Ambiguity Attitudes and Willingness to Pay for Climate Mitigation

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July 2025

Abstract. Ambiguity attitudes, which refer to differences between decisions under risk (known probabilities) and uncertainty (unknown probabilities), are well-established in behavioral economics. Their implications have been increasingly recognized in environmental and climate change economics. However, most discussions about ambiguity in this domain have so far been confined to theoretical applications in normative climate policy analysis. Notably, there has been a lack of descriptive investigations into climate-related ambiguity attitudes, despite their potential relevance for understanding voluntary climate action and climate policy acceptance. The current study addresses this open empirical question by analyzing ambiguity attitudes in the climate context and exploring their link with willingness to pay (WTP) for climate change mitigation. We show that notwithstanding the normative arguments for higher mitigation effort under ambiguity aversion, the effect of ambiguity on people's preferred levels of mitigation may be in the opposite direction, suggesting a potential discrepancy between the prescribed and the publicly acceptable levels of mitigation effort.

Keywords: ambiguity; climate mitigation; willingness to pay

JEL-Classification: C81, D90, D81

1. Introduction

Uncertainties surrounding climate change often involve unknown or unknowable probabilities of future climate conditions and their socio-economic consequences. Most climate management decisions are consequently made under *ambiguity*, which differs from decision-making under risk (i.e., known probabilities). The special relevance of ambiguity for climate decision-making is well acknowledged (Kunreuther et al., 2013; Heal, 2017; Berger & Marinacci, 2020), and has begun to be addressed in the literature (Millner et al., 2013; Lemoine & Traeger, 2014; Berger et al., 2017). However, despite a growing number of prescriptive applications (i.e., analyzing the implication of ambiguity for what the *optimal* climate change mitigation should be), as yet there have been virtually no descriptive investigations of how ambiguity shapes *actual* mitigation preferences—the objective of this paper. Such descriptive insights are important for managers' understanding of the stakeholder mitigation preferences and can help improve their ability to plan the organizations' climate strategy in alignment with the actual preferences of the stakeholders. For prescriptive policy decisions as well, an improved descriptive understanding can be helpful as it allows policymakers to better predict and address the reactions that may arise among the general population in response to their proposed climate policies.

In this paper, we investigate the link between ambiguity and the individual's willingness to pay (WTP) for climate change mitigation. Our empirical investigation builds on a theoretical framework where climate change mitigation is modeled as self-protection against climate risks.[1] In the economics and management science literature, the link between risk attitudes and self-protection has been widely studied (Ehrlich & Becker, 1972; Dionne & Eeckhoudt, 1985; Eeckhoudt & Gollier, 2005; Baillon et al., 2022). For example, a well-known result under the expected utility (EU) model—which excludes ambiguity attitudes—is that risk-aversion does not always lead to increased self-protection (Dionne & Eeckhoudt, 1985). We extend these earlier analyses by incorporating ambiguity attitudes. In line with the descriptive aim of our study, we extend EU through a theoretical framework (Section 2), which allows modeling, in addition to the well-known *ambiguity aversion*, a second component capturing *ambiguity perception*.

[1] Climate change mitigation is defined in Heal & Kristrom (2002, p.4) as "actions that reduce the flow of greenhouse gases into the atmosphere and, thereby, change the probability distribution over future climate states". This corresponds to self-protection in risk analysis. Climate change adaptation, on the other hand, is defined as "actions that reduce the damages associated with a given climate state" and corresponds to self-insurance in risk analysis. For another application of self-protection and self-insurance in climate policy, see Etner et al. (2021).

Different from ambiguity aversion, which reflects a pessimistic attitude towards unknown probabilities, ambiguity perception leads to inability to distinguish between different levels of likelihoods, an effect known as ambiguity-generated likelihood insensitivity (a-insensitivity). In the extreme case of ambiguity perception, the decision-maker may treat all likelihoods, except 0 (impossibility) and 1 (certainty), as a 50-50 blur. Especially in mitigation contexts where costly effort must be traded-off against *changes in likelihood levels* of outcomes (good or bad), it is empirically necessary to model ambiguity perception. For instance, if decision-makers are insufficiently sensitive to changes in likelihoods because of perceived ambiguity, they may undervalue benefits of mitigation effort.

Our model suggests two key hypotheses about the role of ambiguity in climate risk management: (i) perception of ambiguity decreases WTP for emissions reduction, which leads a non-EU individual, who is influenced by ambiguity, to have in general a lower WTP for mitigation compared to an EU maximizer, and (ii) ambiguity aversion decreases WTP for emissions reduction. We empirically test these predictions in an online experiment with real incentives.

Our empirical tests contribute to the extant ambiguity literature by going beyond the classical Ellsberg urn setting and studying a source of uncertainty natural to the climate context. Indeed, despite the ubiquity of ambiguity in many domains of decision-making, experimental research on ambiguity has, until now, primarily relied on context-free artificial sources, as in the classical Ellsberg urn setting (Trautmann & van de Kuilen, 2015). Therefore, the link between field behaviors and measures of context-relevant, natural sources of ambiguity have been understudied. Our study provides new evidence on measures of ambiguity attitudes and their external validity by focusing on climate change context.

Participants in our experiment were presented with different possible events of a future global temperature anomaly. The global temperature anomaly of a given month indicates how much warmer (or colder) that month has been compared to its "normal" temperatures.[2] We measured the degree of ambiguity that participants perceived about a future month's temperature anomaly as well as the degree of aversion that participants displayed towards this source of

[2] In our experiment, we use the monthly global temperature anomalies reported by the National Oceanic and Atmospheric Administration (NOAA) of USA. In NOAA's reports, temperature anomalies are measured as deviations from the 20th century monthly average temperatures. For more information, see https://www.ncei.noaa.gov/access/monitoring/global-temperature-anomalies/.

ambiguity. These measurements are done by using the efficient method of matching probabilities as proposed in Dimmock et al. (2016) and Baillon et al. (2018b). For measuring WTP for emissions reduction, we elicited participants' WTP to reduce 1 metric ton of CO2 emissions, which is an amount approximately equivalent to 13% of the total annual emissions of an average person residing in the European Union. The incentives were calibrated to be compatible with truthful elicitation of levels of WTP ranging from £0 to £200, whereby the upper bound was chosen to encompass the most recent estimates of the social cost of carbon (e.g., see Rennert et al., 2022; Zhao et al., 2023).

Our main findings can be summarized as follows. First, there exist distinct ambiguity attitudes in the climate context. Although participants perceive as much ambiguity about future temperature anomalies as they do when faced with Ellsberg urns with unknown color compositions, ambiguity aversion measured in the climate context is lower than the level of aversion measured in the standard Ellsberg setting. Moreover, whereas climate ambiguity aversion is mainly correlated with context-dependent variables (e.g., agreement and personal experience with climate change), Ellsberg ambiguity aversion is correlated also with context-free measures of economic preferences, such as risk aversion and altruism. Second, ambiguity attitudes matter for WTP for emissions reduction. Consistent with our theoretical predictions, perception of and aversion towards climate ambiguity indeed reduce WTP for climate mitigation. More specifically, a climate-ambiguity averse individual can be willing to pay for 1 ton of CO2 emissions reduction up to 54% less than an EU maximizer who is unaffected by ambiguity. In contrast, measures of participants' ambiguity attitudes towards Ellsberg ambiguity do not correlate with their WTP for emissions reduction.

Our results add to studies addressing ambiguity in climate change mitigation, which have typically involved computational estimations of the economic value of CO2 reductions using integrated assessment models under ambiguity aversion (e.g., Berger et al., 2017; Millner et al., 2013). Unlike the prescriptive aims of these studies, the current study focuses on descriptive understanding of how ambiguity may influence individuals' actual WTP for CO2 emissions reduction. Closest to our study is the recent work by Watanabe & Fujimi (2022) who also examine WTP for different climate policies under ambiguity in a hypothetical choice experiment. Our theoretical and empirical results add a new insight into the topic of ambiguity in climate mitigation. Even if normative principles argue for higher mitigation effort under ambiguity aversion (Berger et al., 2017), the effect of perceived ambiguity on people's preferred levels of mitigation may be in the opposite direction. Thus, our study shows that ambiguity may generate a potentially significant discrepancy between the prescribed and the acceptable levels of mitigation effort.

The remainder of the paper is organized as follows. Section 2 presents our theoretical results on the relationship between preferences under ambiguity and self-protection against climate risks. Section 3 outlines the empirical strategy for measuring ambiguity attitudes. We present our experimental design in Section 4 and the analysis results in Section 5. Section 6 discusses these results in relation to the extant literature. Section 7 concludes.

2. Ambiguity Attitudes and Willingness-to-Pay for Mitigation

This section presents a theoretical analysis of self-protection behavior that demonstrates the potential link between ambiguity attitudes and climate mitigation. We consider an individual who faces a risk of wealth loss L due to climate change. The probabilities of the two possible events—loss and no-loss—are ambiguous. The individual can reduce the probability of the loss event by engaging in mitigation efforts, which have monetary costs. In what follows, we first examine behavior under expected utility (EU) maximization, where ambiguity does not play a role, as in Dionne & Eeckhoudt (1985). Then, we extend the analysis by reckoning with non-expected utility (non-EU) preferences, in order to examine the effect of ambiguity. The proofs of the propositions are in Appendix A.

Self-protection under EU. We start by considering an individual who maximizes EU and is therefore not affected by ambiguity. The individual assigns with confidence subjective probability p_0 to the no-loss event (and probability $1 - p_0$ to the loss event). We assume further that the individual has a strictly increasing and concave utility $u(w)$ over wealth (i.e., $u''(w) > 0$ and $u'(w) < 0$). For an initial wealth w_0, her expected utility is:

$$EU_0 = p_0 u(w_0) + (1 - p_0) u(w_0 - L). \tag{1}$$

We are interested in the variation v in the initial wealth w_0, which compensates the increase in the probability of the no-loss event, say, from p_0 to p_1 (i.e., leaves her expected utility unchanged at EU_0):

$$EU_0 = p_1 u(w_0 - v) + (1 - p_1)u(w_0 - L - v). \tag{2}$$

The individual's willingness-to-pay (WTP) for mitigation can be calculated as:

$$WTP_{EU} \equiv v'(p_0) = \frac{u(w_0) - u(w_0 - L)}{p_0 u'(w_0) + (1 - p_0)u'(w_0 - L)} \tag{3}$$

As shown in Dionne and Eeckhoudt (1985) and further analyzed in Briys & Schlesinger (1990) and Chiu (2000), the impact of risk aversion (captured by utility curvature under EU) on WTP for self-protection depends on certain other characteristics of the utility function and therefore is indeterminate.[3] This result is summarized in the following proposition.

Proposition 1. *Under EU, risk aversion may induce an increase or a decrease in the level of WTP for mitigation.*

Self-protection under non-EU. We now turn to the analysis with non-EU preferences. Under non-EU theories, ambiguity is typically modeled through non-additive decision weights, as in rank-dependent utility / Choquet expected utility (Schmeidler 1989), prospect theory (Tversky & Kahneman, 1992), and source theory (Baillon et al., 2025; Abdellaoui et al., 2011), or through sets of priors, as in (α-)maxmin expected utility (Gilboa & Schmeidler, 1989; Ghirardato et al., 2004). For two-outcome uncertain situations (considered throughout this paper), all these non-EU theories use biseparable utility evaluation. Our analysis also adopts this evaluation and, therefore, applies to all of these theories[4]. In this section, we consider neo-additive expected

[3] Chiu (2000) demonstrates that propensity to take actions of self-protection is determined jointly by down-side risk aversion characterized by the third derivative of the utility function (Menezes et al. 1980), risk aversion, and the initial no-loss probability.

[4] Another prominent ambiguity theory in the literature is the smooth model of Klibanoff et al. (2005), which has strong normative underpinnings. Given the empirical orientation of our study, we adopt a descriptively more suitable

utility (neo-EU) of Chateauneuf et al. (2007), which represents a special case of each of these theories. The neo-additive model is convenient for applications due to its tractability and well-documented empirical performance while still being general enough to accommodate commonly observed ambiguity preferences (see e.g., Abdellaoui et al. 2011; Baillon et al. 2018b; Li et al. 2018). In Online Appendix OA2 we show that the main propositions derived here remain valid also under the more general theories, with the added nuance that the individual's baseline subjective belief p_0 plays a role.

An individual who maximizes neo-EU has a baseline probabilistic belief p_0 for the no-loss event but lacks confidence in p_0, which is thus an ambiguous belief. Her reaction to ambiguity then depends on her degree of *ambiguity perception* and *pessimism*, which determine how much relative importance she assigns to the worst vs. the best possible outcome. Accordingly, neo-EU of the individual is a weighted average of her expected utility (with respect to her belief p_0) and her α-maxmin utility à la Hurwicz (1951), which takes into consideration only the worst and the best possible outcomes. This is written as:

$$\begin{gathered} neo\text{-}EU_0 = (1-\delta)[p_0 u(w_0) + (1-p_0)u(w_0 - L)] + \\ \delta[\alpha u(w_0) + (1-\alpha)u(w_0 - L)], \end{gathered} \tag{4}$$

where $\alpha, \delta \in [0,1]$.

Intuitively, the parameter δ captures the individual's lack of confidence (or her perceived ambiguity) in her subjective belief p_0, so that only the weight $1-\delta$ is assigned to her (belief-based) expected utility. The parameter δ can thus be viewed as an index of deviation from EU. If the individual does not perceive any ambiguity (i.e., $\delta = 0$), she maximizes EU. By contrast, at the maximum level of ambiguity perception (i.e., $\delta = 1$), the individual disregards completely her probabilistic beliefs, and makes her decision by focusing solely on the worst and the best possible outcomes. In general, under ambiguity (i.e., whenever $\delta > 0$), the parameter α measures the individual's degree of optimism (with pessimism as its counterpart $(1-\alpha)$). The smaller the level of α, the higher the level of pessimism, and the larger the relative weight assigned to the worst possible outcome. Of two individuals with the same degree of ambiguity perception δ, the

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approach. For an alternative analysis of self-protection behavior with the smooth model, see Alary et al. (2013). For applications of the smooth model to climate policy analysis, see Berger & Marinacci (2020).

one with the smaller α is more ambiguity averse. For example, an extremely ambiguity averse individual has $\alpha = 0$, overweighting in her decision-making always the worst possible outcomes and the more so the more ambiguity she perceives (i.e., the higher her level of δ).

For a neo-EU maximizer, WTP for protection is:

$$WTP_{neo-EU} = \frac{(1-\delta)[u(w_0) - u(w_0 - L)]}{(1-\delta)[p_0 u'(w_0) + (1-p_0)u'(w_0 - L)] + \delta[\alpha u'(w_0) + (1-\alpha)u'(w_0 - L)]}. \tag{5}$$

From equation (5), it is easy to see that when the individual does not perceive any ambiguity (i.e., $\delta = 0$), her WTP does not differ from that of EU maximizer. If the individual perceives ambiguity (i.e., $\delta > 0$) her WTP for mitigation will be lower compared to that of EU maximizer. The intuition behind this result can also be seen from equation (4). When $\delta > 0$, the probabilistic beliefs of the individual receive less weight in the decision than they would under expected utility. In other words, ambiguity causes the individual to become insensitive to the potential improvements in the likelihood of the no-loss event which may result from mitigation efforts. This a-insensitivity (Baillon et al., 2018a,b; Dimmock et al., 2016) consequently reduces the motivation to make mitigation efforts and the WTP. The following proposition summarizes these observations.

Proposition 2. *A neo-EU maximizer, whose probabilistic beliefs are ambiguous ($\delta > 0$), has a lower WTP for mitigation than an EU maximizer with the same probabilistic beliefs and utility. Furthermore, WTP for mitigation is (ceteris paribus) decreasing in perceived level of ambiguity (i.e., for higher levels of δ).*

Whereas ambiguity perception makes the individual insensitive to changes in the likelihood of the no-loss event, pessimism causes her to overweight the impact of the loss event compared to what its subjective probability would warrant. The next proposition indicates that such overweighting of the worst-case scenario results in a lower WTP for climate protection.

Proposition 3. *Under neo-EU, in the presence of ambiguous beliefs (i.e., $\delta > 0$), the WTP for mitigation is (ceteris paribus) decreasing in pessimism (i.e., for lower levels of α).*

The result in proposition 3 can be seen from the denominator of equation (5). There, pessimism (i.e., lower α) implies a higher weight assigned to the outcome of the loss event, where the marginal utility of wealth is higher than that under the no-loss event. The resulting increase in the perceived expected marginal utility of wealth caused by pessimism decreases the individual's WTP for mitigation. In other words, pessimism increases the perceived marginal cost of mitigation and thus leads to a lower WTP. It should be noted that the effect of pessimism is relevant only under ambiguity (i.e., when $\delta > 0$), as the individual must perceive ambiguity to exhibit optimism or pessimism towards ambiguity.

3. Measuring Ambiguity Attitudes through Matching Probabilities

In our empirical analysis, we derive ambiguity attitudes through matching probability elicitations. Dimmock et al. (2016, Theorem 3.1) showed that a decision maker's matching probabilities can directly reveal her ambiguity attitudes. Dimmock et al.'s (2016) theorem holds true under most ambiguity theories commonly used in the literature, including all the theories mentioned in Section 2 for which the neo-EU model represents a special case. To describe the method, let $X_E 0$ denote a prospect of receiving a prize X if the uncertain event E occurs, and 0 otherwise. Furthermore, let $X_m 0$ denote a prospect of receiving the same prize X with probability m, and 0 otherwise. The matching probability $m(E)$ of the uncertain event E is defined as the probability at which a decision maker is indifferent between receiving a prize X if E happens (and nothing otherwise) and receiving the same prize with that probability. That is, a decision maker's matching probability $m(E)$ of event E is given by the indifference $X_E 0 \sim X_{m(E)} 0$. Under EU, the matching probability $m(E)$ corresponds to the decision maker's (additive) subjective probability $p(E)$. Ambiguity attitudes lead $m(E)$ to deviate from $p(E)$.

To demonstrate the link between matching probabilities and the parameters $\alpha, \delta \in [0,1]$ of the neo-EU model, note that the indifference $X_E 0 \sim X_{m(E)} 0$ implies the following equality under neo-EU:

$$(1-\delta)\left[p(E)u(X)+\left(1-p(E)\right)u(0)\right]+\delta[\alpha u(X)+(1-\alpha)u(0)]$$
$$=m(E)u(X)+\left(1-m(E)\right)u(0). \tag{6}$$

By rescaling the utility, so that $u(X)=1$ and $u(0)=0$, we can immediately see that:

$$m(E)=\delta\alpha+(1-\delta)p(E). \tag{7}$$

Thus, the matching probability is a function of the individual's probabilistic belief and her ambiguity attitude as captured by the parameters α,δ. When $\delta=0$, which represents EU, we have $m(E)=p(E)$ so that matching probabilities represent the decision maker's subjective probabilities. By contrast, $\delta>0$ leads to deviations of matching probabilities from subjective probabilities (and additivity). For instance, in the case of extreme ambiguity perception (i.e., $\delta=1$), $m(E)=\alpha$, regardless of the subjective probability of event E. In this case, all likelihoods are treated as a perceptual 50-50 blur and are ignored, and the individual decides only by looking at the best and the worst outcomes possible (i.e., utility of 1 and 0), with parameter α determining how much relative weight she assigns to them. Lower (higher) values of $\alpha<0.5$ ($\alpha>0.5$) imply $U(X)$ (i.e., the best possible outcome) receiving less (more) weight than $U(0)$ (i.e., the worst possible outcome).

The decision maker's overall level of ambiguity aversion depends on both α and δ. This can be measured by an index computed as $\delta(1-2\alpha)$, as proposed by Abdellaoui et al. (2011) to capture the global level of pessimism of a decision maker. Here, the index can be interpreted as follows. First, a rescaling of α as $1-2\alpha$ results in a measure of average ambiguity aversion "per unit" of perceived ambiguity. Then, the multiplication of $1-2\alpha$ by δ gives the overall measure of ambiguity aversion. The index takes values between -1 and 1, with positive (i.e., ambiguity aversion) values arising when $\delta>0$ and $\alpha<0.5$, and negative values (i.e., ambiguity seeking) when $\delta>0$ and $\alpha>0.5$. The index value of zero indicates ambiguity neutrality, which arises either if the individual is an EU maximizer ($\delta=0$) or if she is ambiguity neutral in Hurwicz's sense with $\alpha=0.5$.

We employ the following empirical strategy to obtain α and δ. We elicit matching probabilities of three mutually exclusive and exhaustive events E_1, E_2, and E_3, and those of their complements $\bar{E}_1$, $\bar{E}_2$, and $\bar{E}_3$. Then, we use the least squares method to estimate for each participant the parameter values $\alpha, \delta \in [0,1]$ together with $p(E_i) \in [0,1]$. The estimated parameter values are rounded to third decimal place. As the optimism parameter α is immaterial when $\delta = 0$ (i.e., under SEU), we take $\alpha = 0.5$ for such observations, which assumes neither averse nor seeking attitude towards ambiguity.

4. The experiment

The online experiment was conducted in May 2023, with 801 participants of the Prolific platform. Full experimental instructions can be found in the Online Appendix. The completion time was 31.5 minutes for the median participant. The participation fee was on average £9.32 per hour, which varied depending on the time taken by the participant to complete the experiment. The experiment consisted of four main parts: (i) elicitation of matching probabilities, (ii) elicitation of WTP to reduce Co2 emissions by one metric ton, (iii) measurement of economic preferences (time, risk, and social), and (iv) measurements of climate change and environmental attitudes.[5] The order of the different parts was randomized. The participants also answered standard demographics questions at the end of the experiment. We paid five in a hundred randomly selected participants a variable amount based on one of their choices in matching probabilities or WTP elicitations.[6]

The following subsections present the details of the experimental design and procedures for each part. Section 4.5 describes the sample of participants.

4.1. Elicitation of Matching Probabilities

We consider two sources of uncertainty for our matching probability elicitations. The first source is a natural source in the climate context. The second source is a typical Ellsberg setting, which is included in our experiment for comparison purposes. For both sources, participants were first presented with the description of the source and could proceed only after having passed a

[5] The experiment also contained measures of general ecological behavior (GEB) (Kaiser and Wilson, 2004; Arnold et al., 2018) and political ideology (Malka et al. 2019). These were collected for another study and are not reported in this paper.
[6] Recent empirical evidence suggests no difference between preference elicitations when all or only some participants are paid based on their decisions in choice experiments (Berlin et al. 2024; Aydogan et al. 2024).

comprehension quiz with a maximum of three attempts. The order of the sources was randomized.

Climate source. Our measurement of ambiguity attitudes in the climate context concerns the global surface temperature anomaly in June 2023. The global temperature anomalies measure departures from a long-term average, which is the 20th century average temperatures in our experiment. For instance, a positive (negative) anomaly in June 2023 indicates warmer (cooler) temperatures than the 20th century average temperature in the month of June.

Global temperature anomalies are a suitable source for measuring ambiguity attitudes in climate context for three reasons. First, they are well-established climate change indicators, providing a broad overview of global temperatures with respect to a reference point. Second, they present a verifiable source of uncertainty due to monthly data availability, which enables us to use real monetary incentives in our measurements. Last, using a global climate index rather than a local index avoids comparative ignorance across our participants residing in different locations in the world. In particular, whereas each participant may be familiar with their own local weather conditions (by direct experience), we assume similar levels of knowledge (or ignorance) about the global temperatures across participants in different locations in the world.

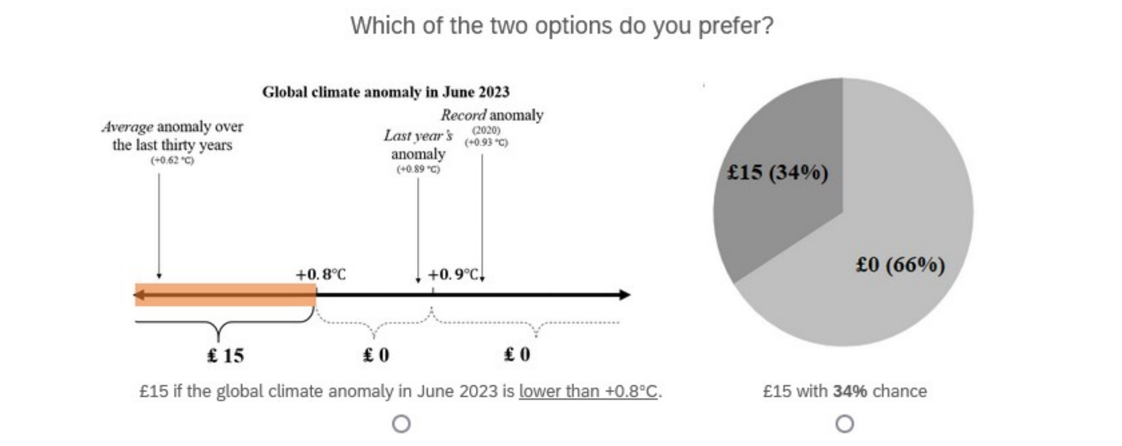
Our matching probability elicitations feature the following three mutually exclusive and exhaustive events regarding global temperature anomaly in June 2023.

1. E_1: Global anomaly in June 2023 is less than +0.8ºC,
2. E_2: Global anomaly in June 2023 is between +0.8ºC and +0.9ºC (boundaries included), and
3. E_3: Global anomaly in June 2023 is more than +0.9ºC.

These events are constructed around three pieces of historical information: (i) the average anomaly in the month of June over the last 30 years (+0.62ºC), (ii) the anomaly in June 2022 (0.89ºC), and (iii) the record anomaly measured in the month of June (+0.93ºC), realized in 2020. Participants were also provided with this information to familiarize them with likely ranges of temperature anomalies.

We elicit the matching probabilities of events E_1, E_2, and E_3 as well as those of their complements $\bar{E}_1$, $\bar{E}_2$, and $\bar{E}_3$. The elicitations are done by using a bisection procedure to find indifferences $£15_{E_i}0 \sim £15_{m(E_i)}0$ and $£15_{\bar{E}_i}0 \sim £15_{m(\bar{E}_i)}0$ for $i = 1,2,3$. In practice, for each anomaly event, participants made four to five binary choices between either receiving £15 depending on the global anomaly event or receiving £15 with a given probability, which is adjusted at every iteration until the indifference point is reached. An example of the display of a binary choice question is in Figure 1. The details of the bisection procedure are in Appendix B.

Figure 1. An Example of a Binary Choice in the Climate Context



Ellsberg source. The elicitations of ambiguity attitudes in Ellsberg source are done similarly, except that we consider draws from a box containing 100 balls with unknown proportions of red, blue and yellow balls. Our elicitations within this source feature the following symmetric events.

1. E_1: drawing a red ball from the box,
2. E_2: drawing a blue ball from the box, and
3. E_3: drawing a yellow ball from the box.

As in our measurements in the climate source, we elicit matching probabilities of these three events and those of their complements. The same bisection procedure is applied to these elicitations (Figure 2).

Payment procedure. Four in a hundred participants were paid a variable amount based on one of their choices in this part. The selection of the participants and of the choice question that mattered for their payment (same question for all) was made randomly prior to the experiment and revealed at the end (for a discussion of the advantages of the prior random incentive system, see Johnson et al., 2021). The selection process was recorded and posted on YouTube before the experiment so that the participants could verify the selection after the experiment. At the end of the experiment, the selected choice question was implemented on a live zoom session with the (non-compulsory) attendance of the eligible participants. The live session was also recorded and shared on YouTube later for future reference. The selected participants received either £15 or £0, depending on their choices and the realizations of the uncertain events.

Figure 2. An example of a binary choice in Ellsberg setting

4.2. Elicitation of WTP to Reduce CO2 Emissions

We measure participants' WTP for climate change mitigation by eliciting their WTP to reduce 1 metric ton of CO2 emissions. The elicitation is done by using a choice list design. Each participant made a series of 24 choices between two options: (i) reducing 1 metric ton of CO2 without any monetary gain and (ii) having a monetary gain without reducing CO2 emissions. The monetary amounts in the list ranged between £0 and £200.[7] To have a higher precision near £0, where we expected much of the data to lie, the amounts were initially incremented with step sizes as small as £1 or £2 and then incremented with gradually increasing step sizes of £4, £5, £10, and £20. Our design adopted an automatic switching feature to prevent multiple switching. For the full choice list, see experimental instructions in the Online Appendix.

Participants were informed that their choices in this part were not hypothetical, and their choice for CO2 reduction would, with some probability, be implemented for real by the

[7] At the time of the experiment, the price of emissions allowances traded on the EU-ETS was at around €100 per metric ton of CO2. The upper bound of €200 was chosen to encompass the estimate of the social cost of carbon in Rennert et al. (2022).

researchers. CO_2 reductions were made possible through purchasing and retiring equivalent European Union Emission Trading Scheme (EU-ETS) allowances. The participants were reminded that CO_2 emissions were the key contributor to climate change and that their choices would indeed have a true consequence for the environment. To help participants make better sense of the consequences of their choices, references to total annual emissions of the average European citizen, as well as equivalent kilometers of a car ride causing 1 metric ton of CO_2 emissions, were provided. Specifically, participants were informed that in 2019 the average European citizen emitted 7.8 tons of CO_2, thus 1 ton representing about 13% of the average European's total annual emissions. Furthermore, participants were informed that 1 ton of CO_2 is roughly equivalent to driving a new car over 8,000 km, which is equivalent to more than 1 year of driving for a typical German citizen and to over 2 years of driving of a typical Dutch citizen.

Payment procedure. We selected one in every hundred participants to implement one of their choices for real. The participants selected in this part were different from those selected for the matching probability questions. Similarly, as in the case of the matching probability elicitations, the selection of participants and of the choice question to be implemented (same for all the selected participants) was made randomly, prior to the experiment, and participants could ascertain this prior selection at the end of the experiment. Following the experiment, the choice question for this part was implemented in a live zoom session. We either paid the selected participant the money amount in the choice question or implemented the CO_2 reduction by purchasing an equivalent emission certificate and retiring it from the market.

4.3. Measures of Other Economic Preferences

We measured risk, time, and social preferences by using the validated questionnaire of Falk et al. (2018, 2023). The items used for the measures and the encoding of the responses are summarized in Table 1. For all items, the participants indicated their willingness or unwillingness to engage in different behaviors (or the extent to which different behavioral tendencies described them as a person) on a scale from 0 to 10, where 0 designated “completely unwilling to do so” (or “does not describe me at all”), and 10 designated “completely willing to do so” (or “describes me perfectly”). In the questionnaire, risk preference is measured by eliciting participants’ general willingness to take risks.

Table 1. Summary of Economic Preferences Questionnaire

Measured Preference	Item	Encoding
Risk aversion	In general, how willing or unwilling are you to take risks?	The response from 0 to 10 is reversed by subtracting it from 10, then rescaled to take a value between 0 and 1 to have a measure of risk aversion.
Impatience	In general, how willing or unwilling are you to give up something that is beneficial for you today in order to benefit more from that in the future?	The response from 0 to 10 is reversed by subtracting it from 10, then rescaled to take a value between 0 and 1 to have a measure of impatience.
Procrastination	I tend to postpone tasks even if I know it would be better to do them right away.	The response from 0 to 10, rescaled to take a value between 0 and 1, measures degree of procrastination.
Altruism	How willing or unwilling are you to give to good causes without expecting anything in return?	The response from 0 to 10, rescaled to take a value between 0 and 1, measures degree of altruism.
Trust	I assume that people have only best intentions.	The response from 0 to 10, rescaled to take a value between 0 and 1, measures degree of trust.
Positive reciprocity	When someone does me a favor, I am willing to return it.	The response from 0 to 10, rescaled to take a value between 0 and 1, measures degree of positive reciprocity.
Negative reciprocity	(i) How willing are you to punish someone who treats you unfairly, even if there may be costs for you? (ii) If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to do so.	The average of the two responses from 0 to 10, rescaled to take values between 0 and 1, measures degree of negative reciprocity.
Indirect negative reciprocity	How willing are you to punish someone who treats others unfairly, even if there may be costs for you?	The response from 0 to 10, rescaled to take a value between 0 and 1, measures degree of indirect negative reciprocity.

Time preferences are captured by two separate items: impatience (willingness to give up a reward now in order to reap a larger reward in the future) and procrastination (tendency to postpone tasks even if knowing that it would be better to do them right away). Social preferences comprise five different items: altruism (willingness to give to good causes without expecting anything in return), trust (tendency to believe in general that people intend well), positive reciprocity (willingness to return favors), negative reciprocity (willingness to punish or take revenge if treated unfairly or unjustly), and indirect negative reciprocity (willingness to punish for unfair or unjust treatment of others).

4.4. Climate Change and Environmental Attitudes, and Other Variables

We furthermore measure various climate-related and environmental variables that are expected to play a role in participants' WTP for climate change mitigation. All variables were measured as the degree to which participants agreed or disagreed with different statements on a scale from 0 to 6, where 0 indicated "strongly disagree" and 6 indicated "strongly agree". Table 2 summarizes the questionnaire items, and the item-composition and encoding of the variables. The variables concern measurements of (i) knowledge of and agreement with the scientific consensus on climate change, using a questionnaire constructed based on the OECD's survey on international attitudes towards climate policies (Dechezleprêtre et al., 2025), (ii) pro-environmental worldview, which is composed of an eco-centrism questionnaire (Thompson & Barton 1994; Broomell et al., 2015) and a short version of the new-ecological paradigm questionnaire (Ziegler, 2021), (iii) perceived personal experience of climate change (Thompson & Barton 1994; Broomell et al., 2015), (iv) sense of responsibility for environmental problems, using a questionnaire developed by Edenbrandt et al. (2021) and adapting the original climate change framing to environmental problems more generally, and (v) perception of self-efficacy (Thompson & Barton 1994; Broomell et al., 2015).

4.5. Demographic Variables

Table 3 summarizes our demographic variables. The details of the demographic questions are provided in the Online Appendix. Our data comprise participants' age, gender, employment status, education, and income. For gender, 13 out of 801 participants chose "other" or preferred not to reveal. As the proportion of such participants is small (1.6%), we do not encode them as a separate category. Majorities in our sample are young (34 years of age or younger), working in a full-time job or enrolled as a student, educated (having or pursuing at least an undergraduate degree), and with income of less than 50K per annum. Gender split in our sample is even. We also ask participants' marriage status and whether or not they have children. 15.11% of our participants are married, and 31.71% have children. Finally, we use participants' IP addresses to construct a proxy variable of their country of residence.

Table 2. Summary of Climate and Environmental Variables Questionnaire

Measured Variable	Items
Knowledge of & agreement with the scientific consensus on CC	• Climate change is happening. • The current climate change is caused mainly by human activities. • Climate change will bring about some serious negative consequences. • Emissions of CO_2 contribute to climate change. • Electricity generated by nuclear power produces more climate-warming gases than electricity generated by coal or natural gas.* • For a family of four traveling 1000km, taking the airplane produces more climate-warming gases than taking the train. • A beef dish produces more climate-warming gases than a pasta dish.
Pro-environmental worldview	• Nature is valuable for its own sake. • If things continue on their present course, we will soon experience a major ecological catastrophe. • Humans are severely abusing the planet. • I need time in nature to be happy. • Nature is strong enough to cope with the impacts of modern industrial nations.* • It makes me sad to see natural environments destroyed. • The balance of nature is very delicate and easily upset. • Humans are as much a part of the ecosystem as other animals.
Perceived personal experience of CC	• I have already noticed some signs of climate change. • Climate change has already impacted my life.
Sense of responsibility for environmental problems	• Because my personal contribution is very small I do not feel responsible for environmental problems.* • I feel co-responsible for environmental problems because I contribute to them through my choices. • I feel moral obligation to change my behavior to reduce environmental problems. • I do not have a responsibility to change my behavior to reduce environmental problems if other people do not.*
Perceived self-efficacy	• There are things that we can do that will have a meaningful effect to alleviate the negative effects of climate change. • Even if we try to do something about global warming, I doubt if it will make any difference.* • There is very little we can do to mitigate the negative effect of global warming.*

Notes: Items marked with "*" are reverse-coded. Throughout, the individual item responses from 0 to 6 are rescaled to take values between 0 and 1, then averaged across items to have an index measure of the relevant variable.

Table 3. Summary of Demographic Variables

Variable		N=801
Age		
	18-24 (=1)	37.45%
	25-34 (=2)	45.44%
	35-44 (=3)	10.24%
	45-54 (=4)	4.12%
	55 or older (=5)	2.75%
Female (Yes=1, No=0)		49.06%
Employment status		
	Full-time (Yes=1, No=0)	49.81%
	Student (Yes=1, No=0)	25.84%
	Other	24.35%
Highest level of education		
	Graduate (Yes=1, No=0)	19.85%
	Undergraduate (Yes=1, No=0)	45.94%
	Less than undergraduate	34.21%
Annual Income		
	≥ €50K (Yes=1, No=0)	17.85%
	€25K-€49.99K (Yes=1, No=0)	31.09%
	No response (Yes=1, No=0)	8.99%
	< €25K	42.07%
Married (Yes=1, No=0)		15.11%
Children (Yes=1, No=0)		31.71%
Nationality		
	European (Yes=1, No=0)	60.18%
Country of residence		
	OECD (Yes=1, No=0)	69.41%

5. Empirical Findings

In the following subsections, we present our empirical findings on ambiguity attitudes and WTP for reducing CO2 emissions. Further results and descriptive statistics on other variables are provided in the Online Appendix.

5.1. Matching Probabilities and Ambiguity Attitudes

Elicited matching probabilities and data quality. Table 4 reports the descriptive statistics of the elicited matching probabilities for the two sources of ambiguity. The matching probabilities display plausible properties, attesting to the quality of the data. Firstly, Table 4 shows that, for both the climate and Ellsberg ambiguities, single event matching probabilities $m(E_1)$, $m(E_2)$, and $m(E_3)$ tend to be smaller than the composite event matching probabilities $m(\bar{E}_1)$, $m(\bar{E}_2)$, and $m(\bar{E}_3)$. Specifically, set monotonicity implies $m(E_i) \leq m(E_i \cup E_j)$ for $i, j \in \{1,2,3\}$. Given that our data comprise matching probabilities for three single and three composite events, we were able to conduct 6 tests of monotonicity per participant. In our data, the number of monotonicity violations does not exceed 1 for 80% (climate ambiguity) and 92% (Ellsberg ambiguity) of the participants. The average numbers of monotonicity violations per participant are 0.72 (out of 6) and 0.30 (out of 6) for the climate and Ellsberg sources of ambiguity, respectively. These proportions of monotonicity violations are comparable to the inconsistency rates observed in other studies of ambiguity attitudes and reassuring for the quality of our data, which can often be a concern for studies conducted online.[8]

Table 4. Elicited Matching Probabilities

	Climate Source			Ellsberg Source		
	Mean	Median	IQR	Mean	Median	IQR
$m(E_1)$	0.36	0.36	[0.16, 0.48]	0.37	0.32	[0.28, 0.48]
$m(E_2)$	0.42	0.40	[0.24, 0.56]	0.38	0.32	[0.28, 0.48]
$m(E_3)$	0.46	0.48	[0.28, 0.60]	0.38	0.32	[0.28, 0.48]
$m(\bar{E}_1)$	0.67	0.68	[0.52, 0.88]	0.59	0.64	[0.48, 0.68]
$m(\bar{E}_2)$	0.60	0.60	[0.48, 0.76]	0.59	0.64	[0.48, 0.68]
$m(\bar{E}_3)$	0.58	0.60	[0.48, 0.76]	0.59	0.64	[0.48, 0.68]

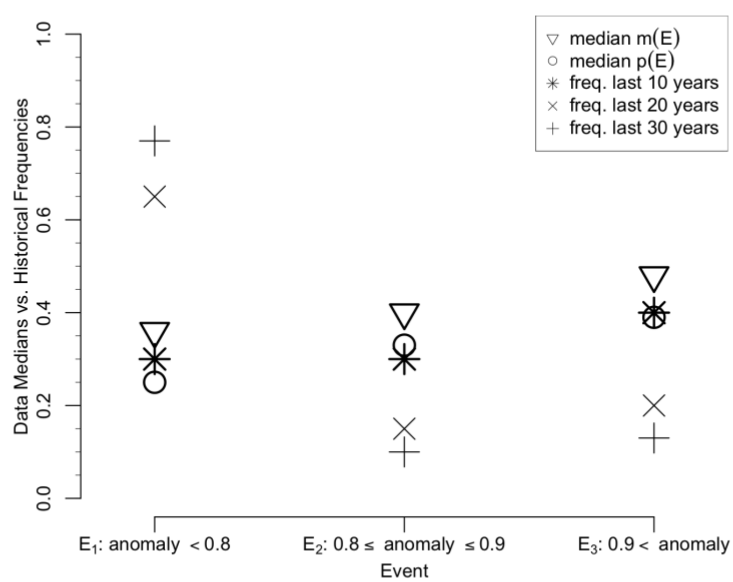
A second observation to note from Table 4 is that the matching probabilities for the Ellsberg events E_1, E_2 and E_3 do not differ from each other (Friedman test, p=0.682), whereas the matching probabilities of the climate events E_1, E_2 and E_3 do differ from each other (Friedman test, p<0.001). A symmetry in beliefs between Ellsberg events is natural, since the participants have no reasons to believe that any one color is more likely to be drawn than any other single color. The absence of symmetry between climate events is also plausible. In

[8] For instance, Baillon et al.'s (2018b) laboratory study with student participants, also involving natural sources of ambiguity, reported an average violation between 0.30 and 0.54 (out of 6). A similar laboratory study by Baillon et al. (2018a) indicated that 12% to 19% of student participants violated the neo-additive model at various stages of the experiment, which suggests that 81% to 88% of the participants did not severely violate monotonicity. Dimmock et al.'s (2016) online experiment with general population showed violation rates of 19.7% and 34.1% in consistency checks.

particular, the participants in our experiment judge the event E_3 (global temperature anomaly in June 2023 being more than +0.9ºC) to be more likely than the other events E_1 and E_2 (Sign-test, p<0.001 for both), indicating stronger subjective beliefs for larger temperature anomalies in June 2023.

To further examine the calibration of our elicitations in the climate context, Figure 3 confronts the elicited matching probabilities $m(E_i)$ and subjective probabilities $p(E_i)$ estimated from thereof (as described in Section 3) to historical frequencies of the climate anomaly events. We observe that both matching and subjective probabilities, reflecting the participants' asymmetric beliefs about the likelihoods of the three events, are very well aligned with the historical frequencies of these events over the last 10 years. As climate change is a trend phenomenon, it is natural that more recently observed frequencies should play a bigger role in belief formation.

Figure 3. Climate event matching probabilities, subjective probabilities, and frequencies



Notes: The historical frequencies are computed from time series of June global temperature anomalies over the period 1850-2023. Data: https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series.

Neo-EU preferences and ambiguity aversion. Table 5 presents the results of the estimated ambiguity perception δ and optimism α parameters of the neo-EU model and the resulting ambiguity aversion index value $\delta(1-2\alpha)$. The data indicate that the median participant in our sample has $\delta > 0$ for both climate and Ellsberg ambiguities (one-sided binomial test, p<0.001 for both sources), and thus EU is clearly violated due to ambiguity perception under both sources of uncertainty. The levels of perceived ambiguity are not different between the two sources (two-sided sign-test, p=0.37). However, participants display different levels of optimism/pessimism under climate vs. Ellsberg ambiguities.

Table 5. Ambiguity preferences under neo-EU

	Climate Source			Ellsberg Source		
	Mean	Median	IQR	Mean	Median	IQR
δ (perceived ambiguity)	0.41	0.36	[0.16, 0.64]	0.42	0.40	[0.11, 0.68]
α (optimism)	0.54	0.53	[0.26, 0.89]	0.44	0.47	[0.10, 0.70]
$\delta(1-2\alpha)$ (ambiguity aversion)	-0.03	-0.02	[-0.17, 0.11]	0.04	0.02	[-0.09, 0.20]

The median participant displays optimism with $\alpha > 0.5$ under climate ambiguity (two-sided sign-test, p<0.01), whereas for Ellsberg ambiguity the median participant displays pessimism with $\alpha < 0.5$ (p<0.001). We consequently observe a negative median value for the ambiguity aversion index under the climate source, indicating ambiguity seeking in that context but a positive index value for the Ellsberg source, indicating ambiguity aversion. A comparison of the two sources confirms significantly less ambiguity aversion under climate ambiguity than under Ellsberg ambiguity (two-sided sign-test, p<0.001). Notably, while the observed aversion toward Ellsberg-type artificial ambiguity in our experiment replicates the common findings in the literature, our finding of no ambiguity aversion toward the climate source is also consistent with other recent studies measuring ambiguity attitudes under various natural sources of uncertainty (e.g., see Li et al., 2018; Li et al., 2020). We summarize these findings as follows.

Result 1. *When probabilities of uncertain events are not known, EU is violated due to ambiguity perception. The natural climate source of uncertainty induces as much ambiguity perception as the commonly studied artificial Ellsberg source. Furthermore, there is significantly less ambiguity aversion toward natural ambiguity than toward artificial ambiguity.*

Determinants of ambiguity aversion. Having shown source dependence in our ambiguity aversion measures, we next explore furthermore these attitudes by examining their covariates.

For this, we run OLS regressions of the ambiguity aversion indexes measured as $\delta(1-2\alpha)$ in the climate and Ellsberg sources over other economic preferences, environmental attitudes and demographic variables.

Table 6. OLS Regressions of the Ambiguity Aversion Indexes

	Climate Source	Ellsberg Source
Risk Aversion	0.050	**0.128****
Trust	0.052	-0.057
Altruism	-0.051	**-0.126****
Impatience	-0.010	0.033
Procrastination	0.014	-0.049
Positive reciprocity	0.024	0.072
Negative reciprocity	-0.037	-0.035
Indirect negative reciprocity	0.026	0.025
Knowledge & agreement with scientific consensus on CC	**0.259****	0.201*
Perceived personal experience with CC	**-0.144****	-0.036
Pro-environmental worldview	-0.090	-0.018
Perceived sense of responsibility	0.060	-0.037
Perceived self-efficacy	-0.037	0.099
Age	**0.046*****	0.022
Female	-0.028	**-0.049****
Full-time employed	0.011	0.016
Student	-0.001	0.044
Residence in OECD	0.005	0.035
Married	-0.012	0.042
Children	-0.007	-0.015
Highest level of education (joint p-value)	0.286	0.487
Level of income (joint p-value)	0.188	0.230
Constant	-0.168	-0.140
N	801	801
Adjusted R-squared	0.035	0.049

Notes. The variables of economic preferences are defined in Table 2. Demographic variables are defined in Table 3. The education controls are two dummy variables, where the base category is less than undergraduate degree. The income controls are three dummy variables, where the base category is an annual income level less than €25K. The table reports the p-value of the joint hypothesis tests of the dummy variables of education and income.
*** p<0.01, ** p<0.05, *p<0.1

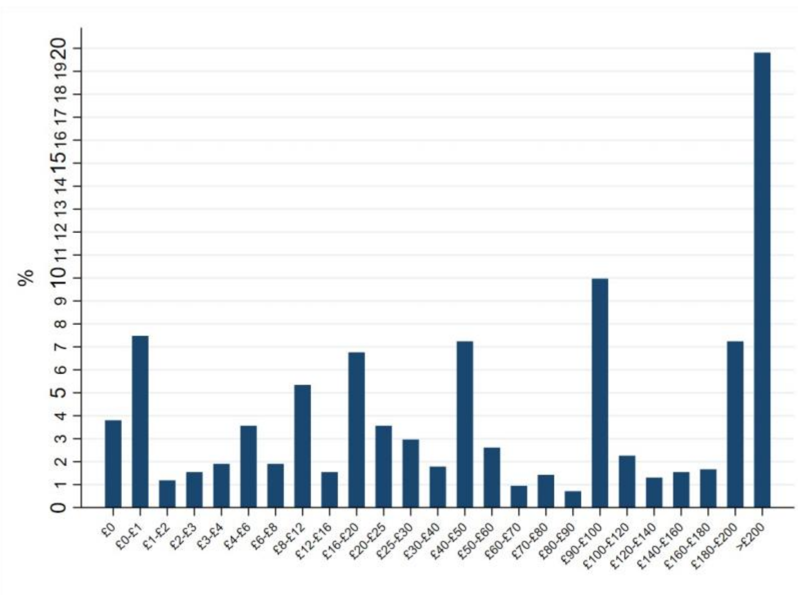
Table 6 presents the results. In the first column, the regression for the climate-ambiguity aversion indicates mainly the effects of climate-change related variables. In particular, we find that ambiguity aversion towards the climate source is increasing in knowledge about and agreement with climate change and decreasing in perceived personal experience with effects of climate change. We find no significant effect of other economic preferences on climate-ambiguity aversion. Among the demographic variables, we only find that older participants have higher climate-ambiguity aversion than younger ones. Turning to the regression for the Ellsberg-ambiguity aversion in the second column, in contrast with climate-ambiguity, we observe some effects of other economic preference variables, such as risk aversion and altruism. Unlike the climate source, ambiguity aversion under Ellsberg does not correlate with perceived experience with climate change and age but with the gender of the participant. These findings corroborate the previous result on differences between ambiguity aversion across climate and Ellsberg sources.

5.2. Willingness to Pay to Reduce CO2 Emissions

Next, we turn to our measurements of WTP to reduce CO2 emissions. Figure 4 shows the distribution of WTP to reduce 1 metric ton of CO2 in our sample. Our choice list design provides us with interval estimates of the WTP measure based on the switching points on the list. Accordingly, the median participant in our sample has a WTP measure between £40 and £50. As can be seen in Figure 4, the modal choice indicates a WTP higher than £200. Specifically, almost 20% of the participants always prefer reducing CO2 emissions even when they were offered £200. This is consistent with Diederich and Goeschl (2014), who found around 17% of participants having a WTP at the upper bound of their choice list. Another common choice in our data is switching from reducing CO2 to the money amount between £90 and £100 (10.24%), which indicates a willingness to pay up to half of the maximum payoff possible. Next, a total of 11.61% of the participants have a maximum WTP of £1. These participants either never choose to reduce CO2 (even when the amount of money is £0) or they switch to choosing the monetary gain at £1.

A common way to analyze choice list data is to use the midpoints of the intervals implied by the switching points as proxies of the measures of interest. Accordingly, for a participant who switches from CO2 reduction to monetary gain at line i on the list, we take $\text{WTP}_{mid} = \frac{\text{£WTP}_{i-1}+\text{£WTP}_i}{2}$ as a proxy of her WTP. For participants who never choose reducing CO2, we have WTP=0. For participants who never switch from reducing CO2 to monetary gain (implying $WTP > 200$), we take $\text{WTP} = 210$ by extrapolation while maintaining the same step size at end of the list. The midpoint estimates thus result in a (conservative) mean WTP of £85.31 in our data. This estimate is close to €94 documented in the study of Alberini et al. (2018) conducted with Czech participants although there is a large variability in estimations of WTP to reduce CO2 in the literature depending on the estimation methods utilized (see a summary of the literature in appendix A of Alberini et al. (2018)).

Figure 4. Distribution of WTP to Reduce CO2 Emissions



5.3. WTP to Reduce CO2 Emissions and Ambiguity Preferences

We next investigate the relationship between WTP to reduce CO2 emissions and ambiguity preferences. Based on the theoretical results presented in Section 2, we empirically test the following two key hypotheses:

H1: *A neo-EU maximizer who perceives climate ambiguity has a lower WTP than an EU maximizer, and ambiguity perception decreases WTP to reduce CO2 emissions.*

H2: *Climate ambiguity aversion decreases WTP to reduce CO2 emissions.*

The first hypothesis follows from proposition 2 in Section 2, focusing on the impact of ambiguity perception (i.e., δ) on self-protection against climate risks. Accordingly, we expect a negative correlation between the WTP measures and the perception parameter δ obtained through matching probability elicitations. The second hypothesis follows from proposition 3 indicating a negative relationship between pessimism (i.e., lower α) and WTP for mitigation, provided that there is ambiguity perception (i.e., $\delta > 0$). Hence, ambiguity aversion, measured by $\delta(1-2\alpha)$ is expected to correlate negatively with WTP to reduce CO2 emissions.

We test our hypotheses by estimating the following econometric model, where the dependent variable is the natural logarithm of the WTP measures. We take $\ln(1+\text{WTP})$ to avoid natural logarithm of zero.

$$\begin{gathered}\ln(1+\text{WTP}) = \beta_0 + \beta_1\delta + \beta_2\delta(1-2\alpha) \\ +\gamma_1 Controls_{EconomicPreferences} \\ +\gamma_2 Controls_{EnvironmentalAttitudes} \\ +\gamma_3 Controls_{Demographics} + \varepsilon.\end{gathered}$$

We expect to observe $\beta_1 < 0$ based on H1 and $\beta_2 < 0$ based on H2. To take into account the interval measures of WTP in our choice list design, we run an interval regression to estimate the model. We furthermore test the robustness of our analysis in Appendix C by running OLS regressions of the midpoint estimates of the WTP measures, which show the same results.

Table 7 presents the results. The first column presents the estimations with the ambiguity parameters obtained under the climate source. Consistent with H2, we find that climate ambiguity aversion decreases WTP to reduce CO2 emissions (p=0.04). The coefficient of the ambiguity perception parameter δ is also negative in line with H1, but it is not significant (p=0.60). This result implies that the effect of ambiguity perception is not significant when $1-2\alpha = 0$, i.e., under ambiguity neutrality. To examine the effect of ambiguity perception for different levels of aversion per unit of perceived ambiguity (i.e., $1-2\alpha$), we compute the average marginal effects of δ for different levels of $(1-2\alpha) > 0$. Figure 5 shows this. We find that the adverse effect of climate ambiguity perception is more pronounced for higher levels of ambiguity aversion (per unit of perceived ambiguity), with the effect becoming significantly negative at 10% when $1-2\alpha > 0.6$.

To furthermore calculate the effect of ambiguity, we compute the estimated differences between the WTP of an EU maximizer and that of an ambiguity-averse neo-EU maximizer, as suggested by H1, for different levels of ambiguity aversion. Table 8 presents the results. As can be observed, the differences between EU and neo-EU individuals are statistically and economically significant at various levels of ambiguity aversion. In the most extreme case, we estimate that a neo-EU maximizer with maximum degree of overall ambiguity aversion (i.e., $\delta(1-2\alpha)$=1) is willing to pay 54% less to reduce 1 metric ton of CO_2 compared to an EU maximizer (p=0.004). We summarize these findings as follows.

Result 2. *Ambiguity aversion decreases WTP for mitigation. Compared to the WTP of an ambiguity-neutral EU maximizer, the WTP of a non-EU decision-maker who is climate-ambiguity averse is significantly lower, with ambiguity aversion resulting in differences in WTP of up to 54%.*

Finally, we look at the results when Ellsberg ambiguity parameters are used in the estimations (second column in Table 7). We find that, contrary to the parameters of climate ambiguity, participants' ambiguity preferences obtained under the Ellsberg source do not show any significant effects explaining their WTP for mitigation (p=0.44 and p=0.53 for ambiguity perception and aversion, respectively). This latter result is summarized as follows.

Result 3. *In contrast with the ambiguity measures obtained in the climate context, the ambiguity measures obtained in the Ellsberg setting do not correlate with the measures of WTP to reduce 1 metric ton of CO_2 emissions.*

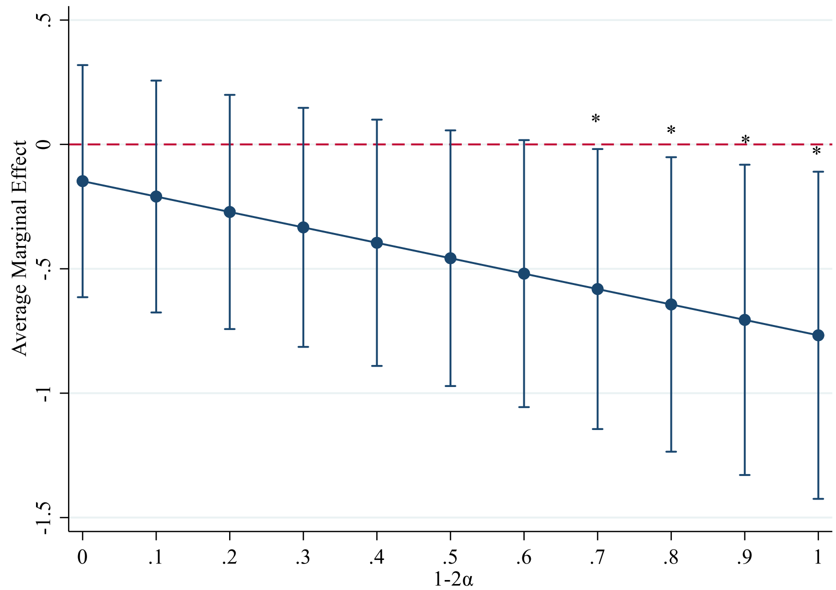
Other covariates of WTP to reduce CO_2 emissions. Our regression analysis points to several other significant covariates of WTP for CO_2 emissions reduction. Besides ambiguity aversion, our data show that economic preferences relating to participants' risk aversion, altruism, and negative reciprocity play a role. We find that risk aversion and altruism correlate positively with WTP for mitigation, whereas negative reciprocity correlates negatively with WTP. Among frequently cited variables capturing participants' climate and environmental attitudes, we observe positive correlations of WTP measures with participants' perceived personal sense of responsibility for environmental problems in general and their knowledge and agreement with the scientific consensus on climate change. Lastly, turning to our demographic variables, older participants and participants residing in OECD countries have larger WTP to reduce CO2 emissions.

Table 7. Interval Regressions of WTP to Reduce CO2 Emissions

	Climate Ambiguity	Ellsberg Ambiguity
Perceived ambiguity (δ)	-0.148	0.191
Ambiguity aversion ($\delta \times (1-2\alpha)$)	**-0.620****	-0.168
Risk Aversion	**0.802****	**0.819****
Trust	0.185	0.161
Altruism	**0.987****	**0.982****
Impatience	-0.500	-0.481
Procrastination	-0.059	-0.081
Positive reciprocity	-0.414	-0.413
Negative reciprocity	**-0.884****	**-0.837****
Indirect negative reciprocity	0.576	0.534
Knowledge & agreement with scientific consensus on CC	1.423*	1.371*
Perceived personal experience with CC	0.621	0.666
Pro-environmental worldview	-1.269	-1.238
Perceived sense of responsibility	**2.227*****	**2.200*****
Perceived self-efficacy	0.587	0.647
Age	0.173*	0.147
Female	-0.138	-0.144
Full-time employed	0.208	0.200
Student	0.033	0.042
Residence in OECD	**0.790*****	**0.854*****
Married	-0.300	-0.276
Children	0.237	0.241
Highest level of education (joint p-value)	0.843	0.816
Level of income (joint p-value)	0.975	0.957
Constant	-0.057	-0.189
N	801	801

Notes: The variables of economic preferences are defined in Table 1, climate and environmental variables in Table 2. Demographic variables are described Table 3. The education controls are two dummy variables, where the base category is less than undergraduate degree. The income controls are three dummy variables, where the base category is an annual income level less than €25K. The table reports the p-value of the joint hypothesis tests of the dummy variables of education and income.
*** p<0.01, ** p<0.05, *p<0.1

Figure 5. Average Marginal Effects of Climate δ with 90% CI



Notes: *** p<0.01, ** p<0.05, *p<0.1

Table 8. Comparison of WTP under neo-EU and SEU

Ambiguity aversion ($\delta(1-2\alpha)$)	Perceived ambiguity (δ)	Ambiguity aversion per unit of perceived ambiguity ($1-2\alpha$)	Estimated % difference from WTP of an SEU maximizer	p-value
0	0	0	0%	-
0	1	0	-14%	0.575
0.25	0.25	1	-17%	0.034
0.25	0.5	0.5	-20%	0.099
0.25	1	0.25	-26%	0.221
0.5	0.5	1	-32%	0.019
0.5	1	0.5	-37%	0.063
0.75	0.75	1	-44%	0.009
0.75	1	0.75	-46%	0.016
1	1	1	-54%	0.004

6. Discussion in Relation to Literature

Ambiguity and climate risk management. Previous research in climate risk management provides estimations of optimal levels of mitigation (or of taxation to be levied on CO2 emissions) under ambiguity aversion in application of ambiguity theories with normative underpinnings, such as the smooth ambiguity model of Klibanoff et al. (2005) or the robust control theory of Hansen & Sargent (2001, 2008) (e.g., Lange & Treich 2008; Millner et al., 2013; Lemoine & Traeger, 2014; Drouet et al., 2015; Berger et al., 2017; Rudik 2020). Our study complements the existing research by measuring people's climate-ambiguity attitudes and estimating their effect on their valuation of climate mitigation.

While much emphasis in the previous applications of ambiguity theories to climate risk management has been put on the phenomenon of ambiguity aversion, our study also points to the role of a lesser known (though empirically well-documented) component of ambiguity attitudes, which is likelihood insensitivity generated by ambiguity perception (e.g., Tversky & Fox 1995; Abdellaoui et al., 2011; for a review of empirical findings, see Trautmann & van de Kuilen, 2015). Likelihood insensitivity implies that ambiguity aversion is in fact not a universal phenomenon but that ambiguity seeking also exists for events with small likelihoods (see also Kocher et al., 2018). Our theoretical and empirical results on ambiguity perception under the neo-EU model reveal the critical role that such a-insensitivity—together and beyond ambiguity aversion—can play in understanding climate risk management decisions.

Our analysis provides an important novel insight into climate mitigation under ambiguity aversion by pointing out a potential discrepancy between different approaches to ambiguity in self-protection decisions. Previous studies with numerical models commonly argue that ambiguity aversion increases optimal levels of mitigation effort (e.g., see Berger et al. 2017) and of optimal tax on CO2 emissions (e.g., see Lemoine & Traeger 2014). On the contrary, our results indicate that ambiguity aversion lowers individuals' willingness to pay for emissions reduction. This suggests that ambiguity can produce a potentially significant difference between the prescribed and the publicly acceptable levels of mitigation. Even if the precautionary principle in environmental risk management dictates stricter climate policies because of the presence of ambiguity, the public may disapprove of those policies. This discrepancy in impact of ambiguity stems from the differences in modelling of ambiguity attitudes in mitigation or, more generally, in self-protection decisions. For example, Snow (2011) and Alary et al. (2013)

also provide a theoretical analysis of self-protection under ambiguity aversion without considering likelihood insensitivity and find that ambiguity aversion increases self-protection efforts. In contrast, and closer to our study, the recent work of Baillon et al. (2022) focus on the role of likelihood insensitivity in self-protection efforts in the health context. Their theoretical analysis demonstrates similar results as ours with neo-additive weighting functions, where pessimism decreases self-protection efforts in the presence of likelihood insensitivity (see their proposition 4). A similar application in the health domain is also presented in Bleichrodt & Eeckhoudt (2006).

An important implication of the aforementioned insight driven from our results concerns the critical role of communication of climate policies and climate-related uncertainties to the public. The adverse effect of ambiguity aversion on individuals' willingness to pay for emissions reduction points to the importance of effective communication strategies for reducing the public's perception of ambiguity and thereby potentially encouraging more public engagement in climate action. Research into determinants of the general public's acceptance of climate mitigation policies has been increasingly showing that potentially by far the most important factors determining people's reactions to proposed climate policies are their perceptions (i.e., subjective beliefs) of the impacts of those policies on emissions and on welfare (e.g., Douenne & Fabre, 2022; Dechezleprêtre et al., 2025; for a review, see Bergquist et al., 2022). At the same time, this research suggests that the general public's perceptions of climate policy impacts are often incorrect or uncertain. Our findings call for more research on the topic of belief formation about climate policy impacts, and in particular, on both the perceived levels of ambiguity associated with those beliefs, as well as communication strategies that can help reduce ambiguity.

Economic preferences as determinants of pro-environmental behavior. Understanding better the drivers of pro-environmental behavior is key to designing effective public policies. Among behavioral sciences, environmental psychology, in particular, has produced a large literature on this topic. In economics, a recently growing literature has begun to investigate the determining role of economic preferences in pro-environmental behavior. For example, risk aversion has been shown to correlate negatively with household energy expenditures on the one hand, yet also negatively with investments in energy efficiency (Volland, 2017; Schleich et al. 2019;

Fischbacher et al., 2021). Pro-social preferences such as altruism (Fuhrmann-Riebel et al., 2021; Lades et al. 2022) and trust (Volland, 2017; Fuhrmann-Riebel et al., 2021) correlate positively with energy-saving or everyday pro-environmental behaviors. Time preferences have also been investigated, and patience (low time discounting) has been shown to correlate negatively with electricity consumption (Groh & Ziegler 2022) and positively with adoption of energy efficient technologies (Schleich et al., 2019).

Ambiguity preferences in the context of pro-environmental behavior have as yet been studied rarely. Among previous studies, Fuhrmann-Riebel et al. (2021) and Watanabe & Fujimi (2022) investigate the effect of ambiguity attitudes on pro-environmental and climate change behaviors. Fuhrmann-Riebel et al. (2021) report that ambiguity aversion, measured in an Ellsberg setting, correlates negatively with monthly electricity consumption, and positively with sustainable plastic consumption. Closer to our study, Watanabe & Fujimi (2022) also measure experimentally ambiguity attitudes in the climate context and investigate the link with willingness to pay for different mitigation policies by estimating a structural model. Differently from our study, they use the smooth ambiguity model of Klibanoff et al. (2005), and their experiment entails hypothetical choice questions concerning different probabilistic predictions of global temperature increases by 2100. Consistent with our results, they document ambiguity seeking (rather than aversion) prevailing in the climate context, and that individuals with ambiguity seeking attitudes tend to support aggressive mitigation policies more strongly.

Despite the growing research on correlations between individuals' economic preferences and their tendencies to engage in different pro-environmental behaviors, decision-theoretical and behavioral theoretical frameworks to make concrete predictions about the effects of the different economic preferences are still lacking in the literature. Moreover, for better understanding the role of economic preferences, more research providing a unified empirical model structuring the various correlational findings is needed. Our study attempts to contribute in both of these directions. Our theoretical analysis with a particular focus on the role of ambiguity preferences suggests that certain classes of pro-environmental behaviors might be modelled as (environmental) risk management problems. While the focus of our study concerned ambiguity attitudes, our empirical model ties to existing body of evidence by also including other economic preferences as covariates. Thus, we are able to extend existing findings by documenting a positive correlation of risk aversion and altruism also with WTP for emissions reduction (in addition to energy-conservation or other everyday pro-environmental behaviors). We also find that WTP for emissions reduction correlates negatively with negative reciprocity but does not correlate with time preferences.

Ambiguity aversion under natural sources of uncertainty. Despite still being relatively few in number, our study is not the first to apply state-of-the-art methods of ambiguity measurements in natural contexts, going beyond Ellsberg's original paradigm. Interestingly, these studies in natural contexts tend to show that ambiguity aversion may not be as common as had been found in studies relying on artificial sources of ambiguity. For example, as mentioned above, Watanabe & Fujimi (2022) find ambiguity seeking in the climate context. Li et al. (2020) compare attitudes towards (naturally occurring) social and strategic ambiguities with attitudes under artificial Ellsberg-urn ambiguity, finding the usual ambiguity aversion for Ellsberg-urn ambiguity but no aversion towards the natural sources. In an experiment involving various natural and artificial sources of ambiguity, using both real incentives and hypothetical choice, Li et al. (2018) conclude that ambiguity attitudes are closer to neutrality for natural uncertainties than for artificial Ellsberg-urn uncertainties. More recently, Watanabe & Fujimi (2024) and Anantanasuwong et al. (2024) find ambiguity aversion on average for natural sources, with Anantanasuwong et al. (2024) pointing out that a sizeable (40%) fraction of the participants display ambiguity seeking or neutrality. Furthermore, virtually all of the studies using natural sources of ambiguity point to the greater empirical significance, as well as more source-dependent variability, of the second component of ambiguity attitude, namely, a-insensitivity. Our study adds new evidence to this literature, coming from a novel natural source of ambiguity, and corroborates the observation that ambiguity aversion may not be as common for natural sources of ambiguity as found for artificial Ellsberg-urn ambiguities, and that ambiguity perception may be an equally (if not more) important parameter.

Finally, our study shows that for understanding and predicting field behaviors under ambiguity, it may be better to use non-artificial sources of ambiguity that are directly relevant to the behaviors being studied. Indeed, we find a link between individuals' ambiguity attitudes and their WTP for mitigation, but only when using the natural climate-relevant source of ambiguity and not for ambiguity measures using the artificial source. This result adds up to other existing evidence in the literature. Watanabe & Fujimi (2024) found that context-relevant, natural ambiguity attitudes were linked to flood preparedness of Japanese residents living in an area with heavy exposure to flood risks, but attitudes towards an artificial ambiguity are not. In a different context, Li et al. (2019) showed that attitudes towards ambiguity about others' trustworthiness were relevant for people's decisions to trust others, even if the previous literature (e.g., Eckel & Wilson, 2004) had not found a clear link between context-independent risk attitudes and trust behaviors. In finance, Anantanasuwong et al. (2024) found that investors' ambiguity attitudes towards investment-relevant ambiguities were linked to their actual portfolio choices, but studies using artificial sources of ambiguity (e.g., Dimmock et al., 2016; Bianchi & Tallon, 2019; Kostopoulos et al., 2022) have also found that ambiguity matters for investment behaviors. An open empirical question for future research is to investigate further the source dependence of ambiguity preferences, by examining their links across different sources as well as with different field behaviors.

7. Conclusion

This study provided an experimental measurement of ambiguity attitudes in the climate change context and examined its link to climate mitigation. We showed that climate ambiguity attitudes are distinct from ambiguity attitudes observed in the commonly studied Ellsberg setting, and contrary to normative arguments supporting stricter climate policies, ambiguity may decrease, rather than increase individuals' motivation to act against climate change. The results point to a potential ambiguity-driven discrepancy between optimal and acceptable levels of climate action, underscoring the importance of communication for climate risk management in business and policymaking.

Appendix A. Proofs of Propositions

Proof of Proposition 1. We consider a more risk averse decision maker, whose utility $v(.)$ is represented by a concave transformation of u: $v = \varphi(u(.))$ where $\varphi' > 0$ and $\varphi'' < 0$. By replacing $u(.)$ with $v = \varphi(u(.))$ in $WTP_{EU} = \frac{u(w_0)-u(w_0-l)}{p_0 u'(w_0)+(1-p_0)u'(w_0-l)}$, we obtain

$$WTP_{EU}^{\varphi} = \frac{\varphi(u(w_0))-\varphi(u(w_0-l))}{p\varphi'(u(w_0))u'(w_0)+(1-p)\varphi'(u(w_0-l))u'(w_0-l)}.$$

To see that the effect of enhanced risk aversion is indeterminate, we observe the following:

i. When $\varphi' > 1$ ($\varphi' < 1$) everywhere in the interval $[u(w_0 - l), u(w_0)]$, both the denominator and the nominator of WTP_{EU}^{φ} is greater (smaller) than those of WTP_{EU}. Therefore, the direction of change is unclear.

ii. When $\varphi' > 1$ at $u(w_0 - l)$ and $\varphi' < 1$ at $u(w_0)$, it is not possible to tell (without further assumptions) the changes in both the nominator and denominator.

Proof of Proposition 2. First, to show that $WTP_{neo-EU} < WTP_{EU}$, we observe $\frac{1}{WTP_{neo-EU}} > \frac{1}{WTP_{EU}}$ when $\delta > 0$.

$$\frac{1}{WTP_{neo-EU}} = \frac{(1-\delta)[p_0 u'(w_0) + (1-p_0)u'(w_0 - l)] + \delta[\alpha u'(w_0) + (1-\alpha)u'(w_0 - l)]}{(1-\delta)[u(w_0) - u(w_0 - l)]}$$

$$= \frac{p_0 u'(w_0) + (1-p_0)u'(w_0 - l)}{u(w_0) - u(w_0 - l)} + \frac{\delta[\alpha u'(w_0) + (1-\alpha)u'(w_0 - l)]}{(1-\delta)[u(w_0) - u(w_0 - l)]}$$

$$= \frac{1}{WTP_{EU}} + \frac{\delta}{1-\delta} \times \frac{\alpha u'(w_0) + (1-\alpha)u'(w_0 - l)}{u(w_0) - u(w_0 - l)}.$$

As the second term is positive when $\delta > 0$, we have $\frac{1}{WTP_{neo-EU}} > \frac{1}{WTP_{EU}}$.

To see that WTP_{neo-EU} is decreasing in δ, we observe that $\frac{1}{WTP_{neo-EU}}$ is increasing in δ due to the second term above.

Proof of Proposition 3. The proposition states that WTP_{neo-EU} is decreasing in pessimism (lower α), which is equivalent to increasing WTP_{neo-EU} with respect to optimism (higher α). To see this, we observe that $\frac{1}{WTP_{neo-EU}}$ above is decreasing in α, which follows from $u'(w_o) < u'(w_0 - l)$ due to concavity of u. ■

Appendix B. Details of the Bisection Procedure

A bisection procedure for eliciting the matching probability of an event E entails a series of binary choices between $£15_E0$ and $£15_p0$, where p is an objective probability adjusted iteratively until convergence to indifference. In our study, the elicitation process for single climate or Ellsberg events (E_i) started with $p = 34\%$, which is adjusted upwards or downwards after every choice. Here, the initial increments were 16% if the first adjustment was downwards and 32% if it was upwards. The increments are then halved each time until reaching an increment size of $\mp 2\%$, resulting in a precision of 4% while determining final indifference points. The process for composite events (e.g. $E_i \cup E_j$) started with $p = 66\%$ and followed symmetrically.

Appendix C. OLS Regressions of the Mid-point Estimates of WTP Measures

In this appendix, we replicate our regression analysis by using the OLS method applied to the mid-point estimates of the WTP measures, encoded as described in section 5.2. Table C1 reports the results. Our conclusions also hold in OLS regression. Climate-ambiguity aversion is still found to decrease WTP to reduce CO2 emissions (p=0.02), whereas the effect of perceived ambiguity for neutral participants (i.e., $1 - 2\alpha = 0$) is negative but not significant (p=0.760). The ambiguity parameters under the Ellsberg source are not found to be correlated with WTP for CO2 reduction in the OLS regressions either. We also replicate the significant effects of the other control variables, such as risk aversion, trust, knowledge about and agreement with climate change, sense of responsibility, and the country of residence.

Table C2 furthermore reports the calculated effects of ambiguity attitudes for an individual with neo-EU preferences compared with an individual with EU preferences. Similar to our main analysis, we find significantly lower WTP measures for neo-EU preferences with different levels of ambiguity perception and aversion, although the estimated differences with respect to SEU here are somewhat lower than those obtained with the interval regression. This latter result can possibly be explained by pre-defined upper bound (£210) of the mid-point estimates of WTP measures, which leads to more conservative estimations here than the interval estimates.

Table C1. OLS Regressions of the Mid-point Estimates of WTP Measures

	Climate Ambiguity	Ellsberg Ambiguity
Perceived ambiguity (δ)	-0.068	0.126
Ambiguity aversion ($\delta \times (1-2\alpha)$)	-0.542**	-0.114
Risk Aversion	0.632**	0.637**
Trust	0.097	0.075
Altruism	0.774**	0.778**
Impatience	-0.291	-0.276
Procrastination	0.016	0.001
Positive reciprocity	-0.095	-0.098
Negative reciprocity	-0.802**	-0.767**
Indirect negative reciprocity	0.489	0.459
Knowledge & agreement with scientific consensus on CC	1.188*	1.110*
Perceived personal experience with CC	0.479	0.528
Pro-environmental worldview	-0.936	-0.897
Perceived sense of responsibility	1.804***	1.780***
Perceived self-efficacy	0.362	0.405
Age	0.142*	0.119
Female	-0.185	-0.184
Full-time employed	0.111	0.106
Student	0.025	0.030
Residence in OECD	0.672***	0.706***
Married	-0.257	-0.238
Children	0.209	0.211
Highest level of education (joint p-value)	0.723	0.816
Level of income (joint p-value)	0.937	0.957
Constant	0.260	0.212
N	801	801

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

Table C2. Comparison of WTP under neo-EU and EU based on OLS regressions

Ambiguity aversion ($\delta(1-2\alpha)$)	Perceived ambiguity (δ)	Ambiguity aversion per unit of perceived ambiguity ($1-2\alpha$)	Estimated % difference from WTP of an SEU maximizer	p-value
0	0	0	0%	0
0	1	0	-7%	0.752
0.25	0.25	1	-14%	0.034
0.25	0.5	0.5	-16%	0.133
0.25	1	0.25	-18%	0.321
0.5	0.5	1	-26%	0.022
0.5	1	0.5	-29%	0.099
0.75	0.75	1	-37%	0.013
0.75	1	0.75	-38%	0.027
1	1	1	-46%	0.007

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