mean sea level has risen between 0 centimeters and 5 centimeters since 1993?

8. What is the probability that the global mean sea level has risen between 5 centimeters and 7 centimeters since 1993?

9. What is the probability that the global mean sea level has risen between 7 centimeters and 12 centimeters since 1993?

10. What is the probability that the global mean sea level has risen between 0 centimeters and 7 centimeters since 1993?

11. What is the probability that the global mean sea level has risen between 5 centimeters and 12 centimeters since 1993?

12. What is the probability that the global mean sea level has risen between 0 centimeters and 5 centimeters **or** 7 centimeters and 12 centimeters since 1993?

13. What is your age?

…

14. How do you identify yourself?

    a. Male
    b. Female
    c. Non-binary
    d. Prefer not to say

15. What is the highest level of education you followed?

    a. Primary education
    b. Secondary education
    c. MBO
    d. HBO/WO
    e. Other education