Experimental Evidence on the Relationship between Perceived Ambiguity and Likelihood Insensitivity

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Abstract

Observed individual behavior in the presence of ambiguity shows insufficient responsiveness to changes in subjective likelihoods. Despite being integral to theoretical models and relevant in many domains, evidence on the causes and determining factors of such likelihood insensitive behavior is scarce. This paper investigates the role of beliefs in the form of ambiguity perception – the extent to which a decision-maker has difficulties assigning a single probability to each possible event – as a potential determinant. Using an experiment, I elicit measures of ambiguity perception and likelihood insensitivity and exogenously vary the level of perceived ambiguity. The results provide strong support for a perception-based explanation of likelihood insensitivity. The two measures are highly correlated at the individual level, and exogenously increasing ambiguity perception increases insensitivity, suggesting a causal relationship. In contrast, ambiguity perception is unrelated to ambiguity aversion – the extent to which a decision-maker dislikes the presence of ambiguity.

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1 Introduction

This paper experimentally studies the relationship between ambiguity perception and choices under ambiguity, with a focus on the observed behavioral pattern of likelihood insensitivity. Likelihood insensitivity is a robust empirical finding, with numerous studies emphasizing its relevance, e.g., Wakker (2010), Abdellaoui et al. (2011), and Baillon et al. (2018b). It is defined as individuals displaying insufficient discriminatory power in differentiating the degree of likelihood of ambiguous events, leading to insufficient responsiveness to changes in likelihoods. To distinguish this finding from probability insensitivity found in choices under risk, it is commonly referred to as ambiguity-generated likelihood insensitivity (a-insensitivity). A-insensitivity is one of the two main empirical patterns that characterize behavior under ambiguity, the other being ambiguity aversion/seeking behavior – the degree to which an individual dislikes the presence of ambiguity.

For a-insensitivity, a growing number of studies find (i) substantial correlations with relevant (real-life) behavior and (ii) large degrees of systematic heterogeneity between different individuals. For example, Dimmock, Kouwenberg, and Wakker (2016) find a significant negative relationship between a-insensitivity and stock market participation. Similarly, for stock market participants, Anantanasuwong et al. (2020) find a-insensitivity to be significantly related to the choice of financial assets. Li, Turmunkh, and Wakker (2019) show that within the context of trust games, people who display more a-insensitivity are less likely to act on their beliefs about the trustworthiness of others. Relatedly, Li, Turmunkh, and Wakker (2020) show that ambiguity about betrayal within social interactions influences subjects' choices through their insensitivity to the likelihoods of actions others will make. Furthermore, Li (2017) and von Gaudecker, Wogrolly, and Zimpelmann (2022) find substantial differences in a-insensitivity among sociodemographic groups.

Despite empirical evidence highlighting the importance of a-insensitivity, evidence on its causes and determining factors is scarce. In particular, what is the underlying mechanism causing observed a-insensitivity? A popular class of ambiguity models, the so-called multiple prior models (Ghirardato, Maccheroni, and Marinacci, 2004; Chandrasekher et al., 2022), propose an answer, as has recently been documented by Dimmock et al. (2015) and Baillon et al. (2018a). In those models, a decision-maker has a set of beliefs (the priors) considered relevant to the decision problem, and the size of the set is interpreted as the perceived level of ambiguity. This perceived ambiguity relates directly to a-insensitivity: the larger the belief set, the greater is the decision-makers' insensitivity to changes in likelihood. The reason is that considering multiple possible probability measures leads the decision-maker to limited confidence in a particular one, resulting in insufficient responsiveness toward likelihood changes. Hence, this theoretical insight provides a potential explanation for a-insensitivity with testable predictions.

This paper empirically investigates the mechanism responsible for likelihood insensitivity proposed by the multiple prior models. I experimentally measure and relate decision-makers' perceived ambiguity to a-insensitivity displayed in incentivized choices under ambiguity. With such a test, I examine the extent to which a-insensitive *behavior* is explainable by a *belief*-based mechanism. In contrast, alternative explanations like the decision weight interpretation (Baillon et al., 2018a) brought forward by models such as prospect theory for ambiguity (Tversky and Kahneman, 1992) do not explicitly relate a-insensitivity to beliefs. Instead, in such models a-insensitivity is explained through psychological motives, source dependent preferences or ambiguity perception not captured by sets of beliefs.

I test for the mechanism explaining a-insensitive behavior using a preregistered experiment with 126 subjects. In the experiment, subjects face four decision parts. In each part, they are presented with weather events. The events concern future temperature changes from one day to another, a natural and easy to understand situation in which ambiguity is present. Using these events, in each decision part I elicit subjects' ambiguity perception, an index capturing a-insensitivity, and an index capturing ambiguity aversion, all at the individual level.

To elicit a-insensitivity and ambiguity aversion, I use matching probabilities following the method proposed by Baillon et al. (2018b). Subjects are presented sequentially with six events, three single events that partition the state space, as well as their pairwise unions. The three single events correspond to a noticeable increase, decrease, or no change in temperature from one day to the other. The pairwise unions are defined accordingly, e.g., the union of the first and third single event means that the day either gets warmer or stays the same, but not colder. For each of these six events, subjects face a multiple-price-list in which they choose between betting on the occurrence of the ambiguous event to receive a prize and a lottery that pays the same prize with a known probability. Between the list's decisions, the probability of the lottery is varied. The probability for which subjects are indifferent between betting on the event and the lottery is their matching probability of the respective event. Baillon et al. (2018b) then define the a-insensitivity index as the average discrepancy of matching probabilities between single events and their pairwise unions. Because a higher discrepancy between the two indicates a lower responsiveness to differences in likelihoods, the index captures a-insensitive behavior. In addition, the ambiguity aversion index is defined as the average matching probability across all events, capturing how much subjects, in general, prefer to bet on the ambiguous event.

To elicit ambiguity perception, I introduce a two-stage elicitation method that captures ambiguity perceptions as defined by commonly used multiple prior models. For the same single events constructed for the elicitation of a-insensitivity, subjects first report their best-guess probability for the event's occurrence. Afterward, they state their belief in the precision of the previously reported probability, revealing a subjective probability interval. I define the index measuring ambiguity perception as the average reported precision over the events of each part, i.e., the average length of the probability intervals. The larger the average length of the probability intervals, the more ambiguity a subject perceives.

Eliciting both ambiguity perception and a-insensitivity at the individual level allows me to assess the empirical relationship between the two. Importantly, the indices of a-insensitivity and ambiguity aversion I elicit in the experiment are valid under all popular ambiguity theories, as shown by Baillon et al. (2021). Thus, the elicitation of a-insensitivity does not require a commitment to a specific model. Moreover, due to the use of matching probabilities, the elicitation controls for risk-induced insensitivity. These features enable me to perform arguably the most general test of the relevance of ambiguity perception for a-insensitivity possible.

In order to investigate whether a causal relationship between ambiguity perception and a-insensitivity exists, I create exogenous variation in ambiguity perceptions. Between decision parts, I vary the time distance of the weather events from four days (*Low Ambiguity* condition) to eight weeks (*High Ambiguity* condition) in the future. That is, in the former, subjects consider whether a day four days in the future is warmer, colder, or has the same temperature as the previous day, while in the latter, they consider a day eight weeks in the future. As weather events further in the future become more ambiguous, the degree of ambiguity increases, and thus should subjects ambiguity perception. At the same time, I make sure that all other aspects of the decision environment, such as the timing of payments or the resolution of uncertainty, are held constant to isolate the effect of a change in ambiguity perception. Furthermore, I randomize the order of the decision parts and randomize the order of elicitation of ambiguity perception and a-insensitivity within each decision part to control for order effects.

With this experimental design, I present three main findings on the relationship between ambiguity perception and a-insensitivity. First, subjects perceive a considerable amount of ambiguity and substantial degrees of a-insensitivity are prevalent. More than 90% of subjects simultaneously report a positive amount of perceived ambiguity and display a-insensitive behavior. Second, the two measures are highly positively related at the individual level. Raw correlations range between $\rho = 0.40$ and $\rho = 0.54$ (pooled $\rho = 0.50$). Once measurement error is taken into account, correlations increase to $\rho = 0.51$ and $\rho = 0.63$. Regression analyses similarly show a significant positive relationship between the two indices when controlling for observable characteristics. Hence, a strong positive association exists between the level of ambiguity perception and the degree of a-insensitive behavior. At the same time, and in line with theoretical considerations, I find no relationship between ambiguity perception and ambiguity aversion (pooled $\rho = -0.02$). Additionally, ambiguity aversion is orthogonal to a-insensitivity (pooled $\rho = 0.01$), replicating the results of previous studies. Third, exogenously increasing the degree of ambiguity increases ambiguity perception and, crucially, a-insensitive behavior. Reported ambiguity perception is significantly higher in the *High Ambiguity* parts compared to the *Low Ambiguity* parts ($p < 0.001$, Wilcoxon signed-rank test). This increase translates into behavior: the index capturing a-insensitivity increases by more than 30% from the *Low Ambiguity* to the *High Ambiguity* parts ($p < 0.01$, Wilcoxon signed-rank test). Importantly, the change in a-insensitivity can be predicted by changes in perceived ambiguity. Subjects who report the largest increases in ambiguity perception also show the largest increase in a-insensitivity. In contrast, subjects who report little to no increase in ambiguity perception show no increase in a-insensitivity. These findings suggest that ambiguity perception causally influences a-insensitive behavior.

Overall, these findings provide strong support for an ambiguity-perception-based explanation of a-insensitivity, as proposed by multiple prior models. Understanding the drivers behind observed behavior helps understand and predict said behavior in distinct environments and between settings. The results of my experiment show that high degrees of a-insensitive behavior are expected in situations where individuals perceive a high degree of ambiguity. For instance, such behavior should be observed when individuals choose between different investment products in high ambiguity situations but not in low ambiguity situations. The results thus help to reconcile the observation that a-insensitivity varies greatly among different sources of uncertainty (Abdellaoui et al., 2011; Li et al., 2017; Anantanasuwong et al., 2020; von Gaudecker, Wogrolly, and Zimpelmann, 2022). Differences in ambiguity perception between the sources can explain these differences. For example, in Anantanasuwong et al. (2020), a-insensitivity was higher for investments into Bitcoin compared to the MSCI World index, which seems plausible since Bitcoin as new technology is subject to more ambiguity. Even within a setting and given source, knowledge of individual ambiguity perception can help to predict subsequent choice behavior, as demonstrated in my experiment. Since ambiguity models are increasingly applied more broadly in many domains, a better understanding of what behavior is expected under which conditions is advantageous.

From a policy perspective, differentiating between mechanisms is indispensable for designing interventions aimed at behavioral change. For example, suppose the goal is to increase stock market participation, where a-insensitivity is a significant predictor, as mentioned earlier. My results suggest that reducing individuals' perceived ambiguity concerning the stock market leads to less insensitivity and thus could directly influence financial decision-making. In contrast, if insensitive choices would reflect underlying source preferences, behavioral responses to changes in perceived ambiguity would be far more limited. Generally, if the normative objective is to have individuals discriminate appropriately between likelihoods, my results suggest that reducing their perceived ambiguity is key.

This paper makes three contributions to the literature. First, the paper contributes to the large empirical literature that studies behavior under ambiguity.It has long been suggested that of the two core behavioral patterns under ambiguity – a-insensitivity and ambiguity aversion/seeking – the former is the cognitive component and the latter the motivational component of ambiguity attitudes (e.g., Baillon et al., 2021). For instance, Baillon et al. (2018b) show experimentally that inducing time pressure in decision-making increases a-insensitivity, but not ambiguity aversion. Anantanasuwong et al. (2020) show, for a representative sample of financial investors, that a-insensitivity is correlated with financial literacy and education, but ambiguity aversion is not. Similarly, likelihood insensitivity decreases in the reported level of competence for a particular source of uncertainty.(Kilka and Weber, 2001)[1] I provide direct evidence that a-insensitivity is indeed a cognitive component because it can be explained through ambiguity perception. I show that beliefs are the cognitive mechanism, as conjectured by theoretical models. Furthermore, my results show that ambiguity aversion is orthogonal to ambiguity perception, further supporting the notion of ambiguity aversion being a motivational component. Related is a paper by Enke and Graeber (2021), who link the occurrence of (risk- and ambiguity-generated) likelihood insensitivity to cognitive uncertainty about the optimal action, building on Bayesian cognition models. Higher uncertainty then leads to compression toward a cognitive default that can result in insensitive behavior. In contrast, I focus on an explanation motivated by ambiguity theories, which are conceptually different from Bayesian cognition models. My approach differs methodologically as well. In their design, both a-insensitivity and ambiguity aversion contribute to the observed compression effect. My design allows me to distinguish a-insensitivity and ambiguity aversion while controlling for risk-induced insensitivity.

Second, the paper's empirical findings help to inform theories of decision-making under ambiguity. Of the many ambiguity models that have been developed (see Machina and Siniscalchi, 2014; Gilboa and Marinacci, 2016, for overviews), most allow for a-insensitive behavior (Baillon et al., 2021). Because the a-insensitivity index I use in the experiment is valid for all popular models that allow for a-insensitive behavior, my results highlight the value of modeling a-insensitivity through belief-based ambiguity perception. In particular, my results support the notion that multiple prior models are not "as-if" revealed preference models with respect to a-insensitivity behavior, but accurately describe the underlying mechanism that is generating a-insensitivity.[2]

[1]There is also a rich literature in psychology documenting that insensitivity can be influenced by affective factors such as emotions or feelings, see, e.g., Rottenstreich and Hsee (2001).

[2]They are thus, to a larger degree, *homeomorphic* rather than *paramorphic* by the notion of Harré (1970). Generally, *homeomorphic* models are best suited for broad applications and are sought for descriptive purposes (Wakker, 2010, p. 3).

Third, the paper contributes to the literature on the elicitation of probabilistic statements. A growing number of studies asks survey respondents for imprecise probabilities, for example by providing respondents the opportunity to respond in probability intervals. Applications range from stock market expectations (Drerup, Enke, and von Gaudecker, 2017), health consequences such as dementia risk (Giustinelli, Manski, and Molinari, 2021), Covid-19-related (Delavande, Bono, and Holford, 2021) and other health outcomes (Delavande and Mengel, 2021) to future sales growth expectations of firm executives (Bachmann et al., 2020) and career track choices of students (Giustinelli and Pavoni, 2017). However, how imprecise probability questions relate to behavioral measures inferred from revealed preferences has so far been an open question (Ilut and Schneider, 2022). I show that there is a tight correspondence between imprecise probabilities and behavioral measures. Not only do expressions of confidence in probabilistic assessments have great predictive power for decision-making in an incentivized and tightly controlled setting, but they also directly relate to a key parameter of ambiguity models.

The paper is organized as follows. Section 2 describes the theoretical framework, providing the definition of likelihood insensitivity and ambiguity perception and how they relate within the class of multiple prior models. Subsequently, Section 3 explains the experimental design and how likelihood insensitivity and ambiguity perception are elicited. Section 4 presents the results of the experiment and Section 5 concludes.

2 Theoretical Background

This section establishes the paper's theoretical background. As a starting point, I provide definitions of the two behavioral regularities found in decision-making under ambiguity, likelihood insensitivity and ambiguity aversion/seeking behavior, following Baillon et al. (2021). Thereafter, I discuss modeling beliefs under ambiguity and provide a commonly used definition and measure of ambiguity perception. In a third step, I describe how the class of multiple prior models relates these beliefs to behavior, thereby explaining insensitivity through ambiguity perception.

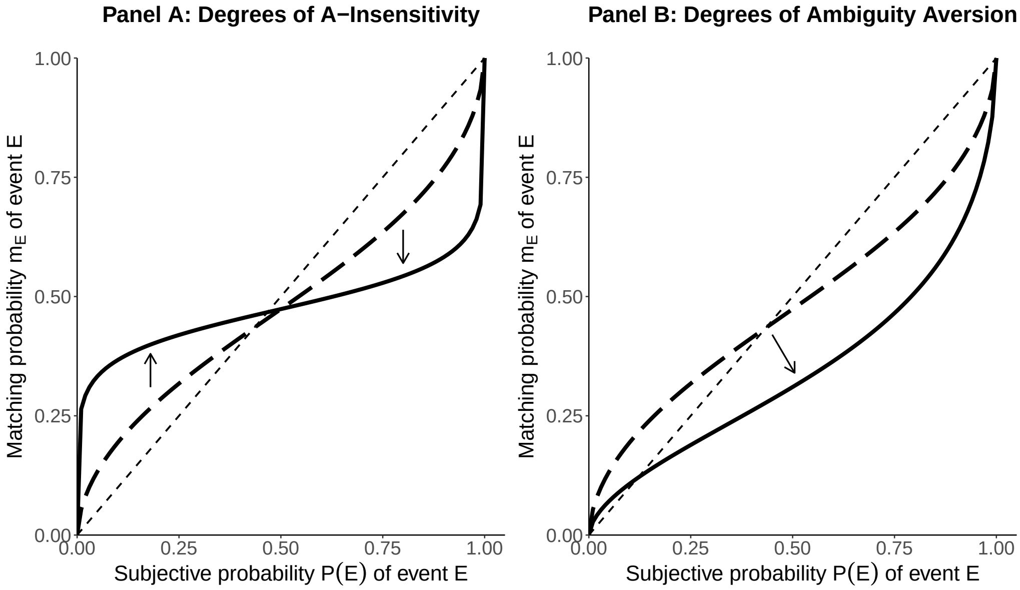
2.1 Behavior under Ambiguity: A-Insensitivity and Ambiguity Aversion

To describe behavior under ambiguity, I start with some notation. Denote by S the state space, whose subsets are events. Events are connected to a set of monetary outcomes X by acts that map S to X. In the following, only binary acts are considered. These are denoted by $\gamma_E\beta$, meaning they pay the amount γ if event E realizes and outcome β otherwise. Similarly, a lottery that pays γ with probability p and β with probability $1-p$ is denoted by $\gamma_p\beta$. A preference relation $\succcurlyeq$ is defined over prospects, which are acts or lotteries. A *matching probability* m_E is defined as $\gamma_E\theta \sim \gamma_{m_E}\theta$ for an event E given amount θ.

In this decision environment, Figure 1 illustrates the main patterns of behavior under ambiguity. The 45-degree line displays the behavior of subjective expected utility maximizers. Their matching probabilities m_E coincide with the respective subjective (or ambiguity-neutral) probabilities $P(E)$, assuming for illustrative purposes that the latter can be specified. It is empirically well established that individuals deviate from this benchmark in two ways.[3] First, they display insufficient respon-

[3] See, e.g., Wakker (2010) or Trautmann and van de Kuilen (2015a) for overviews.

Figure 1: Characterization of Behavior under Ambiguity



siveness to changes in subjective likelihoods in the middle region, as displayed in Panel A. The lower the responsiveness, the larger the deviation from the 45-degree line towards the horizontal for intermediate likelihoods, as indicated by the shift from the dashed to the solid line. This behavior is commonly referred to as likelihood insensitivity. Second, individuals show a tendency to either avoid or seek the presence of ambiguity, as displayed in Panel B. The stronger the avoidance (seeking), the larger the deviation from the 45-degree line downwards (upwards), again indicated by the shift from the dashed to the solid line.

More formally, building on a large literature that uses two parameters to capture the two previously described behavioral patterns, Baillon et al. (2021) define ambiguity-generated likelihood insensitivity (a-insensitivity for short, parameter a) and ambiguity aversion (parameter b) as follows:

$$a = 1 - \frac{Cov\left(m_E, P_n(E)\right)}{Var\left(P(E)\right)} \tag{1}$$

$$b = E\left[P(E) - m_E\right]. \tag{2}$$

The parameter a is defined as the average change in m if P changes by one unit, thus capturing insensitivity. In the extreme of maximal a-insensitivity $a = 1$, i.e., if $Cov\left(m_E, P_n(E)\right) = 0$, the decision-maker does not respond to changes in likelihood at all, treating all events alike. The parameter b is defined as the average difference between m and P, indicating a preference for or against betting on ambiguous events.

Baillon et al. (2021) show that these two parameters are compatible with almost all existing indexes and ambiguity orderings proposed in the literature. In particular, the two parameters coincide exactly with the two parameters of the neo-additive framework of Chateauneuf, Eichberger, and Grant (2007).[4] This framework is often used in empirical applications, and the two parameters

[4]The two parameters of the neo-additive framework serve as linear approximation to the inverse S-shape behavior that is commonly found in decision-making under uncertainty (Tversky and Kahneman, 1992) and displayed in Figure 1.

have been shown to explain choices under ambiguity well (Abdellaoui et al., 2011; Li et al., 2017).

2.2 Subjective Beliefs and Ambiguity Perception

A widely used approach to model beliefs in the presence of ambiguity - when no obvious and commonly agreed upon probability measure exists – is to assume that beliefs are represented by a *set* of priors C, which is a convex set of probability distributions over S. This representation of priors is central to the large statistics literature on *robust Bayesian analysis* (Berger, 1990; Berger, 1994) and numerous decision theory models have been developed to derive them from revealed preferences (Gilboa and Schmeidler, 1989; Ghirardato, Maccheroni, and Marinacci, 2004; Klibanoff, Marinacci, and Mukerji, 2005; Chandrasekher et al., 2022).

A decision-maker is said to *perceive ambiguity* if C contains more than one probability distribution and perceive no ambiguity if C contains a unique probability measure. To elicit such ambiguity perception, probability intervals are a useful concept because their elicitation is straightforward and easy to communicate. Given a set of prior beliefs, a probability interval takes the form $I_E = \{p(E) : p \in C\}$ for event E.[5]

The goal is then to construct a measure of perceived ambiguity, the *perceived level (or degree) of ambiguity*, from probability intervals. Seeing the existence of ambiguity as deviations from unique events probabilities, it is natural to define this measure as the degree to which beliefs deviate from single probabilities for events. For this purpose, denote upper probabilities by $p^*(E) = \sup_{p\in C} p(E)$ and lower probabilities by $p_*(E) = \inf_{p\in C} p(E)$. The literature then quantifies deviations from single probabilities as the average discrepancy between the upper and lower probability, $\overline{p} = (\overline{p^* - p_*})$.[6] Accordingly, I will use $\overline{p}$ as a measure of ambiguity perception and elicit this measure from probability intervals.

2.3 The Multiple Prior Explanation for A-Insensitivity

The class of multiple prior models relate a decision-maker's choices to a set of prior beliefs C. One of the most popular models within this class is the *α-maxmin model* (Hurwicz, 1951; Ghirardato, Maccheroni, and Marinacci, 2004). This model offers a tractable way of differentiating the influence of preferences towards the presence of ambiguity, represented by an ambiguity aversion parameter α, from ambiguity perception through the size of C. Preferences follow the *α-maxmin* representation if a utility function U exists such that for a prospect $\gamma_E\theta$:

$$\gamma_E\theta \mapsto W(E)U(\gamma) + (1 - W(E))U(\theta),$$

with $W(E) = \alpha P_*(E) + (1 - \alpha)P^*(E)$ for $\alpha \in [0, 1]$. The responsiveness of $W(E)$ thus depends directly on the beliefs about the upper and lower probabilities. Hence, the model can accommodate

[5]Probability intervals I_E are more general than sets of priors because they can be defined for each event even if no probability measure exists over the whole state space. For an exact mapping between intervals and priors, it has to be specified how probability intervals relate to the probability measures that form the set of priors. See for example Walley (2000) or Škulj (2006) for a discussion of the relationship between probability intervals and measures.

[6]This approach is closely related to the idea of confidence in probabilistic statements, formalized by Dempster (1967) and Shafer (1976), with a subjective foundation given in Gul and Pesendorfer (2014).

for both a-insensitive and ambiguity averse/seeking behavior, with the former being driven by belief-based ambiguity perception.

Relating the α-*maxmin* model to the two-parameter characterization of ambiguity attitudes described in Section 2.1 requires additional structure on the set of priors. The so-called ε-*contamination model* offers a tractable parameterization, and for this reason, it has been extensively used in applications.[7] In the model, the decision-maker has a subjective probability distribution Q as a reference distribution in mind. However, since the decision-maker does not know the true probabilities, distributions from the general set T of all probability distributions are considered. Hence, the set of priors takes the form $C = \{(1-\varepsilon)Q + \varepsilon T\}$, with $\varepsilon \in [0,1]$ governing the weight given to T. A convenient feature of the model is that ambiguity perception is exactly pinned down by ε, since the resulting probability intervals take the form

$$I_E = \{p : (1-\varepsilon)\pi(E) \leq p \leq (1-\varepsilon)\pi(E) + \varepsilon\}, \text{where } \pi \in Q, \tag{3}$$

and thus $\varepsilon = \overline{p}$.[8] The special feature of those intervals is that the length of an interval is always equal to ε, independent of the events.

Combining these restrictions on the set of priors and assuming preferences follow an α-*maxmin* representation gives the two parameter α-ε-*maxmin model*. As Dimmock et al. (2015) showed, there is a direct mapping between the model parameters to the previously established indices a and b,

$$a = \varepsilon, \tag{4}$$

$$b = (2\alpha - 1)\varepsilon. \tag{5}$$

Therefore, the higher the degree of ambiguity, measured by ε, the greater the decision-maker will display insensitivity by having insufficient responsiveness toward likelihood changes.

To summarize, the indices of Baillon et al. (2021) offer a way to parametrize and elicit ambiguity behavior without committing to a specific model, which makes it possible to test for different mechanisms that cause observed behavior. In the experiment, I directly test the multiple prior mechanism by eliciting ambiguity perception from reported beliefs and relating them to a-insensitivity elicited from choice behavior.

3 Experimental Design

This section presents the experimental design. The aim of the design is to investigate empirically the relationship between ambiguity perception and a-insensitivity, defined in the previous section.

3.1 Source of Ambiguity and Ambiguity Variation

In the experiment, each subject faced four decision parts. Each part contained decisions regarding three weather events E_1, E_2 and E_3. Weather events were defined as changes in the average daily

[7] See OA.3. in Baillon et al. (2021) for a list of applications.

[8] For this reason, many papers interpret ε as level of ambiguity (Walley, 1991; Ghirardato, Maccheroni, and Marinacci, 2004; Chateauneuf, Eichberger, and Grant, 2007; Gajdos et al., 2008; Hill, 2013; Giraud, 2014; Klibanoff, Mukerji, and Seo, 2014; Alon and Gayer, 2016; Shattuck and Wagner, 2016).

Table 1: Weather-Change Events in each Part

Part	Time difference	E_1	E_2	E_3
Low Ambiguity Partition 1	Four days	$(-\infty, -1.8)$	$[-1.8, 1.8]$	$(1.8, \infty)$
Low Ambiguity Partition 2	Four days	$(-\infty, -1)$	$[-1, 1.5]$	$(1.5, \infty)$
High Ambiguity Partition 1	Eight weeks	$(-\infty, -1.8)$	$[-1.8, 1.8]$	$(1.8, \infty)$
High Ambiguity Partition 2	Eight weeks	$(-\infty, -1)$	$[-1, 1.5]$	$(1.5, \infty)$

Notes: Unit is degree Celsius.

temperature between two consecutive future days.[9] These changes have a natural interpretation: a positive change indicates that a day is warmer than the previous day, while a negative change indicates that a day is colder. The three events were chosen to partition the event space, with E_1 corresponding to a noticeably negative change in temperature, E_2 to no noticeable change and E_3 to a noticeably positive change.

Between decision parts, events varied in the time difference between the decision and occurrence of the event and in the way the events partitioned the event space. Table 1 displays the events used and highlights the differences between the four parts. In *Low Ambiguity Partition 1*, the time difference between the decision and the event was four days, and the events were $E_1 = (-\infty, -1.8)$, $E_2 = [-1.8, 1.8]$ and $E_3 = (1.8, \infty)$, where the numbers denote changes in degrees Celsius. For example, event E_1 describes the situation wherein the average daily temperature falls by more than 1.8 degrees Celsius four days into the future compared to three days in the future. In *Low Ambiguity Partition 2*, the middle event E_2 shrinks to $[-1, 1.5]$, with the other two adjusted accordingly. The two *High Ambiguity* parts concern the same events but with eight weeks as time difference between the choice and the realization of the event instead of the four days in the two *Low Ambiguity* parts.

I chose weather as source of ambiguity because it is a source familiar to subjects and changes in temperature create easy-to-interpret events. Importantly, it is well known and embedded in most weather reports that the further weather events are in the future, the more difficult their prediction becomes. For example, reported confidence bounds for rain probability are higher for days further into the future. Similarly, weather forecasts of different providers are usually much more dispersed the larger the time distance.[10] Hence, varying the time distance to temperature events creates a natural and intuitive increase in ambiguity. Comparing the behavior in *High Ambiguity* with *Low Ambiguity* thus allows me to assess the impact of an exogenous change in the degree of ambiguity. Varying the event space partition from *Partition 1* to *Partition 2* allows me to assess the extent of measurement error, which is explained in more detail in Section 4.6.

The order of the parts was randomized. Subjects faced either the two *Low Ambiguity* or the two *High Ambiguity* parts first, followed by the remaining two. Within each part, the indices capturing a-insensitivity and ambiguity perception were elicited using the respective events, which is explained next. The order in which the two indices were elicited within each part was also randomized.

[9] The average temperature of a day is obtained by averaging all air temperature values measured on the hour from 12 midnight to 11 p.m.

[10] I verified that this was also the case for the time interval in which the experiment took place.

3.2 Elicitation of A-Insensitivity

To elicit likelihood insensitivity, I use the method proposed by Baillon et al. (2018b). The method uses the previously described events E_1, E_2, and E_3 as well as their pairwise unions, i.e., $E_{12} = E_1 \cup E_2$, $E_{13} = E_1 \cup E_3$, and $E_{23} = E_2 \cup E_3$. For each of the six events, subjects choose between two options, A and B. Option A pays 10 euros if the respective event E realized and 0 euros otherwise. Option B pays 10 euros with probability p. Subjects thus choose whether to bet on the ambiguous event or on a lottery with a known probability. By varying p for each event E_i, it is possible to elicit the matching probability m for which a subject is indifferent between receiving 10 euros under event E and receiving 10 euros with probability m. Denote this matching probability for E_i by m_i.

The index capturing a-insensitivity is derived from the extent to which the matching probabilities of single events deviate from composite events. The higher the insensitivity toward likelihood changes, the less additive are the matching probabilities of two single events compared to the matching probability of the respective composite event. Accordingly, define the average single event matching probability as $\overline{m_s} = (m_1 + m_2 + m_3)/3$ and the average composite event matching probability as $\overline{m_c} = (m_{12} + m_{23} + m_{13})/3$. Then, the index capturing a-insensitivity is:

$$a = 3 \cdot \left(\frac{1}{3} - (\overline{m_c} - \overline{m_s}) \right) \tag{6}$$

Under perfect discrimination of likelihoods and ambiguity neutrality, $\overline{m_s} = \frac{1}{3}$ and $\overline{m_c} = \frac{2}{3}$ and thus $a = 0$. The higher the difference between the two averages, the higher is a, indicating insensitivity toward likelihood changes whenever $a > 0$. At maximal insensitivity ($a = 1$), no distinction is made between levels of likelihood ($\overline{m_c} - \overline{m_s}$), e.g., all events are taken as fifty-fifty. The index can also take negative values $a < 0$, which implies oversensitivity to changes in likelihoods.

The elicitation method also allows the elicitation of ambiguity aversion as motivational component of ambiguity attitudes. The index b capturing ambiguity aversion can be defined as:

$$b = 1 - \overline{m_c} - \overline{m_s} \tag{7}$$

Intuitively, the index captures how much, on average, a subject prefers to bet on the ambiguous event compared to the lottery. $b = 0$ means the individual is ambiguity neutral, while $b > 0$ corresponds to ambiguity aversion and $b < 0$ to ambiguity seeking, with $b = 1$ corresponding to maximal ambiguity aversion and $b = -1$ to maximal ambiguity seeking.

In order to elicit the indices, the method requires six matching probabilities, one for each of the six events. In the experiment, these are elicited using choice lists. An example can be seen in Figure B.1 in the appendix. In each row of the list, subjects could choose between the two options described previously, with p varying in each row from 0% to 100% in 5% increments. To make answering less strenuous and to enforce monotonicity in probabilities, subjects could fill out a choice list with a single click: they only had to indicate their switching point by choosing either Option A or B in the respective row, and the computer automatically filled out the rest. For example, if a subject indicated a preference for betting on the event over the lottery with probability $p = 30\%$, then all input fields for Option B below 30%, and all input fields for Option A above 30% were filled out. Subjects could always revise their switching point and had to confirm their final choices before moving on. As is common in the elicitation of matching probabilities, the average of the probabilities in the two rows defining a respondent's switching point from Option A to B was taken as the indifference point and thus as the matching probability for the respective event.

As Baillon et al. (2021) show, the two indices directly correspond to the indices defined in equations (1) and (2) independent of different state space partitions under minimal assumptions about preferences and measurement design.[11] The method identifies the two indices independent of risk attitudes or subjective beliefs over the likelihood of events, and can be applied to natural events such as the weather movements used in this experiment.[12] Furthermore, the elicited indices are compatible with almost all ambiguity models developed so far, making the elicitation method ideal for the purpose of this study.

3.3 Elicitation of Ambiguity Perception

The subject's degree of ambiguity perception was elicited using a two-step procedure.[13] The goal was to make the elicitation as easy as possible to understand and answer while still capturing ambiguity perception as defined in Section 2.2. As such, everything was explained to the subjects in both intuitive and in quantitative terms.

In the first step, subjects are asked to provide for the same events E_1, E_2, and E_3, as in eliciting a-insensitivity, their best-guess probability that the respective event will occur. See Figure B.2 in the appendix for an example. It was explained in a way such that subjects unfamiliar with probabilities and probability theory could equally give their assessments. In this first step, it was enforced that the probabilities sum up to one.

In a second step, subjects could state their belief in the precision of the previously reported probabilities and thus the probability interval that they consider by using a slider. The slider scale ranges from absolutely imprecise to absolutely precise, and an example can be found in Figure B.3.[14] Displayed below the slider was the implication of the slider movement for the considered probability set.[15] If a subject indicated that the guess was absolutely precise, the interval collapsed to the probability guess stated in the first step. For each slider increment, the interval increased by one percentage point in each direction. Therefore, by moving the slider, subjects could specify the set $[p_{*i}, p_i^*]$ of probabilities they considered likely for event E_i. The distance $\bar{p}_i = p_i^* - p_{*i}$ is then a measure of perceived ambiguity for each event individually. Following the theoretical considerations of Section 2.2, the average length across all three events then corresponds to the perceived level of

[11]Preferences only need to be complete, transitive and monotone, which are standard assumptions in the literature. Further, for every event E, there must exist a matching probability. Assumptions on the measurement design include sufficient richness of the event space and that there are no extreme events which either have a $P_n(E)$ close to zero or one chosen for elicitation (see Baillon et al., 2021, for details).

[12]A benefit of using natural events is that ambiguity is not artificially created through the deliberate withholding of relevant information such as the color composition of an urn by the experimenter.

[13]Manski (2004) discusses the use of one-step questions to elicit the degree of confidence for binary events. Giustinelli, Manski, and Molinari (2021) use a similar two-step procedure.

[14]The slider itself only appeared once subjects clicked somewhere on the scale in order to avoid anchoring or default effects.

[15]The design of the slider used for the elicitation was inspired by the design of the elicitation method of Enke and Graeber (2021).

ambiguity:

$$\overline{p} = \frac{1}{3}(\overline{p}_1 + \overline{p}_2 + \overline{p}_3) \tag{8}$$

The maximum level of ambiguity perception at $\overline{p} = 1$ is attained when all probability ranges are from 0 to 1, i.e., for each event, the probability set considered is the unit interval. The minimum level of $\overline{p} = 0$ is attained when all probability sets collapse to a single value, in which case subjects are certain of a single probability distribution.

In the experiment, subjects stated their degree of ambiguity perception without monetary consequences. Incentives would make the elicitation more complex, which is not desirable here because the concept of ambiguity perception might already be difficult conceptually for subjects. Furthermore, incentivization combines the elicitation of beliefs with preferences over potential rewards, requiring assumptions about the form of preferences and thus commitment to a specific model. Moreover, since ambiguity perception is subjective, no true values are attainable for the experimenter that could be used to incentive answers.[16]. For those reasons, the elicitation of ambiguity perception was not financially incentivized.[17]

It should be noted that by the design of the experiment, subjects have no reason or incentive to misreport their beliefs. For such a case, numerous studies have found that nonincentivized belief elicitations perform well in accuracy and the extent of truth-telling compared with incentivized elicitations (Manski, 2004; Armantier and Treich, 2013; Trautmann and van de Kuilen, 2015b; Danz, Vesterlund, and Wilson, 2022). Another concern would be that because of the nonincentivization, subjects lack motivation to take the questions seriously and thus answer randomly or inattentively. The exogenous increase in the degree of ambiguity from *Low* to *High Ambiguity* can be used to assess this concern. If subjects were answering randomly or inattentively, the exogenous increase should have no effect on reported ambiguity perception. The results presented in Section 4.1 show that the opposite is the case. I find that subjects' answers are highly responsive to the exogenous increase and respond in the predicted direction, implying that subjects are engaged and answer deliberately. To further alleviate concerns about measurement errors that could result from a lack of deliberation, I purposefully designed the experiment such that a measurement error correction technique could be employed. See Section 4.6 for the details and results.

3.4 Hypotheses

The previous section has shown how the two central indices a-insensitivity a and perceived ambiguity $\overline{p}$ are elicited using matching probabilities and hypothetical queries, respectively. The relationship between the two will be analyzed by investigating their correlation at the individual level and the impact of an exogenous increase in the degree of ambiguity. For this purpose, the first step is to validate the ambiguity perception index. If the index captures relevant ambiguity perception, it should

[16]Methods like the Bayesian Truth Serum (Prelec, 2004) and subsequent refinements do not need knowledge of true values, but require strong assumptions on preferences such as risk-neutral expected utility or ambiguity neutrality (Karni, 2020). Recently, Schmidt (2021) and Hill, Abdellaoui, and Colo (2021) proposed methods to infer ambiguity perception from choice data, requiring that preferences follow a multiple prior representation.

[17]Consequently, many experimental studies on insensitivity in decision-making under uncertainty have used subjective likelihood judgments, e.g., Tversky and Fox (1995), Fox, Rogers, and Tversky (1996), Fox and Tversky (1998), Wu and Gonzalez (1999), and Kilka and Weber (2001).

respond to exogenous variation in ambiguity. The *Low Ambiguity* and *High Ambiguity* parts were purposefully designed to offer such an exogenous variation. Increasing the time difference for the weather event from four days (*Low Ambiguity*) to eight weeks (*High Ambiguity*) induces higher ambiguity in the latter. Therefore, the exogenous increase should be reflected within-subject in a higher reported ambiguity perception in the *High Ambiguity* part compared to the *Low Ambiguity* part.[18]

Hypothesis 1. *The index $\overline{p}$ captures relevant ambiguity perception: exogenous increases in ambiguity increase ambiguity perception ($\overline{p}^H > \overline{p}^L$).*

The next hypothesis then concerns the empirical relationship between ambiguity perception and a-insensitivity. Across all parts, the two are expected to be significantly correlated, if the mechanism proposed by the multiple prior models is indeed responsible for a-insensitivity:

Hypothesis 2. *Ambiguity perception is positively related to a-insensitivity: $\overline{p}$ and a are positively correlated.*

The last hypothesis concerns the causal relationship between the two measures. The increase in the degree of ambiguity from the *Low Ambiguity* to the *High Ambiguity* decision parts were designed to influence only subjects' ambiguity perception, not factors which influence preference-based consideration. Specially, the lotteries used in the elicitation of a-insensitivity, if chosen by subjects, were played out at the same time as when the uncertainty over the event was resolved. This feature ensures that the timing of the resolution of uncertainty was kept constant. Furthermore, for each choice, subjects received their payment via bank transfer at the same time, irrespective of which option they picked. This features ensures that time preferences do not differentially influence decisions between the *Low Ambiguity* and *High Ambiguity* parts.

Therefore, I argue that investigating the impact of the exogenous increase in ambiguity is informative about whether a causal relationship between ambiguity perception and a-insensitivity exists. If a causal relationship exists, a-insensitivity should be higher in *High Ambiguity* than in *Low Ambiguity*, and, importantly, these changes should be predicted by changed in ambiguity perception:

Hypothesis 3. *Ambiguity perception causally influences a-insensitivity: the exogenous increase in ambiguity increases a-insensitivity ($a^H > a^L$), and this increase is larger the larger the increase in ambiguity perception ($\Delta\overline{p}$ predicts Δa).*

As mentioned previously, the indices should not depend on a particular partition of the event space. Therefore, there should be no significant differences between the two partitions, and thus all hypotheses can be applied to both partitions.

3.5 Procedure

Overall, 126 subjects (median age = 24, SD = 7.62, 75 female) participated in the experiment, almost all being students from various study areas. They were recruited from the subject pool of the BonnEconLab using the software *hroot* (Bock, Baetge, and Nicklisch, 2014), and the experiment was conducted as a virtual lab experiment. That is, the experiment took place online but at a prespecified

[18] It is possible that the relevant ambiguity increases with more information, as shown by Shishkin and Ortoleva (2023). Thus, it is important to validate that subjects perceive weather events closer to the present as less ambiguous

Table 2: Descriptive Statistics

	Event Partition 1			Event Partition 2		
	$\overline{p}_1$	a_1	b_1	$\overline{p}_2$	a_2	b_2
Low Ambiguity						
Mean	0.27	0.46	-0.13	0.27	0.51	-0.13
Median	0.20	0.45	-0.08	0.23	0.50	-0.10
Standard Deviation	0.20	0.34	0.23	0.20	0.37	0.22
High Ambiguity						
Mean	0.45	0.66	-0.14	0.45	0.67	-0.11
Median	0.40	0.70	-0.13	0.41	0.75	-0.10
Standard Deviation	0.25	0.32	0.23	0.25	0.35	0.26

time and date. For the entire time, an experimenter was available to answer questions,[19] as it is usual for laboratory experiments. Subjects were sent individual links, ensuring that everyone participated in the experiment only once. The experiment was conducted using oTree (Chen, Schonger, and Wickens, 2016). Subjects received 5 euros as a show-up fee, and one of their choices was randomly selected for real implementation, where they could earn as much as 10 additional euros. On average, subjects earned 11.27 euros, and the experiment took about 40 minutes. The translated instructions can be found in Appendix G.

Of the 126 participating subjects, 9 violated weak monotonicity more than once, i.e., for more than one of the four parts, set-monotonicity was violated such that $a > 1$.[20] Repeated violations of set-monotonicity are very difficult to rationalize under any decision rule and hence, are likely driven by erratic answers. Following the preregistration, these subjects are excluded from the analysis. Two subjects chose Option A for *every* decision, regardless of the event or the lottery option's probability. In accord with the preregistration, those subjects were similarly excluded from the primary analysis. This leaves 113 subjects for the analysis discussed in the next section. None of the results change when the full sample is analyzed instead (see Appendix E for the results).

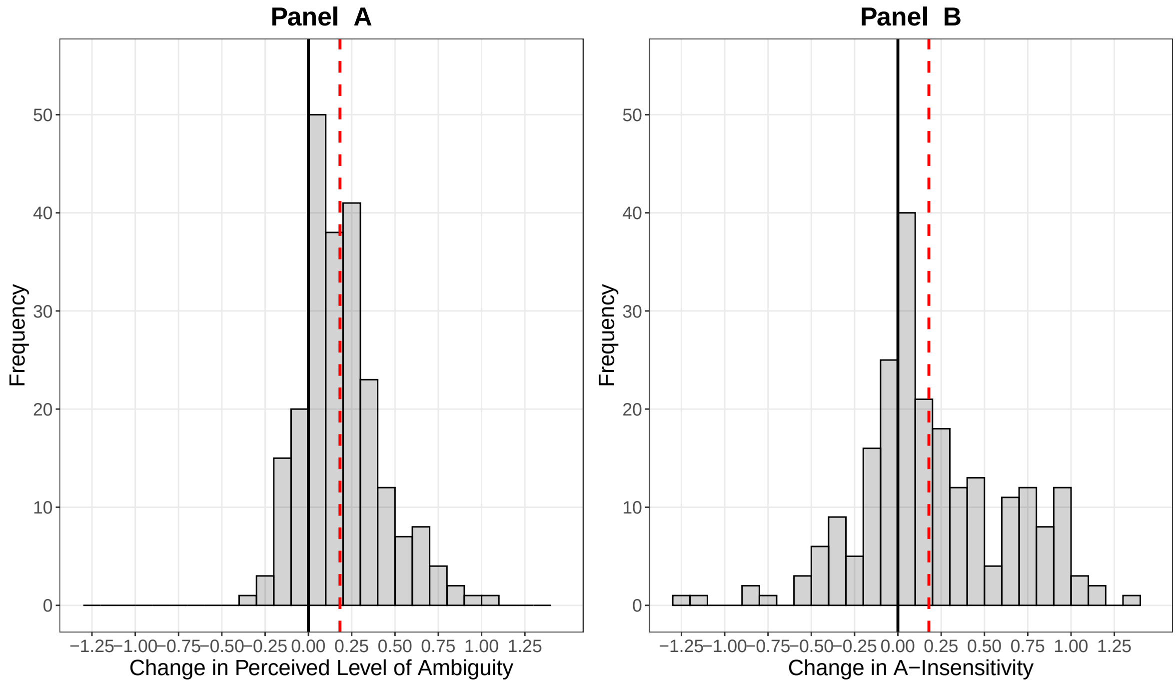
4 Results

Table 2 shows summary statistics for the main variables in each part. Across all parts, subjects report a considerable amount of perceived ambiguity $\overline{p}$, with, for example, an average probability interval of 0.27 in the two *Low Ambiguity* parts. Subjects display substantial a-insensitivity (index a) with values ranging between 0.46 and 0.67. Subjects are slightly ambiguity seeking (index b) on average, with values between -0.11 and -0.14. As expected, averages between the two event space partitions are nearly identical for all indices. The finding of substantial a-insensitivity is consistent with earlier

[19]Communication was possible via email or telephone, allowing for direct (anonymous) one-to-one communication.

[20]This is the case whenever $\overline{m_c} < \overline{m_s}$, meaning that matching probabilities of single events are higher than composite events containing the very same single events.

Figure 2: The Impact of an Increase in the Degree of Ambiguity on Perceived Ambiguity and A-Insensitivity



Notes: **Panel A:** Histogram of the change in perceived ambiguity from *Low Ambiguity* to *High Ambiguity* with a bin size of 0.1. **Panel B:** Histogram of the change in a-insensitivity from the *Low Ambiguity* to the *High Ambiguity* part with a bin size of 0.1. The red dotted line represents the mean change.

studies that use the same elicitation method (e.g., Baillon et al., 2018b; Anantanasuwong et al., 2020; von Gaudecker, Wogrolly, and Zimpelmann, 2022). Baillon et al. (2018b) also find ambiguity seeking behavior on average, with values of b ranging from -0.06 to -0.11.

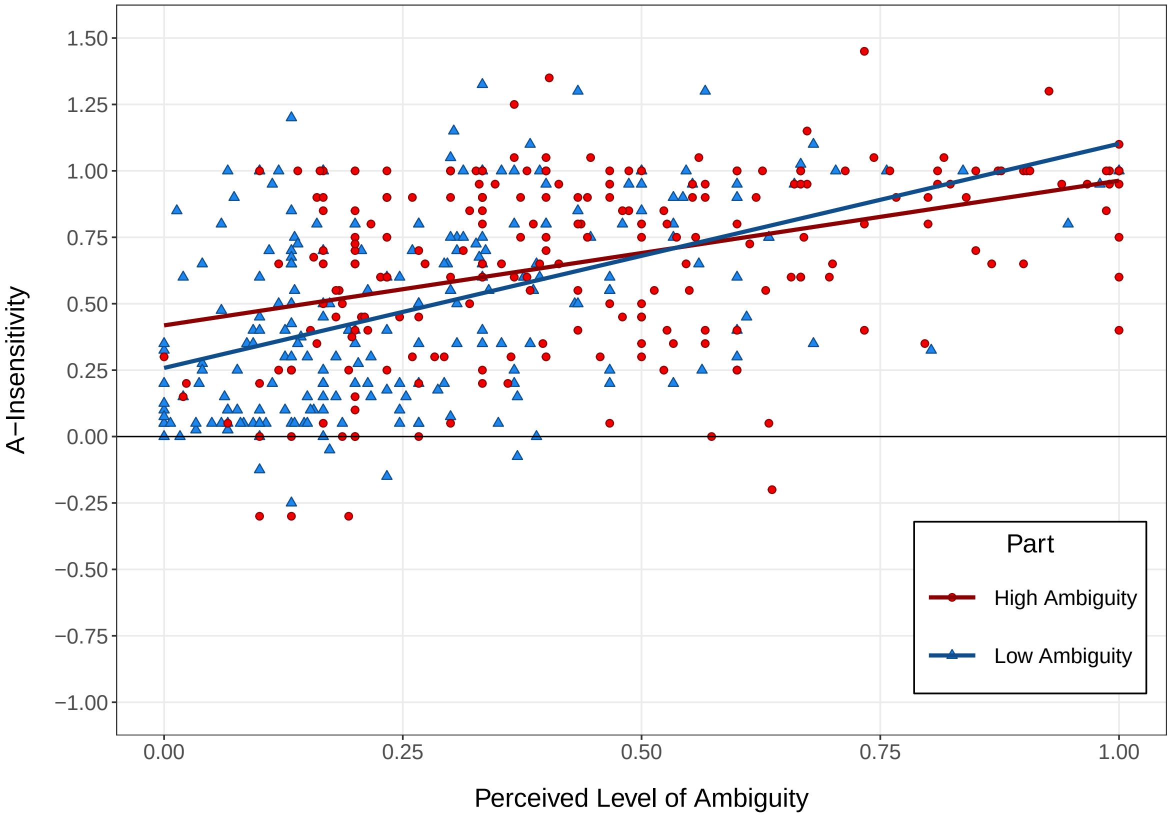
At the individual level, 97% to 99% of subjects report a positive amount of perceived ambiguity. Similarly, 94% to 96% display positive values for the a-insensitivity index across the parts. Negative values are possible with the econometric definition proposed by Baillon et al. (2021), indicating oversensitive behavior. However, for ambiguity perception as a mechanism, a must be nonnegative. Given that values are nonnegative for almost all subjects, this constraint imposed by the multiple prior models does not seem restrictive here.[21] The index b is negative for 66% to 75% of subjects and positive for 18% to 29%. Thus, a majority of subjects is ambiguity seeking, although most display only modest ambiguity seeking behavior.

4.1 Validating the Ambiguity Perception Measure

Hypothesis 1 states that ambiguity perception $\overline{p}$ should be higher in the *High Ambiguity* than the *Low Ambiguity* part. Table 2 provides aggregate evidence that this is indeed the case. For both event space partitions, reported ambiguity perception $\overline{p}$ is significantly higher in the *High Ambiguity* part (for both partitions $p < 0.001$, Wilcoxon signed-rank test). On average, ambiguity perception increased

[21]This is in line with other studies that use matching probabilities to elicit a-insensitivity. For example, von Gaudecker, Wogrolly, and Zimpelmann (2022) find a fraction of 4% with negative a values, and Anantanasuwong et al. (2020) find between 5% and 12%. Earlier studies that do not use matching probabilities to elicit insensitivity typically find higher fractions; see, e.g., Abdellaoui et al. (2011), Li et al. (2017), and Baillon et al. (2018a). One potential explanation for the discrepancy is the influence of risk-induced (in)sensitivity, for which matching probabilities control. This would suggest that oversensitivity is relevant for risk but not for ambiguity.

Figure 3: Relationship between Ambiguity Perception and A-Insensitivity at the Individual Level



Notes: Scatter plot of the relationship between the index capturing perceived ambiguity and the index capturing a-insensitivity. The dots represent a combination of the two indices from a subject for each part, with the *Low* and *High Ambiguity* parts colored differently, so each subject appears four times in the plot. Each line represents an OLS-regression of the a-insensitivity index on the perceived ambiguity index.

by 67%. Panel A of Figure 2 confirms this pattern at the individual level. The Figure displays the change in perceived ambiguity between the *High Ambiguity* and *Low Ambiguity* parts in a histogram. A positive change implies that a subject reported higher perceived ambiguity in the *High* compared to the *Low Ambiguity* part. As evident from the Figure, the overwhelming majority of subjects reported a higher perceived ambiguity in the *High Ambiguity* condition. The change in perceived ambiguity is strictly positive for 79% of subjects for the first event space partition and 77% for the second. In contrast, perceived ambiguity decreased for only 17% and 18% of subjects. The ambiguity perception index is thus responsive to changes in the degree of ambiguity. Hence, these results support the notion that my index captures the extent to which subjects perceive the events as ambiguous. This validity allows me to relate my index to the index capturing a-insensitivity.

4.2 Relationship between Ambiguity Perception and A-Insensitivity

As starting point of the analysis of the relationship between ambiguity perception and a-insensitivity, I investigate the correlation between the two measures at the individual level. I find strong support for Hypothesis 2: all correlations between ambiguity perception and a-insensitivity, whether calculated for each part individually or pooled together, are positive and significantly ($p < 0.001$) different from zero. When the parts are pooled together, the correlation coefficient is $\rho = 0.50$, and similar correlations are found for each part individually. In the two *Low Ambiguity* parts, correlations are

Table 3: OLS-Regression of A-Insensitivity on Perceived Ambiguity

	Dependent variable:			
	A-Insensitivity Index a			
	(1)	(2)	(3)	(4)
Perceived Ambiguity Index $\overline{p}$	0.704***	0.697***	0.816***	0.816***
	(0.066)	(0.066)	(0.111)	(0.117)
High Ambiguity			0.160***	0.165***
			(0.056)	(0.055)
Partition 2			0.004	0.007
			(0.039)	(0.039)
Perceived Ambiguity$\times$*High Ambiguity*			$-$0.299**	$-$0.307**
			(0.130)	(0.132)
Perceived Ambiguity$\times$Partition 2			0.056	0.048
			(0.085)	(0.085)
Constant	0.321***	0.350*	0.256***	0.288
	(0.035)	(0.186)	(0.045)	(0.184)
Controls		X		X
Observations	452	452	452	452
Subjects	113	113	113	113
R^2	0.238	0.256	0.254	0.273

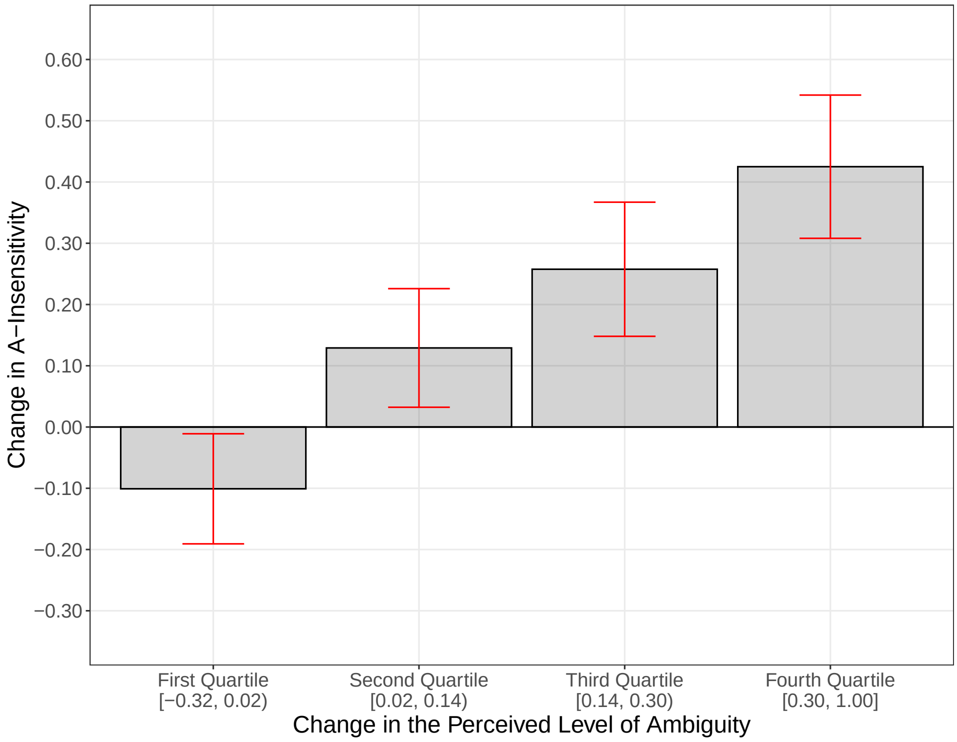
Notes: The table displays OLS-estimates. Robust standard errors (in parentheses) are clustered at the subject level. Controls include age, gender, final high school grade, and current subject of studies. Significance levels are *p<0.1; **p<0.05; ***p<0.01.

$\rho = 0.43$ for the first event space partition, and $\rho = 0.54$ for the second. Correlations in the *High Ambiguity* parts are $\rho = 0.40$ for the first partition, and $\rho = 0.43$ for the second. The results are visualized in Figure 3, which shows a scatter plot for each subject and part the combination of perceived level and a-insensitivity. For the figure, the *Low Ambiguity* and *High Ambiguity* parts are displayed with separate colors, and the corresponding regression lines are provided alongside.

Table 3 confirms the previously found pattern using an OLS-regression. In column (1), the index capturing perceived ambiguity is regressed on the index capturing a-insensitivity, pooling over all parts. The effect is sizable, suggesting that an increase from no perceived ambiguity ($\overline{p} = 0$) to maximum perceived ambiguity ($\overline{p} = 1$) leads to an increase of 0.70 in the a-insensitivity index. Since the a-insensitivity index similarly attains its maximum at $a = 1$, this corresponds to a sizable increase in a-insensitivity. The estimate is unaffected by the inclusion of controls, as can be seen in column (2). The controls added are subjects' age, gender, final high school grade, and current subject of studies. In columns (3) and (4), interaction effects for the individual parts are added. Reassuringly, there are no significant differences in the relationship between the two different event partitions. When looking at differences between *Low Ambiguity* and *High Ambiguity*, the relationship between perceived ambiguity and a-insensitivity is lower in the *High Ambiguity* condition compared to *Low Ambiguity*, mainly because more variance in perceived ambiguity exists in the former.

Having established a positive correlation between the two measures, I now turn to the assessment of whether there exists a causal relationship between the two. As formulated in Hypothesis 3, I test the impact of the exogenous increase in the degree of ambiguity on a-insensitivity. Table 2 again provides aggregate evidence. Increasing the degree of ambiguity and thus the ambiguity subjects

Figure 4: The Relationship between Changes in Ambiguity Perception and Changes in A-Insensitivity



Notes: Average value of the a-insensitivity index for four bins of changes in perceived ambiguity. Each bin corresponds to a quartile. The corresponding cutoff values are displayed on the x-axis description. Error bars show 95% confidence intervals.

perceive significantly increases a-insensitivity, from 0.46 to 0.66 in Partition 1 and from 0.51 to 0.67 in Partition 2 (for both partitions $p < 0.01$, Wilcoxon signed-rank test). At the individual level, the increase in ambiguity induced by the *High Ambiguity* part leads to increased a-insensitivity for most subjects, as displayed in Panel B of Figure 2. Overall, 60% of the subjects for the first event space partition, and 55% for the second, have a positive change in a-insensitivity. Only 27% of subjects for the first partition and 35% for the second display a reduction in a-insensitivity.

The second part of Hypothesis 3 predicts which subjects should show a higher increase in a-insensitivity: those that report a higher increase in perceived ambiguity. To assess this part of the hypothesis, I categorize subjects into quartiles by their change in perceived ambiguity. Using this categorization, Figure 4 shows the average changes in a-insensitivity within each quartile, pooled across both partitions. For example, the first quartile consists of subjects with a change in perceived ambiguity $\Delta\overline{p}$ between -0.32 and 0.02. The average change in a-insensitivity Δa for this quartile is -0.10. The fourth quartile, on the other hand, consists of subjects with the highest increase in perceived ambiguity. For those, the a-insensitivity index increases substantially by 0.43, on average. Overall, for both partitions, the quartiles show a monotone pattern, with higher quartiles having a higher average increase in a-insensitivity. Investigating the correlation between the two changes reveals a positive and statistically significant relationship. For the first partition, Spearman's rank correlation coefficient between $\Delta\overline{p}$ and Δa is $\rho = 0.49$, and for the second partition, the coefficient is $\rho = 0.43$. Both are significant at any conventional level ($p < 0.001$).

To summarize, I find evidence for all three hypotheses. My measure of ambiguity perception captures relevant ambiguity and is strongly related to a-insensitivity. The relationship appears to be causal, because exogenously increasing perceived ambiguity increases a-insensitivity. Hence, these results provide support for the perceived ambiguity mechanism as driving force of a-insensitivity.

4.3 Relationship between Perceived Ambiguity and Ambiguity Aversion

Theoretically, a-insensitivity and ambiguity aversion are orthogonal, as can be seen from Equations (2) and (1). Similarly, ambiguity perception and preferences are interpreted as distinct components. While this does not necessarily rule out an empirical relation, my findings support the separation by also finding orthogonality empirically. First, the exogenous increase in ambiguity from the *Low Ambiguity* to the *High Ambiguity* part had no effect on average ambiguity aversion. As Table 2 shows, the average ambiguity aversion index in the *Low Ambiguity* parts for both partitions is -0.13, nearly identical to the averages in the *High Ambiguity* parts, with -0.15 for the first partition, and -0.11 for the second. Further, there are no significant differences in distributions ($p = 0.60$ for the first partition, and $p = 0.19$ for the second, Wilcoxon signed-rank test).

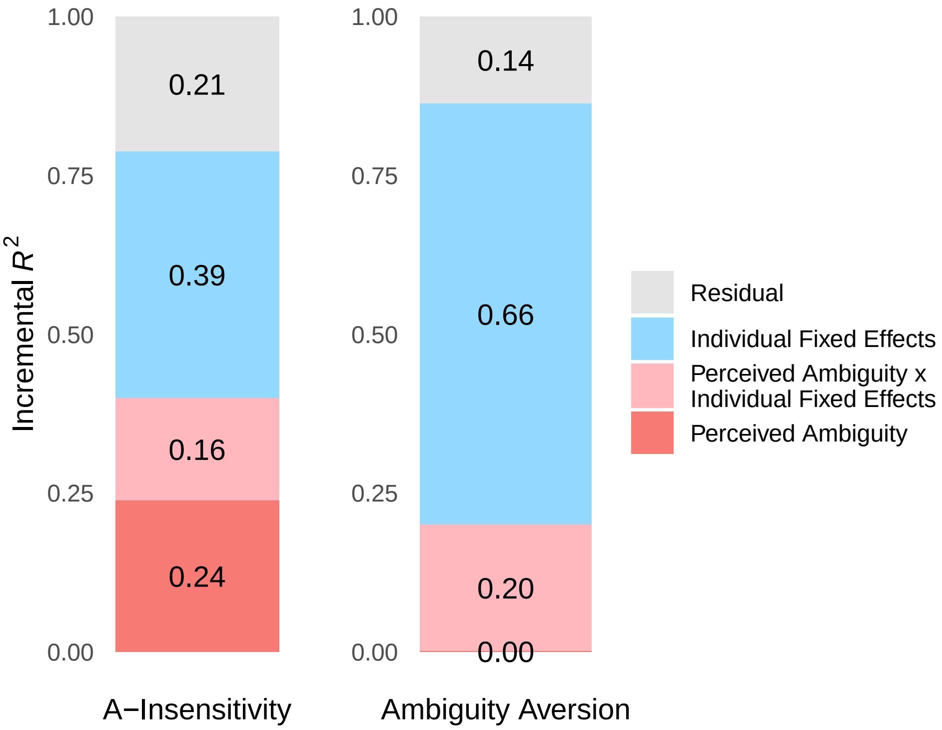
Second, the overall correlation between ambiguity aversion and perceived ambiguity is almost exactly zero when pooling over all parts at $\rho = -0.02$. Within each part, correlations are small and do not point systematically in one direction. Correlations are $\rho = -0.07$ ($p = 0.42$) and $\rho = -0.24$ ($p = 0.01$) for the two *Low Ambiguity* parts and $\rho = 0.14$ ($p = 0.13$) and $\rho = 0.10$ ($p = 0.31$) for the *High Ambiguity* parts. The correlations between a-insensitivity and ambiguity aversion are similar (pooled $\rho = 0.01, p = 0.79$), and are not significant at any conventional level, in line with the findings of Baillon et al. (2018b) and other studies. In the appendix, Figures D.1 and D.2 replicate Figures 3 and 4 from the main text for ambiguity aversion instead of a-insensitivity. Similarly, Table D.1 in the appendix repeats the analysis of Table 3 with ambiguity aversion as dependent variable. As expected, perceived ambiguity and ambiguity aversion are not related.

4.4 Explaining Variation in A-Insensitivity and Ambiguity Aversion

The previous results have demonstrated that ambiguity perception influences a-insensitivity. In this section, I investigate how much of the variation in a-insensitivity can be explained by ambiguity perception and how much by individual-specific preferences. To distinguish between the two, I exploit the fact that I have four observations of a-insensitivity and perceived ambiguity for each subject. I stack all observations and investigate the incremental R^2 for a series of regressions in which I add, first, perceived ambiguity, then individual fixed effects and lastly an interaction of individual fixed effects and perceived ambiguity. How much each step contributes to the R^2 is informative for the relative importance of perceived ambiguity as belief-based explanation compared to a preference-based explanation, the later being captured by the fixed effects.

Figure 5 shows the results. Overall, perceived ambiguity explains 24% of the variation in a-insensitivity directly and a further 16% through the interaction with fixed effects. Fixed effects in itself explain 39%, while 21% of the variation remains unexplained. These suggest that both belief and preferences are at play driving a-insensitive behavior. To assess the magnitude of these results, I repeat the analysis with ambiguity aversion as dependent variable. Here, fixed effects explain 66% of the variation, and perceived ambiguity alone essentially explains 0% of the variation. These results further supports the notion of a-insensitivity as a measure that is strongly influenced by beliefs while

Figure 5: The Explanatory Power of Ambiguity Perception and Individual Fixed Effects for Variation in A-Insensitivity and Ambiguity Aversion



Notes: This figure presents the incremental R^2 for a series of stacked regressions of all four decision parts. That is, I regress sequentially the index capturing a-insensitivity on the index capturing ambiguity perception, individual fixed effects, and an interaction of ambiguity perception and individual fixed effects.

ambiguity aversion is not.

4.5 Order Effects

One potential concern is that the method for eliciting the perceived level of ambiguity affects the measurement of a-insensitivity. Recall that in the former, subjects are asked to state their best guess probability for each event. The guesses have to add to one, constituting a proper probability measure. This might induce a tendency to act (or think) in accordance with this measure, for example, through priming or anchoring effects, that would not happen in the absence of the elicitation method. This could distort subjects behavior displayed during the measurement of a-insensitivity. To test for this possibility, the order of elicitation was randomized in the experiment. Half of the subjects first faced the elicitation of ambiguity perception, while for the other half, a-insensitivity was elicited first. Therefore, it is possible to test between-subject whether eliciting ambiguity perception has an effect on the measurement of a-insensitivity.

Looking at the parts individually, a-insensitivity is slightly lower on average in the two *Low Ambiguity* parts when elicited before, compared with after the perceived level of ambiguity, with the average decreasing from 0.49 to 0.44 for the first partition, and 0.51 to 0.50 for the second. For the two *High Ambiguity* parts, the opposite holds, with averages increasing when a-insensitivity is elicited first, from 0.62 to 0.70 for the first partition, and 0.60 to 0.74 for the second. Contrarily, the perceived level in the two *Low Ambiguity* parts is lower when elicited first (differences are -0.02

and -0.002 for the two partitions) and higher in the two *High Ambiguity* parts (differences are 0.06 and 0.07 for the two partitions). The use of Mann-Whitney U tests for each part reveals that these differences are not significant for neither of the two relevant measures.[22] As a result, all results are robust to the order of elicitation.

Another kind of order effect might be of potential concern. It is possible that through learning or experience effects on the elicitation methods, the timing of the parts itself affects decision-making. If a-insensitivity and the perceived level are partly driven by confusion or unfamiliarity with the elicitation method, both indices could be initially higher. Contrary to this hypothesis, both indices are slightly increasing in the order they appear. For example, a-insensitivity increases by about 0.06 when elicited the second time, while the perceived level index increases by 0.004. Table A.1 in the appendix shows that this pattern also holds for the other parts. In fact, the relationship between ambiguity perception and a-insensitivity becomes stronger the more parts subjects complete. Ordering the parts in sequence as they appear to subjects reveals an increasing pattern. The correlation between the two indices when elicited for the first time is $\rho = 0.42$. The correlation increases to $\rho = 0.49$ when looking at the second time the two indices are elicited, and then further to $\rho = 0.54$ and $\rho = 0.56$ for the third and fourth time, respectively. These results suggest that the relationship I find is not an artifact that vanishes with experience in the elicitation methods.

4.6 Correcting for Measurement Error

Measurement error in elicitation methods can decrease observed correlations between two measures. If the error is sufficiently strong, one might conclude from a low correlation that the two are distinct variables when they in fact measure the same underlying concept. Such measurement error is inevitably present, be it by variations in subjects' attention and focus or induced by the experimental design. For example, the matching probabilities in the experiment are discrete approximations since they are elicited using 5% probability increments.

To correct for such measurement error, I use the Obviously Related Instrumental Variables (ORIV) technique of Gillen, Snowberg, and Yariv (2019).[23] The technique relies on duplicated elicitations of the same variable. Under the assumption that the measurement error of duplicated elicitations is orthogonal, the technique provides a more efficient estimator of correlations between two variables. For that purpose, in the experiment, I used two different event space partitions. As noted in Section 2, under minimal assumptions on the event space, the elicitation of ambiguity attitudes is not affected by changes in the event space partition. Therefore, theoretically, the elicitation of the indices for different partitions is a duplicated measurement of the same indices. As such, ORIV can be used.

Applying ORIV, I find, as expected, that the correlation between the perceived level of ambiguity and a-insensitivity becomes even stronger once measurement error is taken into account. Correlations are $\rho^{ORIV} = 0.63$ for the *Low Ambiguity* part and $\rho^{ORIV} = 0.51$ for the *High Ambiguity* part. Reassuringly, the correlation between ambiguity aversion and perceived ambiguity is unaffected by the measurement error correction and remains close to zero. The correlations are $\rho^{ORIV} = -0.07$ for the *Low Ambiguity* part and $\rho^{ORIV} = 0.06$ for the *High Ambiguity* part. Therefore, it is not the

[22]For a-insensitivity, p-values are 0.52 and 0.79 for the two *Low Ambiguity* parts, and 0.19 and 0.08 for the two *High Ambiguity* parts. Similarly, the p-values for testing differences for the perceived level of ambiguity are 0.72 and 0.95 for the two *Low* and 0.18 as well as 0.10 for the two *High Ambiguity* parts.

[23]See Sargan (1958) or Hansen (1982) for earlier work from which the technique can be derived.

case that measurement error is falsely responsible for the low correlations between the two measures, providing further evidence for the theoretically predicted orthogonality.

4.7 Testing the Predictions of the α-ε-Maxmin Model

Having established the existence of a tight empirical relationship between perceived ambiguity and a-insensitivity, I now turn to investigate two specific predictions that the ε-α-*maxmin model* makes. As highlighted in Section 2, the model predicts that: (i) the perceived level of ambiguity is uniform across different events within each part (see Equation 3), and (ii) the two indices coincide exactly, i.e., $a = \varepsilon$ (see equation 5). My experimental design makes it possible to test both predictions, the first by testing for deviations from uniformity using the proposed elicitation of perceived ambiguity[24], the second by comparing both indices directly.

To quantify deviations from uniformity, I define the following simple distance measure, with $\overline{p}_i$ as the perceived ambiguity measures for each event:

$$\text{Distance to uniformity} = \sqrt{\frac{1}{3}\left((\overline{p}_1 - \overline{p}_2)^2 + (\overline{p}_2 - \overline{p}_3)^2 + (\overline{p}_1 - \overline{p}_3)^2\right)}$$

The measure evaluates differences between the three individual levels of perceived ambiguity for each event using a least-squares criterion. Higher values mean larger deviations from uniformity, with the maximum at 1 and 0 indicating full uniformity.

In all parts, perceived ambiguity appears to be close to uniformity, with the median being below 0.1 for all parts and averages ranging from 0.12 to 0.15. For only 15% of subjects, the measure is larger than 0.4 at least once, with only 8% showing this sizable deviation within each part.[25] See Figure C.1 in the appendix for the full distribution of the measure for each part. One-way ANOVA tests using the four conditions as factors and ambiguity perception as dependent variable further reveal that the null-hypothesis of uniformity can neither be rejected for the two *Low Ambiguity* conditions ($p = 0.62$ and $p = 0.35$) nor for the *High Ambiguity* conditions ($p = 0.25$ and $p = 0.85$). Similarly, a Kruskal-Wallis test yields the same conclusion. Consequently, assuming a uniform level of perceived ambiguity across events appears well supported by the experimental evidence.

Regarding the second testable prediction of the ε-α-*maxmin model*, Figure 3 provides a first graphical impression. If the two indices coincide ($a = \varepsilon$), one should observe that the dots in the graph are close to the 45-degree line. Instead, most dots appear to be quite far from the line, with few bordering or being on the line. Figure C.2 in the appendix quantifies these deviations with histograms of the absolute differences at the individual level between the two indices for each part. For most subjects, the absolute differences are substantial, being around 0.3 on average. Only for a minority of subjects, about 16% to 27%, is the absolute difference between the two indices smaller than 0.1. Similarly, a Kolmogorov-Smirnov test rejects, for each part, that the two distributions of indices come from the same distribution (all p-values < 0.001). Therefore, it appears that the two indices do, in general, not coincide exactly. However, the assumption of a monotone relationship between the two

[24]Note that this is not a strict model test, since the model is written for revealed preferences, not belief data. However, given the strong association between beliefs and behavior, I would argue that this test is still informative for the underlying assumptions of the model.

[25]Furthermore, the measure is highly correlated at the individual level, i.e., subjects that deviate more from uniformity in one part are significantly more likely to do so in the other parts.

indices seems well justified given the results.

5 Conclusion

Using an experiment, I assessed the interpretation of a-insensitivity behavior as ambiguity perception, a hypothesis brought forward by multiple prior models. I indeed find strong empirical support for the hypothesis. Eliciting measures of a-insensitive behavior and ambiguity perception, I find that the two are highly correlated at the individual level. Experimentally varying ambiguity perception increases a-insensitivity, suggesting ambiguity perception causally influences a-insensitivity. The results emphasize the role of ambiguity perception in shaping decision behavior under ambiguity. Having identified ambiguity perception as the mechanism driving a-insensitivity may help to predict in which situations a high or low degree of a-insensitive behavior is prevalent. The results can also be used to inform and refine models of decision-making under ambiguity that have a descriptive goal.

The findings open the door for a couple of potentially interesting directions. For one, there seems to be a lot of heterogeneity in ambiguity perception between subjects for a given situation. Some subjects report high confidence in a proper probability measure, while others perceive a high degree of ambiguity. A natural question to ask is whether these perceptions are purely determined by the source of ambiguity to which different subjects respond differently or whether there are more fundamental determinants of ambiguity perception. Combining the evidence discussed in the introduction that a-insensitivity is related to cognitive function (Baillon et al., 2018a; Anantanasuwong et al., 2020) with the findings obtained in this paper, it does seem that ambiguity perception is a cognitive component of ambiguity attitudes. What exact cognitive processes are responsible for ambiguity perception remains to be explored. This question is related to the question of how subjects form beliefs in situations where ambiguity is present, which remains imperfectly understood.

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Appendix

A Additional Tables

Table A.1: OLS-Regression of Order Effects

	Dependent variable:	
	Perceived Ambiguity Index $\overline{p}$	A-Insensitivity Index a
	(1)	(2)
Constant (First Part)	0.338^{***}	0.515^{***}
	(0.020)	(0.032)
Second Part	0.004	0.063^{**}
	(0.012)	(0.030)
Third Part	0.044	0.095^{**}
	(0.028)	(0.040)
Fourth Part	0.043	0.083^{*}
	(0.026)	(0.045)
Subjects	113	113
R^2	0.007	0.011

Notes: The table displays OLS-estimates. Robust standard errors (in parentheses) are clustered at the subject level. Controls include age, gender, final high school grade, and current subject of studies. Significance levels are *p$<$0.1; **p$<$0.05; ***p$<$0.01.

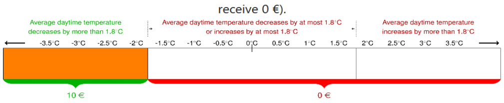
B Screenshots of Main Decision Screens

Figure B.1: Screenshot of a choice list used to elicit a-insensitivity

Choice List 1

Section 1

Event 1 of 6

Option A			Option B
You receive 10 €, if on **June 12th (in four days)** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day (otherwise you will receive 0 €). 	A	B	You receive 10 € with the following probability (otherwise you will receive 0 €).
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **0 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **5 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **10 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **15 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **20 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **25 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **30 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **35 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **40 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **45 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **50 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **55 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **60 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **65 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **70 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **75 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **80 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **85 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **90 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **95 %**
10 €, if on **June 12th** the average daytime temperature will **decrease by more than 1.8 °C** compared to the previous day.	○	○	10 € with a probability of **100 %**

Confirm Decisions

Figure B.2: Screenshot of the questions used to elicit ambiguity perception (step 1)

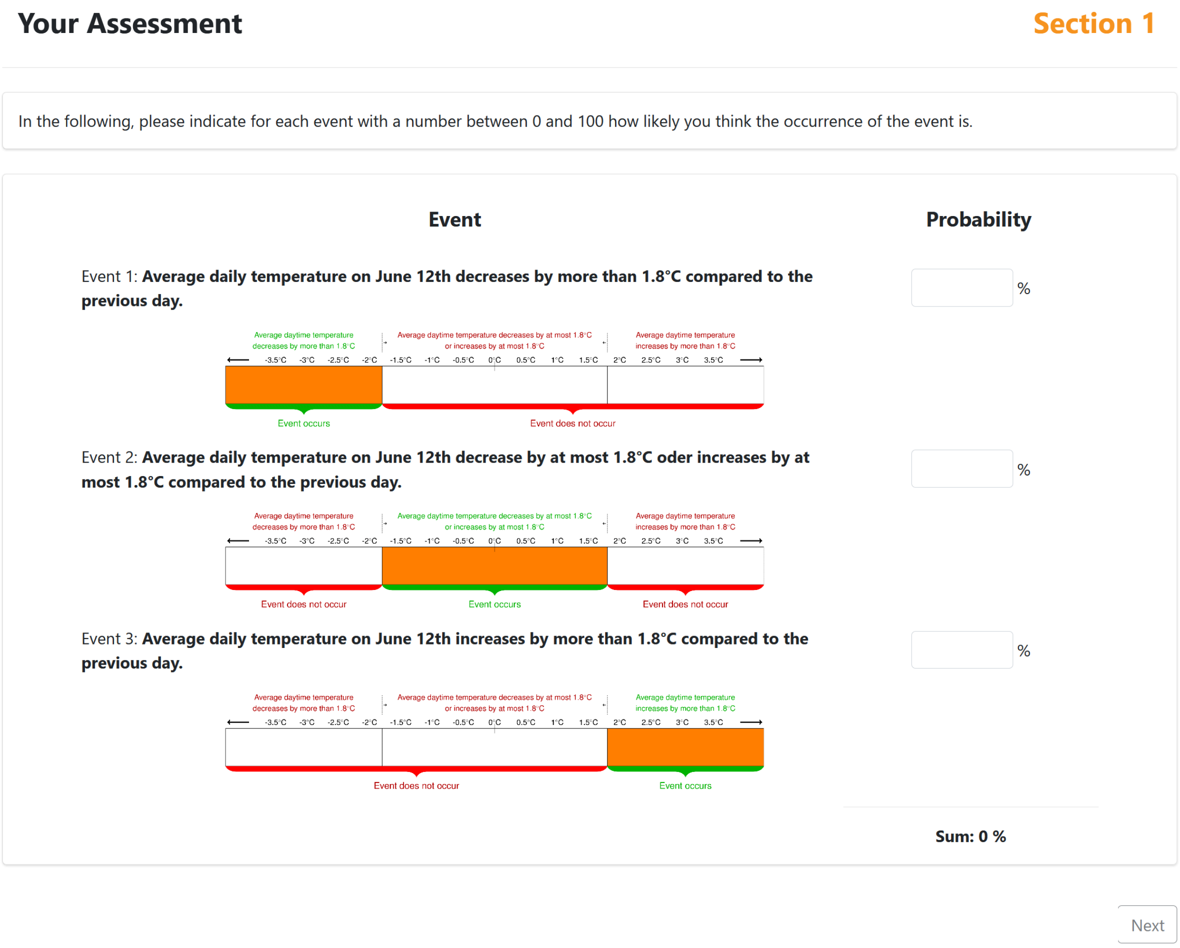


Figure B.3: Screenshot of the questions used to elicit ambiguity perception (step 2)

Your Assessment

Section 1

In the following, please use a slider to indicate how precise you think the probabilities for the three events given on the last screen page are. The associated slider appears when you click on the respective scale.

Event 1

You have indicated, that you think that the event "average daily temperature on June 12th decreases by more than 1.8°C compared to the previous day" occurs with a probability of 25 %.

What do you think is the precision of your specified probability value of **25 %** for the event that the **average daily temperature on June 12th decreases by more than 1.8°C compared to the previous day**?

Absolutely imprecise — Absolutely precise

I'm sure that the probability that the event occurs is between **-Click the scale- and -Click the scale-** .

Event 2

You have indicated, that you think that the event "average daily temperature on June 12th decrease by at most 1.8°C oder increases by at most 1.8°C compared to the previous day" occurs with a probability of 55 %.

What do you think is the precision of your specified probability value of **55 %** for the event that the **average daily temperature on June 12th decrease by at most 1.8°C oder increases by at most 1.8°C compared to the previous day**?

Absolutely imprecise — Absolutely precise

I'm sure that the probability that the event occurs is between **-Click the scale- and -Click the scale-** .

Event 3

You have indicated, that you think that the event "average daily temperature on June 12th increases by more than 1.8°C compared to the previous day" occurs with a probability of 20 %.

What do you think is the precision of your specified probability value of **20 %** for the event that the **average daily temperature on June 12th increases by more than 1.8°C compared to the previous day**?

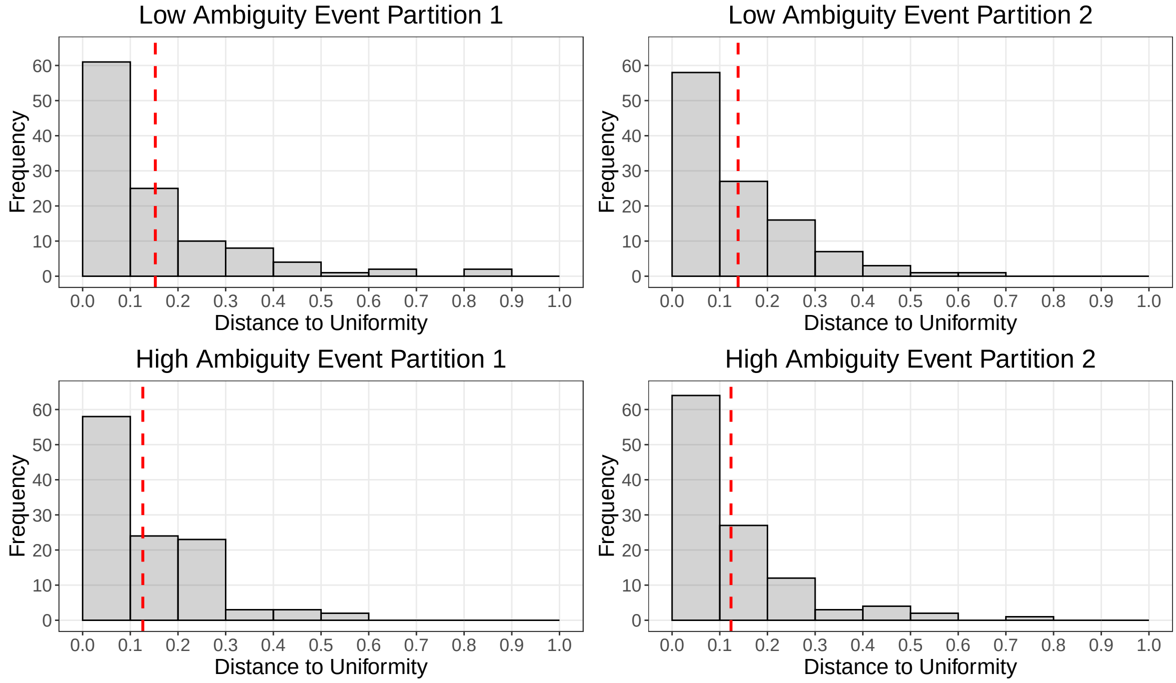
Absolutely imprecise — Absolutely precise

I'm sure that the probability that the event occurs is between **-Click the scale- and -Click the scale-** .

Next

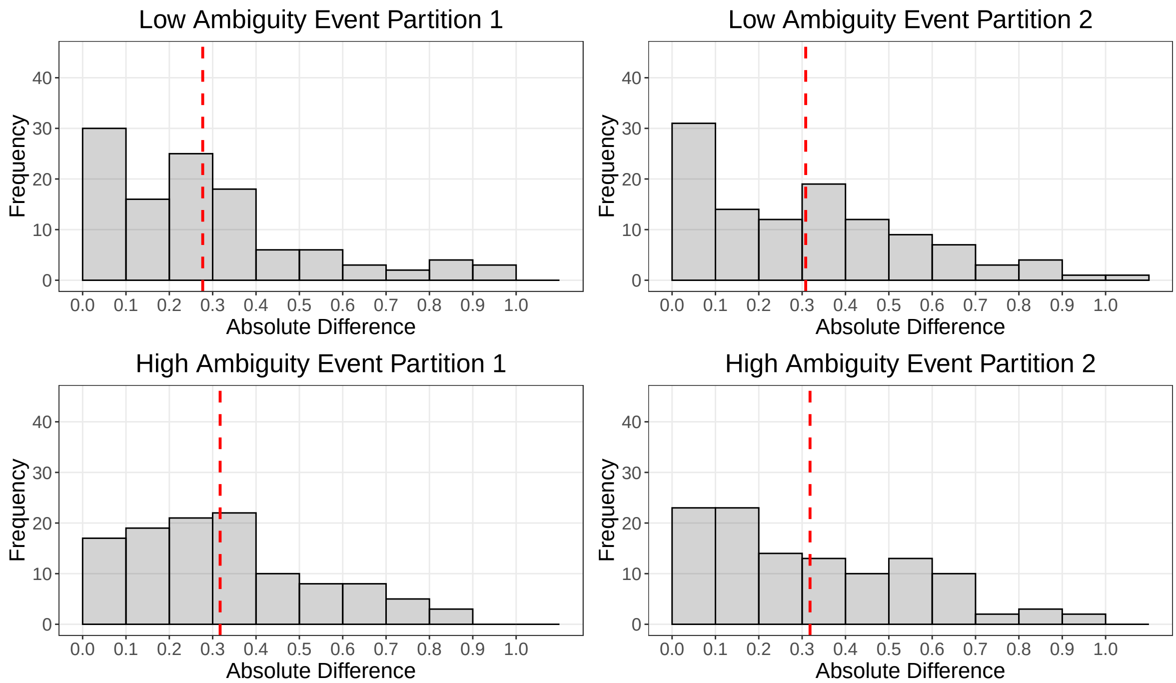
C Additional Results on Testing the α-ε-Maxmin Model

Figure C.1: Testing for Uniformity of Perceived Ambiguity across Events



Notes: Histogram of the distance to uniformity measure defined in Section 4.7 with a bin size of 0.1. The red dotted line represents the mean of the measure.

Figure C.2: Testing for Equality of Indices



Notes: Histogram of the absolute difference between the index capturing ambiguity perception and the index capturing a-insensitivity at the individual level with a bin size of 0.1. The red dotted line represents the mean absolute difference.

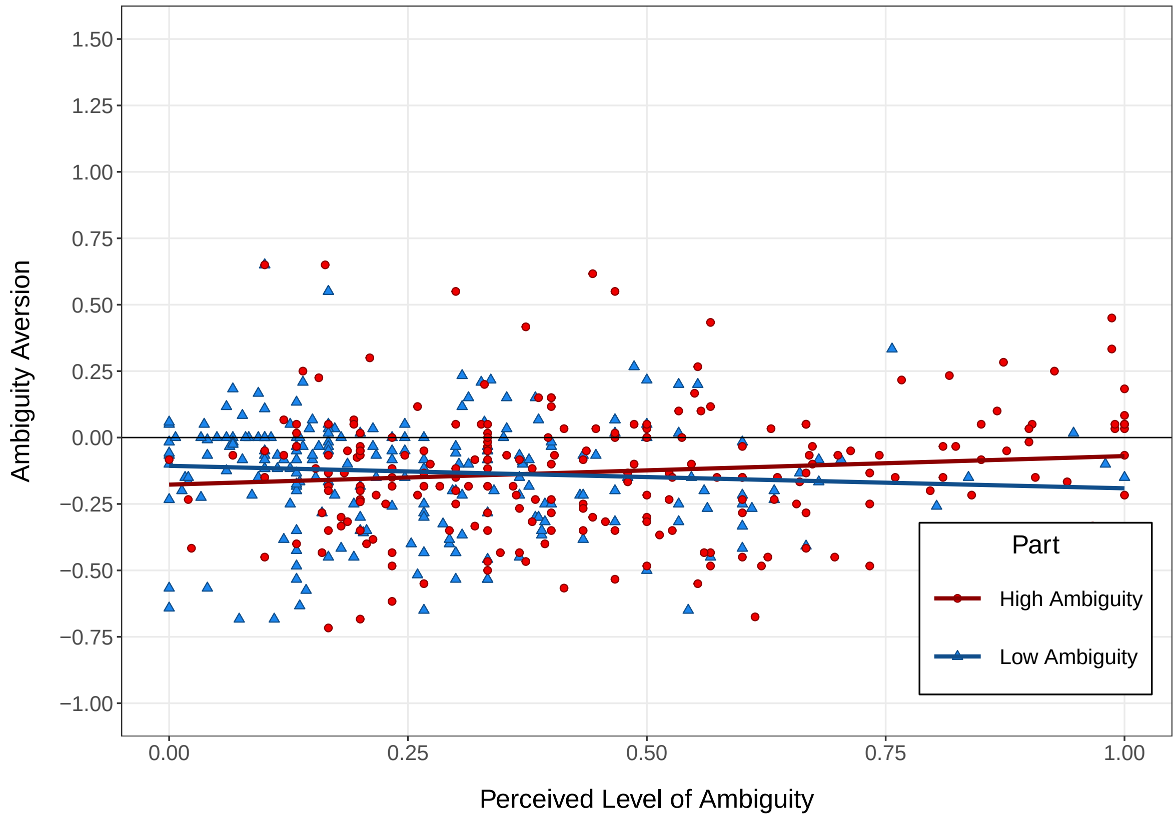
D Additional Results on the Relationship between Perceived Ambiguity and Ambiguity Aversion

Table D.1: OLS-Regression of Ambiguity Aversion on Perceived Ambiguity

	Dependent variable:			
	Ambiguity Aversion Index b			
	(1)	(2)	(3)	(4)
Perceived Ambiguity Index $\overline{p}$	0.029	0.057	-0.066	-0.027
	(0.067)	(0.064)	(0.086)	(0.088)
High Ambiguity			-0.071^{*}	-0.075^{*}
			(0.040)	(0.040)
Partition 2			0.029	0.032
			(0.022)	(0.022)
Perceived Ambiguity $\times$ *High Ambiguity*			0.192^{**}	0.189^{**}
			(0.091)	(0.092)
Perceived Ambiguity $\times$ Partition 2			-0.037	-0.048
			(0.049)	(0.050)
Constant	-0.140^{***}	-0.129	-0.121^{***}	-0.115
	(0.031)	(0.082)	(0.034)	(0.087)
Controls		X		X
Observations	452	452	452	452
Subjects	113	113	113	113
R^2	0.001	0.037	0.011	0.047

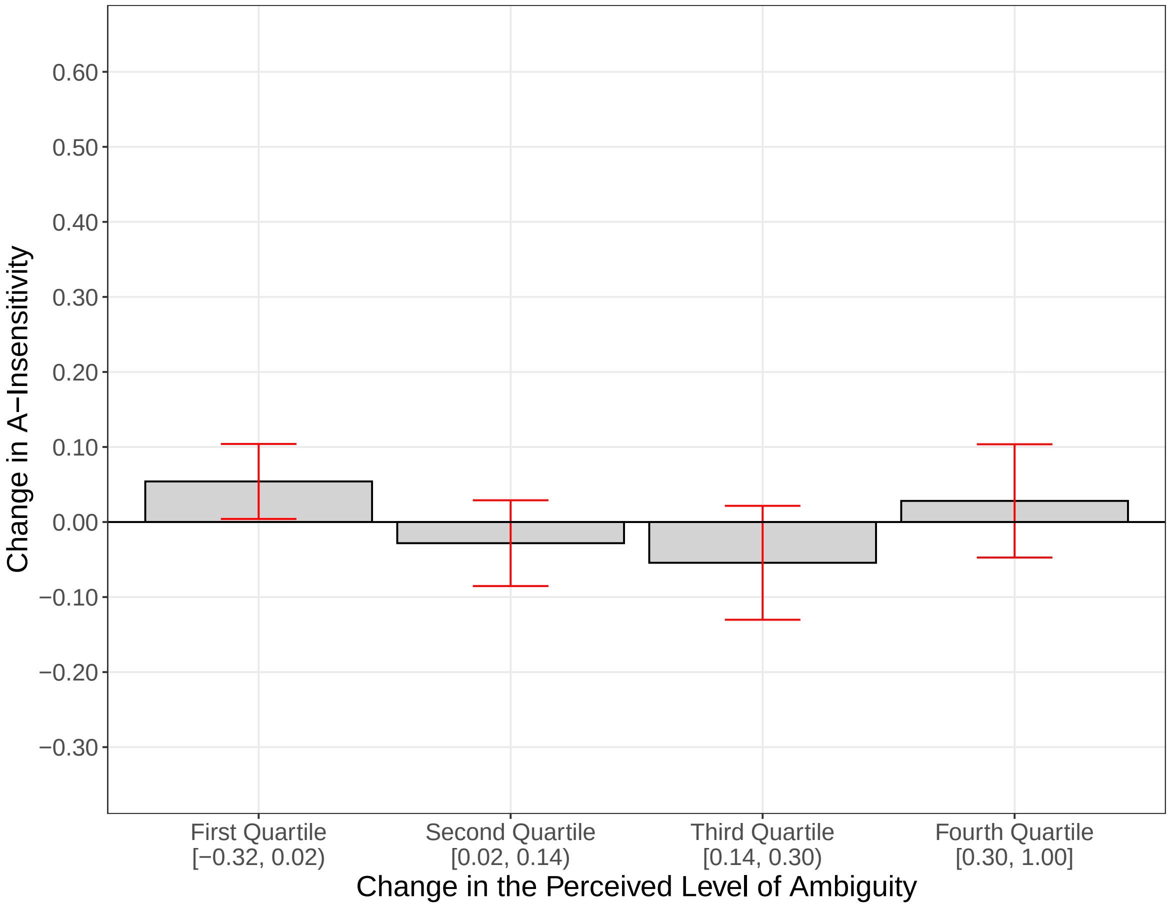
Notes: The table displays OLS-estimates. Robust standard errors (in parentheses) are clustered at the subject level. Controls include age, gender, final high school grade, and current subject of studies. Significance levels are $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Figure D.1: Relationship between between Ambiguity Perception and Ambiguity Aversion on the Individual Level



Notes: Scatter plot of the relationships between the index capturing perceived ambiguity and ambiguity aversion. The dots represent a combination of the two indices from a subject for each part, with the *Low* and *High Ambiguity* parts colored differently, so each subject appears four times in the plot. Each line represents an OLS-regression of the a-insensitivity index on the ambiguity aversion index.

Figure D.2: The Relationship between Changes in Ambiguity Perception and Changes in Ambiguity Aversion



Notes: Average value of the ambiguity aversion index for four bins of changes in perceived ambiguity. Each bin correspond to a quartile. The corresponding cutoff values are displayed on the x-axis description. Error bars show 95% confidence intervals.

E Full Sample Results

This section replicates the main results of the paper using the full sample of 126 subjects. As with the sample used in the main text, reported ambiguity perception $\overline{p}$ is significantly higher in the *High Ambiguity* part compared to the *High Ambiguity* part, confirming Hypothesis 1: average ambiguity perception increases from 0.28 to 0.44 for the first event partition, and from 0.28 to 0.45 for the second (both $p < 0.001$, Wilcoxon signed-rank test). Assessing Hypothesis 2, the direct correlations between ambiguity perception and a-insensitivity are $\rho = 0.44$ for *Low Ambiguity Partition 1*, $\rho = 0.52$ for *Low Ambiguity Partition 2*, $\rho = 0.29$ for *High Ambiguity Partition 1* and $\rho = 0.38$ for *High Ambiguity Partition 2*, all significant $(p < 0.001)$. Pooled together, the correlation coefficient amounts to $\rho = 0.45$, which is fairly close to the one reported in the main text. When applying the same measurement error correction used in Section 4.6, correlations increase to $\rho^{ORIV} = 0.62$ for the *Low Ambiguity* and $\rho^{ORIV} = 0.44$ for the *High Ambiguity* part. Again, the correlations are substantial and closely resemble those reported in the main text. Table E.1 replicates Table 3 of the main text using the full sample. Regarding Hypothesis 3, increasing the degree of ambiguity significantly increases a-insensitivity, from 0.52 to 0.70 in Partition 1 and from 0.57 to 0.70 in Partition 2 (for both partitions $p < 0.01$, Wilcoxon signed-rank test). Similarly, the correlation between $\Delta\overline{p}$ and Δa is $\rho = 0.44$, and for the second the coefficient is $\rho = 0.44$, both being significant at any conventional level $(p < 0.001)$, just like with the main sample.

Table E.1: OLS-Regression of A-Insensitivity on Perceived Ambiguity (Full Sample)

	Dependent variable:			
	A-Insensitivity Index a			
	(1)	(2)	(3)	(4)
Perceived Ambiguity Index $\overline{p}$	0.672***	0.662***	0.864***	0.849***
	(0.077)	(0.077)	(0.132)	(0.135)
High Ambiguity			0.202***	0.200***
			(0.058)	(0.057)
Partition 2			−0.008	−0.007
			(0.037)	(0.038)
Perceived Ambiguity×*High Ambiguity*			−0.445***	−0.432***
			(0.142)	(0.140)
Perceived Ambiguity×Partition 2			0.087	0.082
			(0.084)	(0.085)
Constant	0.380***	0.423**	0.297***	0.348*
	(0.041)	(0.201)	(0.050)	(0.199)
Controls		X		X
Observations	504	504	504	504
Subjects	126	126	126	126
R^2	0.186	0.230	0.209	0.251

Notes: The table displays OLS-estimates. Robust standard errors (in parentheses) are clustered at the subject level. Controls include age, gender, final high school grade, and current subject of studies. Significance levels are *p<0.1; **p<0.05; ***p<0.01

Lastly, I report the results from comparing ambiguity perception with ambiguity aversion as done in Section 4.3 using the full sample. Pooling all parts together, the correlation is again almost exactly zero with $\rho = -0.01$. For the individual parts, correlations are $\rho = -0.08$ ($p = 0.41$, Spearman correlation) and $\rho = -0.18$ ($p = 0.04$, Spearman correlation) for the two *Low Ambiguity* parts and $\rho = 0.13$ ($p = 0.16$, Spearman correlation) and $\rho = 0.09$ ($p = 0.32$, Spearman correlation) for the *High Ambiguity* parts.

F Research Transparency

The experiment was preregistered at `https://aspredicted.org/blind.php?x=ek7wr5`. The preregistration includes details on the experimental design, the sampling process and planned sample size, exclusion criteria, hypotheses, and the main analyses.

The experimental design and sampling process (Sections 3.1 to 3.3) were implemented and the exclusion criteria (Section 3.5) were applied as preregistered. The preregistration specified two sets of analyses. The first set consists of three tests. The first test concerns the change in perceived ambiguity between *Low Ambiguity* and *High Ambiguity*. This test is reported in Section 4.1. The second test concerns the change in a-insensitivity between *Low Ambiguity* and *High Ambiguity*. This test is reported in Section 4.2. The third test concerns the change in ambiguity aversion between *Low Ambiguity* and *High Ambiguity*. This test is reported in Section 4.3. The second set of analyses concerns the empirical relationship between the perceived level of ambiguity and a-insensitivity. This analysis is reported in Section 4.2, and the accompanying measurement error correction in Section 4.6, all implemented as specified in the preregistration. The additional preregistered exploratory analyses of order and learning effects are reported in Section 4.5. The analyses conducted in Sections 4.4 and 4.7 were not preregistered.

G Experimental Instructions

G.1 Introduction

Welcome to the study

Welcome and thank you for your interest in today's online study!

For completing the study in full, you will receive 5 Euros. In this study, you will make decisions on the computer. You can make additional money through your choices. You will receive all payments, i.e. both the payment for your participation and any additional payments based on your decisions, by bank transfer.

In order to participate in today's study, you must consent to the processing of your personal data. To do this, check the box next to "Declaration of consent". If you do not consent to the processing of your data, you will unfortunately not be able to participate in this study.

Because the payment is made by bank transfer and therefore your bank details are required, the data collection in this study is not carried out completely anonymously - unlike usual. Your personal data will, of course, be treated confidentially and will not be passed on to third parties under any circumstances. They will only be used to conduct the payment in this study. Both the data analysis and the possible publication of the results of this study are carried out anonymously.

[Data protection form and declaration of consent]

Structure of the study and your payout

Today's study consists of several sections. In each, you will make different decisions. The decisions in each section may sound similar but are independent of each other. Your decisions in one section will not affect the consequences or payouts in other sections, nor does a similar-sounding decision-making situation necessarily imply that your decision should be similar.

From all decisions with monetary consequences that you will make today, one decision will be randomly selected by a computer. The consequence of the decision will be implemented exactly as described in the corresponding decision. Each of your decisions has the same chance of being selected. So since one of your decisions will actually be implemented, you should think carefully about each decision and treat each decision as if it were actually implemented.

Please note: All decisions concern your personal assessment and preference. Therefore, there is no "right" or "wrong" in any decision to be made. Furthermore, all statements made in the instructions are true. In particular, all consequences of actions are carried out exactly as they are described. This applies to all studies of the Bonn Laboratory for Experimental Economic Research (BonnEconLab) and therefore also to this study.

Events

Your decisions in this study will revolve around specific weather events. These weather events deal with changes in the average daytime temperature.

The average daily temperature is the average of all hourly measured air temperatures of a day and thus describes how warm a day is on average. For the change in the average daytime temperature, the average daytime temperature for a certain day is compared with the average daytime temperature of the previous day. If the change is positive, the day has become warmer than the previous day. If the change is negative, the day has become colder compared to the previous day.

Example: On a day X, an average daily temperature of 20° C was measured. The day before, an average daily temperature of 17°C was measured. The change in the average daily temperature on day X compared to the previous day is, therefore 20°C - 17°C = 3°C. Day X has become 3°C warmer on average.

An example of a weather event that revolves around a change in the average daytime temperature is: "The average daytime temperature on dd.mm. increases by 1°C compared to the previous day". The event occurs when the measured temperature on the dd.mm. is on average 1°C higher than the temperature on dd.mm.

G.2 Elicitation of A-Insensitivity

Your next decisions

In the next decisions in this section, you will have the choice to bet on either a weather event or a computer-generated lottery with given probabilities. The weather event concerns changes in the average daytime temperature in Bonn (weather station Cologne/Bonn Airport) on a certain day compared to the previous day. As just explained, the change in the average daytime temperature describes whether a day has become warmer or colder compared to the previous day.

Each of the choices on the next few screens consist of the following two options:

Option A

If you choose option A, you win 10 Euros if the weather event specified in the decision occurs on the day described.

A possible event of a decision is for example "on dd.mm. does the average daytime temperature decrease by more than 1.8°C". For this event to occur, the average daytime temperature in Bonn must be on dd.mm. fall by more than 1.8°C compared to the previous day (dd.mm). To illustrate this with a numerical example, assume that the average daytime temperature on dd.mm is 18°C. If the average daytime temperature on dd.mm. drops to, for example, 15°C, i.e. dropped by 3°C, you would receive 10 Euros. On the other hand, if the average daytime temperature on dd.mm. is 17°C, you would receive 0 Euros, since the average daytime temperature in this case has only dropped by 1°C.

Option B

If you choose option B, you win 10 Euros with a probability of p% and receive 0 Euros with the opposite probability (1-p)%. The probability p varies in every decision and takes values between 0 and 100. For example, with p = 60% you would have a 60 percent chance of winning 10 Euros, while with a 40% chance you would get 0 Euros. So the higher the probability p, the higher the chance that you will win 10 Euros. The resulting lottery is computer-generated and played out with the respective probability.

Payment

If you choose option A, the average daily temperature measured by the German Weather Service for the day described in the event is compared with the temperature of the previous day. It is then checked whether the respective event has occurred and whether you have won 10 Euros as a result. If you choose option B, a computer-generated decision is made at the same time to determine whether you have won 10 Euros with the respective probability p%.

If you have won the prize of 10 Euros by choosing one of the two options, you will receive the 10 Euros by bank transfer (in addition to your payment for participation). Note that the timing of when you receive the payment does not depend on your decision.

On the next screen you can see an example of the next decisions.

Automatic completion help

In order for you to have to click less, a fill-in help has been activated for all decisions of a single decision screen. With this completion help, you can fill in the lists of decisions on a screen with just one click of your mouse. Therefore, you don't have to click in for each line one of the two options.

All you have to do is decide for what amount of money you want to switch from option A to option B and choose option B in the corresponding decision. It is then assumed that you also choose option B for all decisions on the respective screen page for which the monetary amount of option B is higher, and choose option A for all options for which the monetary amount of option B is lower.

Of course, you can change your decisions at any time. The best thing to do in the example below is to click several times on different options on different lines so that you can familiarize yourself with the mechanism.

[Example of the matching probability elicitation]

To check your understanding, please answer the following questions. You can make your decisions on the next few screens once you have correctly answered all of the questions.

[Comprehension questions]

[Matching probability choices]

G.3 Elicitation of Ambiguity Perception

Your next decisions

The next decisions in this section are about your assessment of various weather events. These events again relate to changes in the average daily temperature in Bonn (weather station Cologne/Bonn Airport) on a specific day compared to the previous day. As just explained, the change in average daytime temperature describes whether a day has become warmer or colder compared to the previous day.

You give your assessment of the weather events in two steps:

- Step 1: You give your assessment of the probability of occurrence of various weather events.

- Step 2: You give your assessment of how accurate you consider the probability of occurrence given in the first step to be.

The two steps in detail are:

Step 1

In the first step, you will be asked for three different events how likely you think it is that a certain temperature change will occur.

To do this, you can specify a probability as a percentage (0% - 100%) for each event. The higher your stated probability, the more likely you think the event will occur. A probability of 0% implies that you believe that the event will not occur under any circumstances. A 100% probability implies that you believe the event is certain to happen.

For example, a possible event is "on dd.mm. does the average daytime temperature increases by more than 1.8°C". Your assessment is then about how likely you think it is that the average daytime temperature on dd.mm. will increase by more than 1.8°C compared to the previous day, i.e. that the temperature on dd.mm. will be more than 1.8°C higher than on dd.mm.

A given probability of, for example, 0% implies that you believe that under no circumstances will the average daily temperature increase by more than 1.8°C compared to the previous day during the given period. In other words, you believe that under no circumstances will the dd.mm. be warmer than the day before. On the other hand, a probability of 90% implies that you consider it very likely that the average daytime temperature on dd.mm. will rise by more than 1.8°C compared to the previous day, so the day will most likely be warmer.

Step 2

The second step relates to the probabilities you specified in the first step. You may be unsure whether the probabilities you have specified correspond exactly to the probability with which the event will occur. Step 2 is, therefore, about the accuracy of your stated probabilities in step 1. In this step, you can use a slider to specify how accurate you consider the probability of occurrence given in step 1 to be.

For example, you may find your probability statement for some events very accurate, while you are rather uncertain about other events. Suppose you think it is rather unlikely that on dd.mm. the average daytime temperature will increase by more than 1.8°C compared to the previous day. Because of this, you have stated a probability of 15% in the first step. In your opinion, the probability could just as easily be 14%, 15% or 17%. However, you are sure that the probability is not too high, for example, not higher than 30%. You can specify this degree of accuracy in the second step.

On the next two screen pages you can see an example of how you can give your assessment in the two steps.

[Example]

To check your understanding, please answer the following questions. You can make your assessments on the next screen pages as soon as you have correctly answered all questions.

[Comprehension questions]

[Ambiguity perception elicitation]