# Experimental Evidence on the Relationship between Perceived Ambiguity and Likelihood Insensitivity

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**Abstract**

Observed individual behavior in the presence of ambiguity is characterized by insufficient responsiveness to changes in subjective likelihoods. Such likelihood insensitivity under ambiguity is integral to theoretical models and predictive of behavior in many important domains such as financial decision-making. However, there is little empirical evidence on its causes and determining factors. 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 exogenously vary the degree of ambiguity while eliciting measures of likelihood insensitivity and ambiguity perception. The results provide strong support for an ambiguity perception based explanation of likelihood insensitivity. Not only are the two measures highly correlated on the individual level, but changes in ambiguity perception due to the exogenous variation also directly induce changes in likelihood insensitivity. My evidence thus substantiates the perception based interpretation of likelihood insensitivity brought forward by multiple prior models in contrast to preference based explanations of other commonly used models.

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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 importance and empirical relevance, e.g., Wakker (2010), Abdellaoui et al. (2011), and Baillon et al. (2018b). It is characterized by 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).[1]

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 Gaudecker, Wogrolly, and Zimpelmann (2021) find substantial differences in a-insensitivity among sociodemographic groups.

Despite the 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., 2021), 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 highlights a potential explanation for observations of a-insensitivity while generating 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) relate a-insensitivity to psychological motives or source dependent preferences.

To test the mechanism, I conducted a preregistered experiment containing three key features that

[1] Insensitivity in choices under risk describes the well-known pattern of inverse-S probability weighting, where there is insensitivity towards changes in (objective) probabilities.

are necessary to adequately answer the research question. First, an index capturing a-insensitivity measured on the individual level that is independent of risk-induced insensitivity and valid under all currently popular ambiguity theories. For this purpose, I use matching probabilities following the method proposed by Baillon et al. (2018b), which has been empirically validated (Baillon et al., 2018b) and theoretically justified (Baillon et al., 2021).

Second, an index capturing subjects' ambiguity perception that directly relates to multiple prior models and is straightforward to elicit. To do so, I designed a two-stage elicitation method to elicit subjective probability intervals. Subjects first report their best-guess probability for the occurrence of an event. Afterward, they state their belief in the precision of the previously reported probability, revealing the subjective probability interval. The average reported precision (i.e., the average length of the probability intervals) is then used as measure of ambiguity perception, which maps into representations of commonly used multiple prior models.

Third, exogenous variation in the degree of ambiguity complemented with repeated measures of the two indices. In the experiment, subjects face future weather events. Between choice situations, I exogenously vary the time distance to the weather events within-subject and measure subjects' responses to this change. Since weather events become more ambiguous as their occurrence is pushed further into the future, the degree of ambiguity faced by subjects plausibly increases. This variation serves two purposes. First, I use the variation to validate the ambiguity perception index. If the index measures ambiguity perception relevant to subjects, reported perception should rise as the degree of ambiguity increases. Indeed, I find that subjects report a significantly higher level of ambiguity perception for weather events occurring further into the future. Reassuringly, observed a-insensitivity is also higher in this case, consistent with a-insensitivity being caused by the degree of ambiguity. Second, and more importantly, I can investigate how exogenous shifts in the level of ambiguity perceived by subjects relate to a-insensitivity to understand the causal relationship better.

With this experimental design, I present two main findings on the relationship between stated ambiguity perception and a-insensitivity. The first one is that increases in ambiguity perception caused by the exogenous increases in ambiguity lead to increases in a-insensitivity. Subjects who report the largest increases in ambiguity perception also show the largest increase in a-insensitivity, while subjects who report little to no increase in ambiguity perception show no increase in a-insensitivity. As the second main finding, I show that the indices capturing ambiguity perception and a-insensitivity are highly positively related at the individual level. Raw correlations range between $\rho = 0.40$ and $\rho = 0.54$. 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 observable characteristics are taken into account. At the same time, and in line with theoretical considerations, I find no relationship between ambiguity aversion, which I also measure using the method of Baillon et al. (2018b), and ambiguity perception, further supporting the validity of the index. Additionally, ambiguity aversion is found to be orthogonal to a-insensitivity, replicating the results of previous studies. Furthermore, the a-insensitivity index is nonnegative for nearly all subjects, which is a necessary condition for the multiple prior explanation and consistent with previous studies that have documented a-insensitivity using matching probabilities, as discussed later.

Overall, these findings provide strong support for an ambiguity-perception-based explanation of a-insensitivity, as proposed by multiple prior models. My results thus 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]. Even though these models, like most ambiguity models, are ultimately concerned with revealed preference behavior and not beliefs, a differentiation between explanations for a-insensitivity is nevertheless important.

Understanding the mechanisms 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; Gaudecker, Wogrolly, and Zimpelmann, 2021). 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 view, 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.

My experimental results add to the empirical literature investigating the determinants of likelihood insensitivity for decisions made under ambiguity. Recent experiments have related the occurrence of a-insensitivity to impairments in cognitive processes. 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. My results complement those studies by showing that as a specific cognitive component, ambiguity perception is a mechanism that drives a-insensitivity. Enke and Graeber (2021) relate the occurrence of (risk- and ambiguity-generated) likelihood insensitivity to cognitive uncertainty about the optimal action. Higher uncertainty then leads to compression toward a cognitive default that can result in insensitive behavior. My paper differs by focusing on an explanation motivated by ambiguity theories rather than on the noisy Bayesian cognition models upon which their theory and evidence are built on. My approach differs methodologically as well since, in contrast to their paper, I focus on ambiguity-generated insensitivity while controlling for risk-induced insensitivity and ambiguity aversion.

[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).

Earlier studies on likelihood insensitivity emerged partly from the well-known finding that financial investors prefer to invest in domestic rather than foreign stocks - the so-called home bias (French and Poterba, 1991; Coval and Moskowitz, 1999)[3]. Heath and Tversky (1991) as well as Keppe and Weber (1995) document that individuals prefer to bet on sources of uncertainty in which they feel competent and knowledgeable. This behavior has been linked to insensitivity because evidence shows that likelihood insensitivity decreases in the reported level of competence for a particular source of uncertainty (Kilka and Weber, 2001)[4]. Ambiguity perception as an explanation for observed a-insensitivity creates a rationale for these findings.

My paper also contributes to the literature on the elicitation of probabilistic statements. It has been suggested that when asked for precise probability statements, respondents use the response "50%" as an expression of ambiguity (Fischhoff and Bruine de Bruin, 1999; De Bruin et al., 2000; Hudomiet and Willis, 2013). Consequently, a growing number of studies explicitly 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 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). How these probabilistic statements relate to behavioral measures inferred from revealed preferences has so far been an open question (Ilut and Schneider, 2022). My results show that such expressions of confidence in probabilistic assessments have great predictive power for decision-making behavior in an incentivized and tightly controlled setting and directly relate to a key index in the ambiguity literature.

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 discuss modeling beliefs under ambiguity and provide a commonly used definition and measure of ambiguity perception. Thereafter, I show how an index of a-insensitivity can be derived from choice behavior, following Baillon et al. (2021). I then provide the details on how ambiguity perception is related to a-insensitivity within the class of multiple prior models.

[3]The first formal definitions of likelihood insensitivity were developed by Tversky and Wakker (1995), and explicitly empirically investigated by Tversky and Fox (1995) and Wu and Gonzalez (1999).

[4]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).

## 2.1 Subjective Beliefs and Ambiguity Perception

Theories and applications that consider beliefs of decision-maker usually assume that they can be represented by a unique probability measure $P$ on a state space $S$[5]. This, in turn, implies that each event $E$ (subsets of $S$) is assigned a single probability $p(E)$. As noted by many authors, such a unique representation of beliefs is unrealistic for situations where no obvious and commonly agreed upon probability measure exists - i.e., ambiguity is present. Given that ambiguity is arguably prevalent in most relevant decision environments, numerous ways to relax the restriction of a unique probability measure have been developed. A widely used approach is to assume that subjects' 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*; see Berger (1990) and Berger (1994) for overviews. A variety of decision theory models (Gilboa and Schmeidler, 1989; Ghirardato, Maccheroni, and Marinacci, 2004; Klibanoff, Marinacci, and Mukerji, 2005; Chandrasekher et al., 2021) have been developed to derive such beliefs from revealed preferences.

A decision-maker is said to *perceive ambiguity*, if $C$ contains more than one probability distribution and perceive no ambiguity if $C$ contains solely a unique probability measure. With the presence of a set of prior beliefs, probability intervals of the form $I_E = \{p(E) : p \in C\}$ can then be constructed[6] for each event $E$. For the elicitation of ambiguity perception, I will focus on belief reports that take the form of such probability intervals. Probability intervals have the crucial benefit that their elicitation from subjects is straightforward and easy to communicate. Thus, the goal is to construct a measure of perceived ambiguity, called the *perceived level (or degree) of ambiguity*, from probability intervals.

To do so, denote upper probabilities by $p^*(E) = \sup_{p \in C} p(E)$ and lower probabilities by $p_*(E) = \inf_{p \in C} p(E)$. Seeing the existence of ambiguity as deviations from unique events probabilities, it is natural to define a measure of perceived ambiguity as the degree to which beliefs deviate from single probabilities for events. In order to quantify such deviations, the average discrepancy between the upper and lower probability, $\overline{p} = (\overline{p^* - p_*})$, is commonly used. 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). Accordingly, I will use $\overline{p}$ as a measure of ambiguity perception. In the experiment, I will elicit $\overline{p}$ by directly eliciting probability intervals for a collection of events that partition the state space. It immediately follows that a monotonic relationship exists between $\overline{p}$ and the size of the set of priors: assuming the existence of a unique set of priors, the larger $\overline{p}$ is, the larger the set of priors $C$ that a subject considers.

So far, no restrictions have been assumed on the set of priors. While not necessary for the existence of a monotonic relationship, putting additional structure on the set of priors enables parametric analysis. The so-called *$\varepsilon$-contamination model* offers a tractable parameterization, and for this reason, it has been extensively used.[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

[5]Or, alternatively, that when asked to, subjects are able and willing to express their beliefs in such a probabilistic form.

[6]Probability intervals $I_E$ can be defined for each event even in the absence of a set of priors and are therefore more general. As such, the existence of probability intervals is a necessary condition for the existence of a set of priors. For an exact mapping, 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 mathematical differences and properties of the two measures.

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

probabilities, distributions from the general set $T$ of probability distributions are considered. Hence, the set of priors takes the form $C = \{(1-\varepsilon)Q + \varepsilon T\}$. Here, $\varepsilon \in [0,1]$ governs the weight given to $T$. A convenient feature of the model is that ambiguity perception is exactly pinned down by $\varepsilon$, since the resulting probability intervals take the form

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

and thus $\varepsilon = \overline{p}$.[8] The special feature of those intervals is that the length of an interval is always equal to $\varepsilon$, independent of event $E$. It will later be shown that $\varepsilon$ directly agrees with an index capturing a-insensitive behavior (defined next) when using a subclass of the contamination model.

## 2.2 A-Insensitivity and Behavior under Ambiguity

While the previous section considered beliefs, this section considers choice behavior, starting with some notation. Events are connected to a set of monetary outcomes $X$ by acts, that map $S$ to $X$. Only binary acts are considered, denoted by $\gamma_E\beta$, and they pay the amount $\gamma$ if event $E$ realizes and outcome $\beta$ otherwise. Similarly, a lottery that pays $\gamma$ with probability $p$ and $\beta$ with probability $1-p$ is denoted by $\gamma_p\beta$. A preference relation $\succcurlyeq$ is defined over prospects, which are acts or lotteries. Then, define a *matching probability* $m(E)$ by $\gamma_E\theta \sim \gamma_{m(E)}\theta$ for an event $E$ given some amount $\theta$. Let $P_n$ be a probability measure on $S$ that will serve as ambiguity-neutral belief measure to measure deviations from neutrality.

Baillon et al. (2021) show that it is possible to elicit two ambiguity indexes valid under nearly all ambiguity theories from choice behavior that require only minimal assumptions about preferences and measurement design (the collection of events used for elicitation). Preferences only need to be complete, transitive and monotone[9], 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). Under these assumptions and defining $\nu$ as the event size[10], they construct the following two indices:

$$b = 1 - 2\bar{m} = E\left[P_n(E) - m(E)\right] \tag{2}$$

$$a = 1 - \frac{Cov\left(m(E), v\right)}{Var\left(v\right)} \approx 1 - \frac{Cov\left(m(E), P_n(E)\right)}{Var\left(P_n(E)\right)}. \tag{3}$$

The index $b$ represents *ambiguity aversion*, capturing the preference component of ambiguity attitudes. Index $a$ is called *a(mbiguity-generated) insensitivity* and is the focus of this paper. It captures the degree of responsiveness of a decision-maker towards changes in the likelihood of events and is commonly interpreted as a cognitive component. In the extreme of maximal a-insensitivity $(a = 1)$,

[8] For this reason, many papers interpret $\varepsilon$ 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).

[9] A preference is monotone if the following three conditions are satisfied: (1) A weak improvement of an outcome of a prospect weakly improves the prospect, (2) a strict improvement strictly improves an act if the event is nonnull (can affect preferences), and (3) strict improvements in outcomes with a positive probability strictly improves the lottery.

[10] Event size is defined as $\nu(E) = \frac{|E|}{n}$, with $|E|$ being the number of events forming the smallest nonempty intersection of the measurement design.

the decision-maker does not respond to changes in likelihood at all, hence treating all events alike. Baillon et al. (2021) show that the two indices are compatible with nearly all existing indexes and ambiguity orderings proposed in the literature. In particular, under the previous assumptions, the two indices coincide exactly with the two parameters of the neo-additive framework of Chateauneuf, Eichberger, and Grant (2007)[11]. This framework is often used in empirical applications, and the two parameters have been shown to explain choices under ambiguity very well (Abdellaoui et al., 2011; Li et al., 2017). The next section will show how ambiguity perception and a-insensitivity are related in the multiple prior models.

### 2.3 The Multiple Prior Mechanism for A-Insensitivity

Following the discussion in Section 2.1, multiple prior models distinguish themselves from other ambiguity models by relating a decision-maker's choice to a set of prior beliefs $C$. Within the class of multiple prior models, the $\alpha$-*maxmin model* (Hurwicz, 1951; Ghirardato, Maccheroni, and Marinacci, 2004) offers a tractable way of differentiating the impact of ambiguity preferences, represented by an ambiguity aversion parameter $\alpha$, from ambiguity perception through the size of $C$. Preferences follow the $\alpha$-*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. A subclass of the $\alpha$-*maxmin model*, the $\varepsilon$-$\alpha$-*maxmin model*, provides a convenient characterization in which parametrized ambiguity perception directly coincides with a-insensitivity. Conceptually, this model combines the restrictions on the belief set of the $\varepsilon$-*contamination model* with the utility representation of the $\alpha$-*maxmin model*. Accordingly, the decision-makers set of priors takes the previously introduced form $C = \{(1-\varepsilon)Q + \varepsilon T\}$, and preferences follow an $\alpha$-*maxmin* representation. There is then a direct mapping between the model parameters to the previously established indices $a$ and $b$, as Dimmock et al. (2015) showed:

$$b = (2\alpha - 1)\varepsilon, \tag{4}$$

$$a = \varepsilon \tag{5}$$

Therefore, the higher the degree of ambiguity, measured by $\varepsilon$, the greater the decision-maker will display insensitivity by having insufficient responsiveness toward likelihood changes. The model thus offers an explanation of likelihood insensitivity based on ambiguity perception, with the two coinciding for the case of the $\varepsilon$-$\alpha$-*maxmin model*.

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.

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

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.

# 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

The source of ambiguity in the experiment concerns future temperature movements. Using this source has the advantage that the weather is a familiar source of ambiguity, and it is straightforward to generate easy-to-interpret natural events from it. Specifically, the events used in the experiment are about differences in the average daily temperature between two consecutive future days[12]. Such differences have a natural interpretation: if the difference is positive, the latter day is warmer than the previous; if negative, the latter day is colder. 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.[13] Hence, varying the distance to temperature events creates a natural and intuitive increase in ambiguity.

In the experiment, each subject faced four decision parts. Each part contained decisions about weather events, and the events in the parts differed only along two dimensions: (1) the time difference between the decision and occurrence of the event and (2) how the event space was partitioned. The goal of (1) is to have an exogenous increase in the degree of ambiguity. Varying the event space partition makes a measurement error correction possible, which is explained in more detail in Section 4.6.

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 $E_1$ in this case 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 an increased time difference between choice and event realization of eight weeks instead of the four

[12]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.

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

days in the two *Low Ambiguity* parts. Comparing the behavior in *High Ambiguity* to *Low Ambiguity* thus allows the impact of a change in the degree of ambiguity to be measured. 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, both a-insensitivity and ambiguity perception using the respective events were elicited, with the order being randomized as well.

### 3.2 Elicitation of A-Insensitivity

To elicit likelihood insensitivity, I use the method proposed by Baillon et al. (2018b), which utilizes matching probabilities. It allows the elicitation of the two indices $a$ and $b$ as defined in Section 2 for natural events such as the weather movements used in this experiment[14]. The method identifies the two indices independent of risk attitudes or subjective beliefs over the likelihood of events. 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. 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 could choose between two options, A and B. Option A paid 10 euros if the respective event $E$ realized and 0 euros otherwise. Option B paid 10 euros with probability $p$. Subjects thus could choose whether to bet on the ambiguous event or on a lottery with a known probability[15]. 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:

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

[14] 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.

[15] In the experiment, the lottery was played out at the same time as when the uncertainty over the event was resolved so 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 to abstract from time preferences.

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.

As Baillon et al. (2021) show, the two indices directly correspond to the indices defined in equations (2) and (3) and are independent of different state space partitions under mild regularity assumptions. 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.

### 3.3 Elicitation of Ambiguity Perception

The subject's degree of ambiguity perception was elicited using a two-step procedure[16]. The goal was to make the elicitation as easy as possible to understand and answer while still capturing ambiguity perception as defined in Section 2.1. 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[17]. Displayed below the slider was the implication of the slider movement for the considered probability set[18]. 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

[16]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.

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

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

$[p_{*_i}, p_i^*]$ of probabilities they considered likely for event $E_i$. The distance $\overline{p}_i = p_i^* - p_{*_i}$ is then a measure of perceived ambiguity for each event individually. Following the theoretical considerations of Section 2.1, the average length across all three events then corresponds to the perceived level of 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 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.[19]. For those reasons, the elicitation of ambiguity perception was not financially incentivized.[20]

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 Kuilen, 2015; Danz, Vesterlund, and Wilson, 2020). 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 opposite to be 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

[19]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.

[20]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).

between the two will be analyzed by investigating the impact of an exogenous increase in ambiguity on the two indices and directly assessing their correlation. To do so, the first step is to validate the ambiguity perception index. If the index captures relevant ambiguity perception, it should 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[21].

**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 builds on the exogenous increase in ambiguity perception and relates it to a-insensitivity. If the two are related, increases in index $a$ due to the exogenous increase in ambiguity should be higher if the reported increase in $\overline{p}$ is higher:

**Hypothesis 2.** *Increases in ambiguity perception are positively related to increases in a-insensitivity: $\Delta\overline{p}$ predicts $\Delta a$.*

Lastly, as a direct test of the relationship between the two indices, across all parts, the two are expected to be significantly correlated, if the mechanism proposed by the multiple prior models is indeed causing a-insensitivity:

**Hypothesis 3.** *Ambiguity perception is positively related to a-insensitivity: $\overline{p}$ and $a$ are positively correlated.*

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

In total, 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 time and date. For the entire time, an experimenter was available to answer questions,[22] 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 D.

[21] It is possible that the relevant ambiguity increases with more information, as shown by Shishkin and Ortoleva (2021). Thus, it is important to validate that when more information is available and less ambiguous, subjects indeed perceive weather events closer to the present.

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

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 |

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 $a > 1$[23]. 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 C 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. Similarly, subjects display substantial a-insensitivity (index $a$), consistent with earlier studies, for example work by Baillon et al. (2018b), Anantanasuwong et al. (2020), and Gaudecker, Wogrolly, and Zimpelmann (2021). Analogous to the results obtained by Baillon et al. (2018b), subjects are slightly ambiguity seeking (index $b$) on average. As expected, behavior between the two event space partitions is quite similar, and aggregate averages are nearly identical. In none of the four parts did more than three subjects display a negative insensitivity parameter $a$. Negative values are possible with the econometric definition proposed by Baillon et al. (2021), as displayed in Equation (3). However, for ambiguity perception as a mechanism, $a$ must be nonnegative. Given that fewer than 3% of subjects in each part displayed such behavior, this constraint imposed by the multiple prior models does not seem restrictive here.[24]

[23]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.

[24]This is in line with other studies that use matching probabilities to elicit a-insensitivity. For example, Gaudecker, Wogrolly, and Zimpelmann (2021) find a fraction of 4% that have negative $a$ values (personal communication), and Anantanasuwong et al. (2020) find between 5% and 12% (p. 17). Earlier studies that do not use matching probabilities

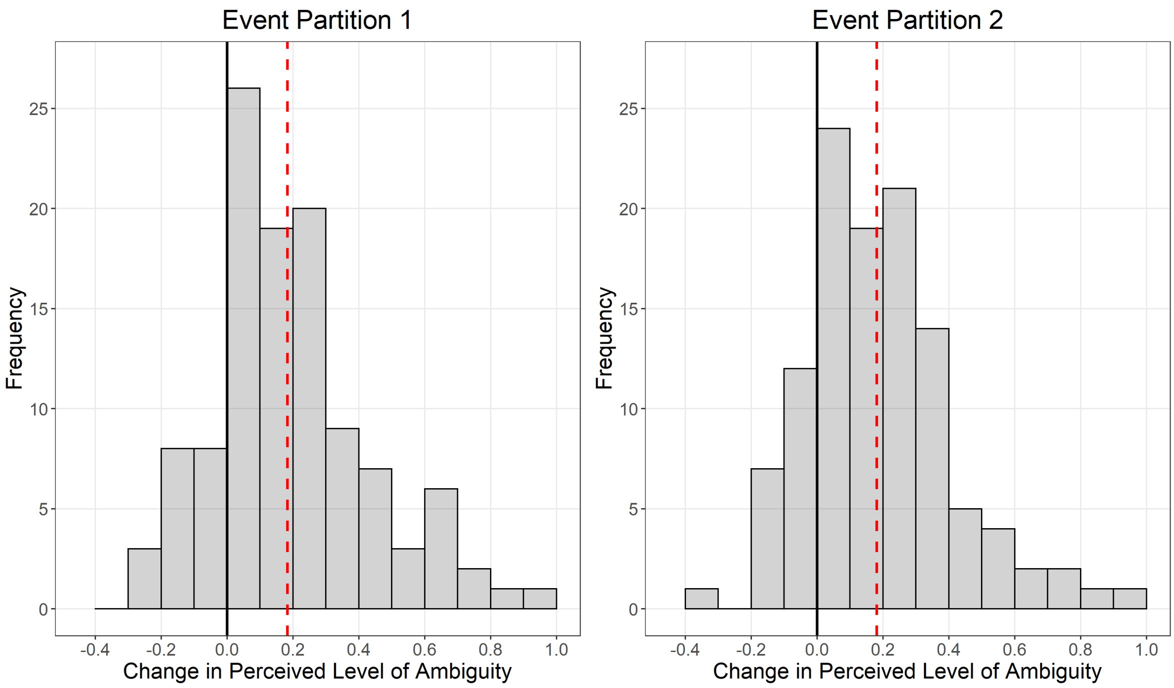


Figure 1: Histogram of the change in perceived ambiguity from *Low Ambiguity* to *High Ambiguity* with a bin size of 0.1. The red dotted line represents the mean change.

### 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 by almost a fifth of the unit interval, constituting a 67% increase. Figure 1 confirms this pattern on 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. These results thus show that the ambiguity perception index is responsive to changes in the degree of ambiguity.

### 4.2 Relationship between Ambiguity Perception and A-Insensitivity

Having validated that the proposed measure of ambiguity perception is related to the degree of ambiguity, I now turn to the relationship between a-insensitivity and ambiguity perception as formulated in Hypotheses 2 and 3. A prerequisite for Hypothesis 2 is that the exogenous increase in ambiguity should increase a-insensitivity. Table 2 again provides aggregate evidence. Similar to the increase in

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.

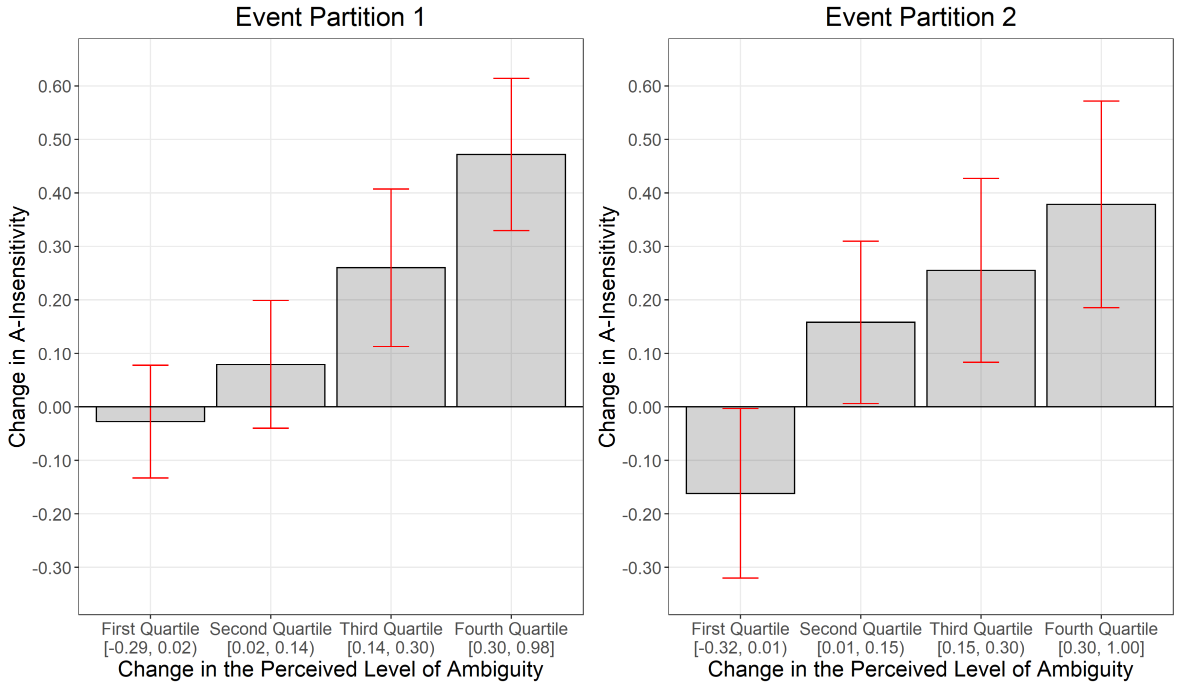


Figure 2: Average value of the a-insensitivity index for four bins of changes in perceived ambiguity. Each bin corresponds to a quartile. The corresponding cutoff values are displayed on the x-axis description. Error bars show 95% confidence intervals.

ambiguity perception, a-insensitivity is higher in *High Ambiguity* than in *Low Ambiguity*. On average, the index rises by about a third, a substantial and significant increase (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. In total, 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. Figure B.4 in the appendix shows this pattern using a histogram similar to Figure 1. Hence, the exogenous increase in ambiguity leads to an increase both in perceived ambiguity and a-insensitivity.

According to Hypothesis 2, subjects that reported a higher increase in perceived ambiguity from *Low Ambiguity* to *High Ambiguity* are expected to show a larger increase in a-insensitivity. To assess this hypothesis, subjects are categorized into quartiles by their change in perceived ambiguity. Using this categorization, Figure 2 shows the average changes in a-insensitivity within each quartile. For example, the first quartile consists of subjects with a change in perceived ambiguity $\Delta\overline{p}$ between $-0.29$ and $0.02$ for the first partition. The average change in a-insensitivity $\Delta a$ for this quartile is $-0.03$, which is statistically indistinguishable from zero. 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, on average $0.47$. 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 $\Delta a$ is $\rho = 0.49$, and for the second partition, the coefficient is $\rho = 0.43$. Both are significant at any conventional level ($p < 0.001$). Hence, the results suggest that increases in a-insensitivity are closely related to increases in perceived ambiguity and support Hypothesis 2.

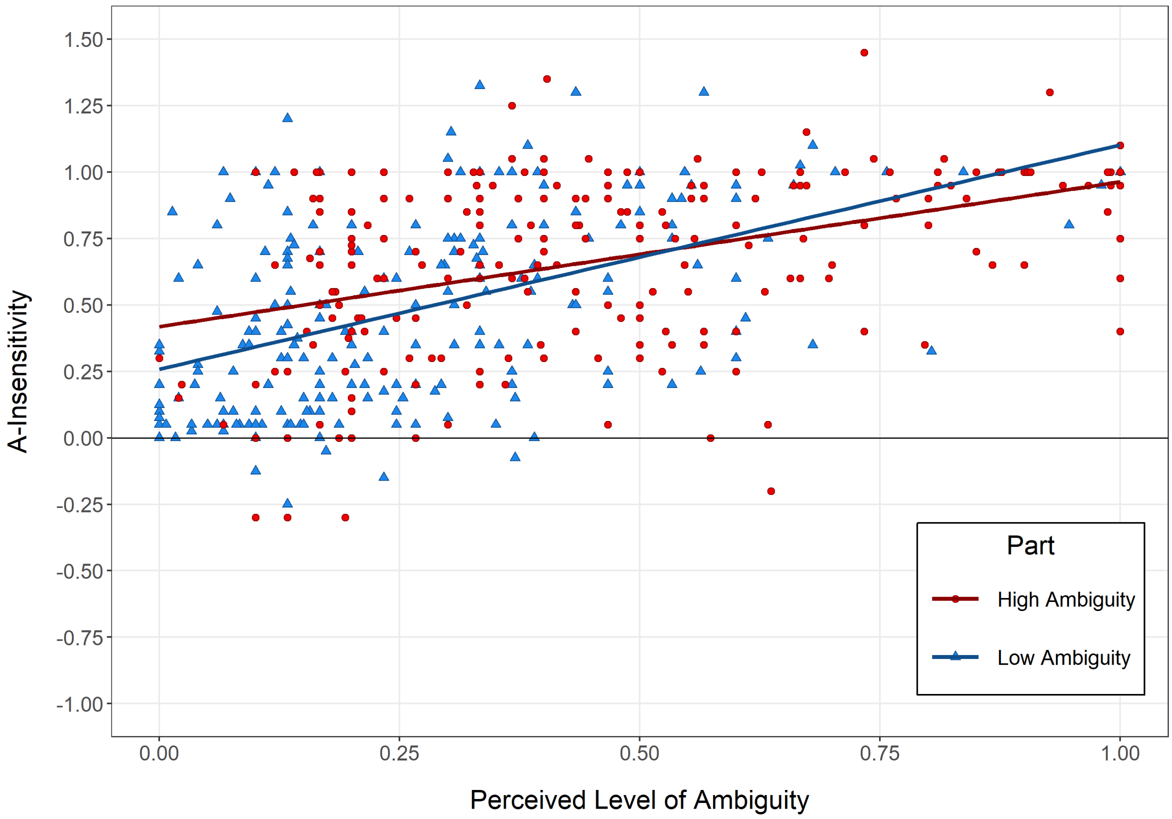


Figure 3: Scatter plot of the relationship between the index capturing perceived ambiguity and the index capturing a-insensitivity. The dots represent a combination of the two indices from a subject for each part, with the *Low* and *High Ambiguity* parts colored differently, so each subject appears four times in the plot. Each line represents an OLS-regression of the a-insensitivity index on the perceived ambiguity index.

Having established the previous result, the next investigation concerns Hypothesis 3 and thus the direct correlation between the two measures. All correlations, 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 $\rho = 0.43$ 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 scatterplot 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

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×*High Ambiguity* | | | −0.299** | −0.307** |
| | | | (0.130) | (0.132) |
| Perceived Ambiguity×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.

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. All in all, I find evidence for all three hypotheses and therefore strong support for the perceived ambiguity mechanism as driving force of a-insensitivity.

### 4.3 Testing the Predictions of the $\alpha$-$\varepsilon$-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 *$\varepsilon$-$\alpha$-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 1), 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[25], the second by comparing both indices directly.

To quantify deviations from uniformity, I define the following simple distance measure, with $\overline{p}_i$

[25]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.

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[26]. See Figure B.5 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 *$\varepsilon$-$\alpha$-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 B.6 in the appendix quantifies these deviations with histograms of the absolute differences on 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 indices seems well justified given the results.

### 4.4 Relationship between Perceived Ambiguity and Ambiguity Aversion

Theoretically, a-insensitivity and ambiguity aversion are orthogonal, as can be seen from Equations (2) and (3). 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

[26]Furthermore, the measure is highly correlated on 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.

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 looking similar, 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 B.7 and B.8 replicate Figures 2 and 3 from the main text for ambiguity aversion instead of a-insensitivity. Similarly, Table A.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.

### 4.5 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[27]. 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.2 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

[27]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.

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

## 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, with elicited measures of a-insensitivity behavior and ambiguity perception being highly correlated and causally related. The results emphasize the role of ambiguity perception in shaping decision behavior under ambiguity. They can be used to better predict such behavior in different situations. They 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

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

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 at least partly cognitive. What exact cognitive processes are responsible for it remains to be explored. This 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 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×*High Ambiguity* | | | $0.192^{**}$ | $0.189^{**}$ |
| | | | (0.091) | (0.092) |
| Perceived Ambiguity×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 |

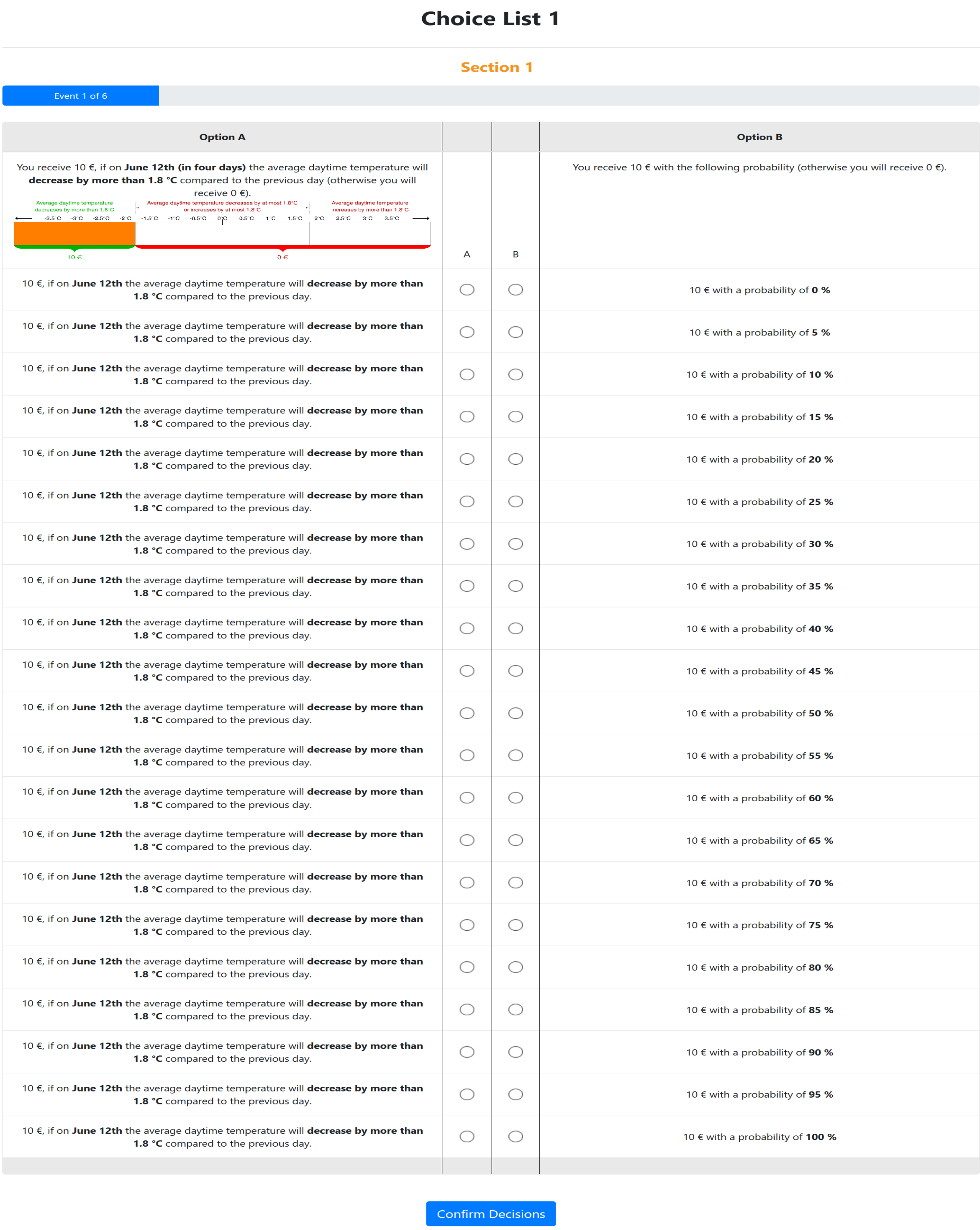
*Notes:* The table displays OLS-estimates. Robust standard errors (in parentheses) are clustered at the subject level. Controls include age, gender, final high school grade, and current subject of studies. Significance levels are $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.2: 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 Additional Figures



## Choice List 1

Section 1

Event 1 of 6

| Option A | A | B | 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 €). | | | 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.1: Screenshot of a choice list used to elicit a-insensitivity

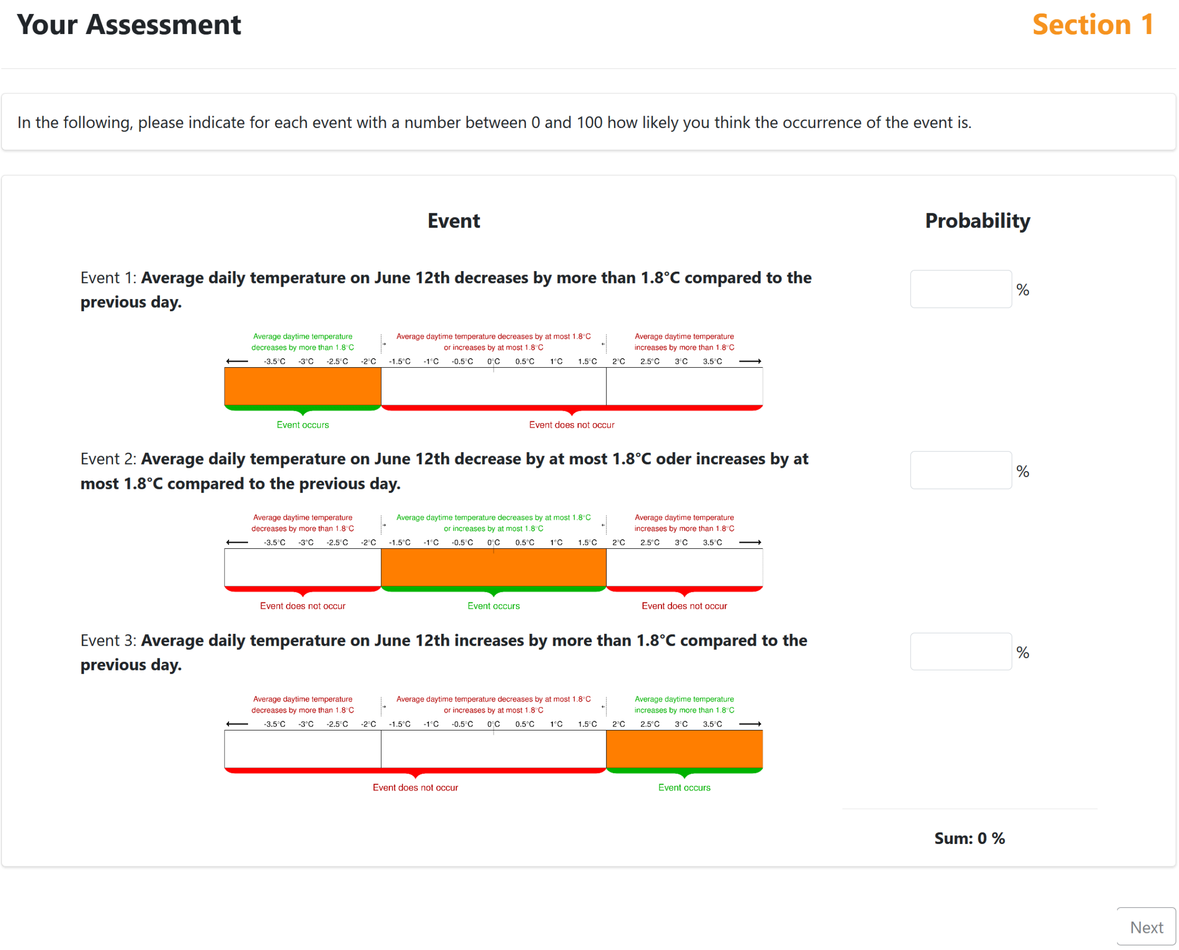



Figure B.2: Screenshot of the questions used to elicit ambiguity perception (step 1)


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

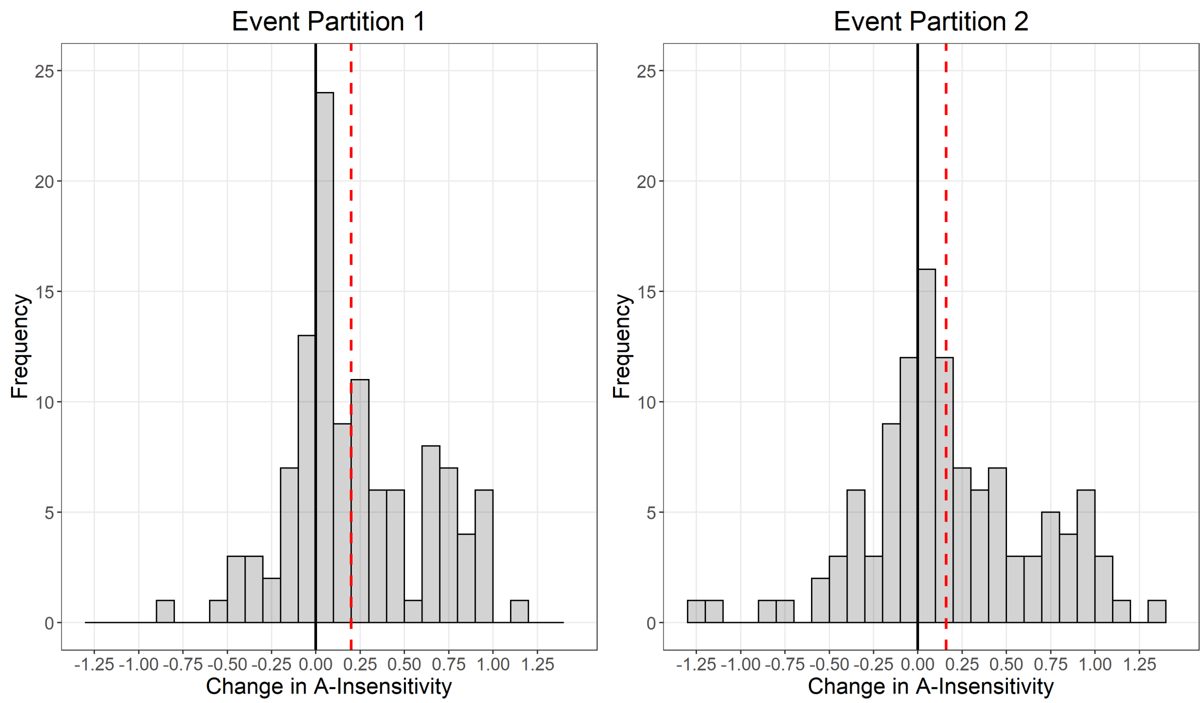



Figure B.4: Histogram of the change in a-insensitivity from the *Low Ambiguity* to the *High Ambiguity* part with a bin size of 0.1. The red dotted line represents the mean change.

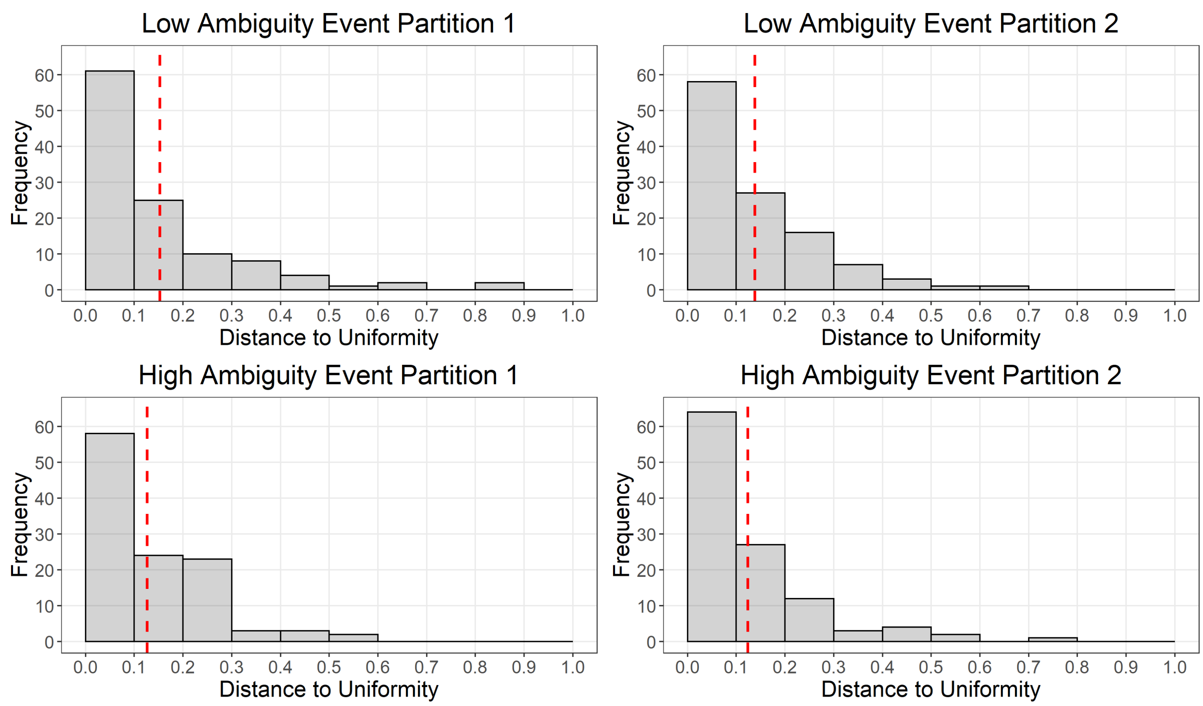



Figure B.5: Histogram of the distance to uniformity measure defined in Section 4.3 with a bin size of 0.1. The red dotted line represents the mean of the measure.

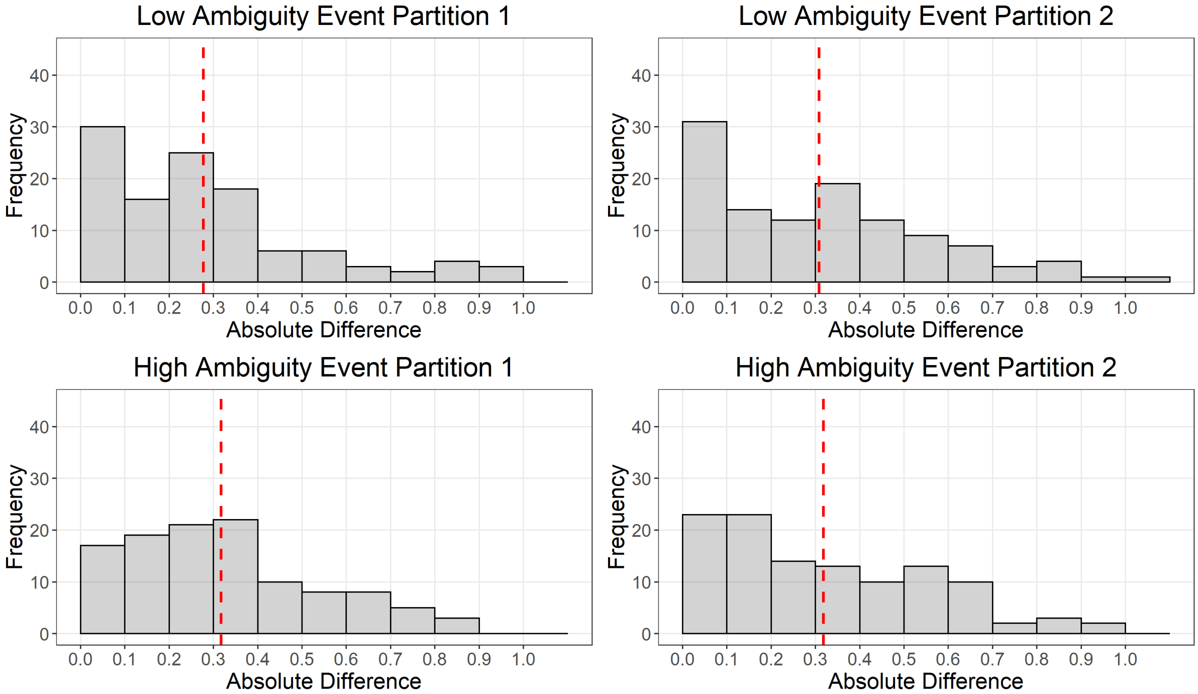



Figure B.6: Histogram of the absolute difference between the index capturing ambiguity perception and the index capturing a-insensitivity on the individual level with a bin size of 0.1. The red dotted line represents the mean absolute difference.

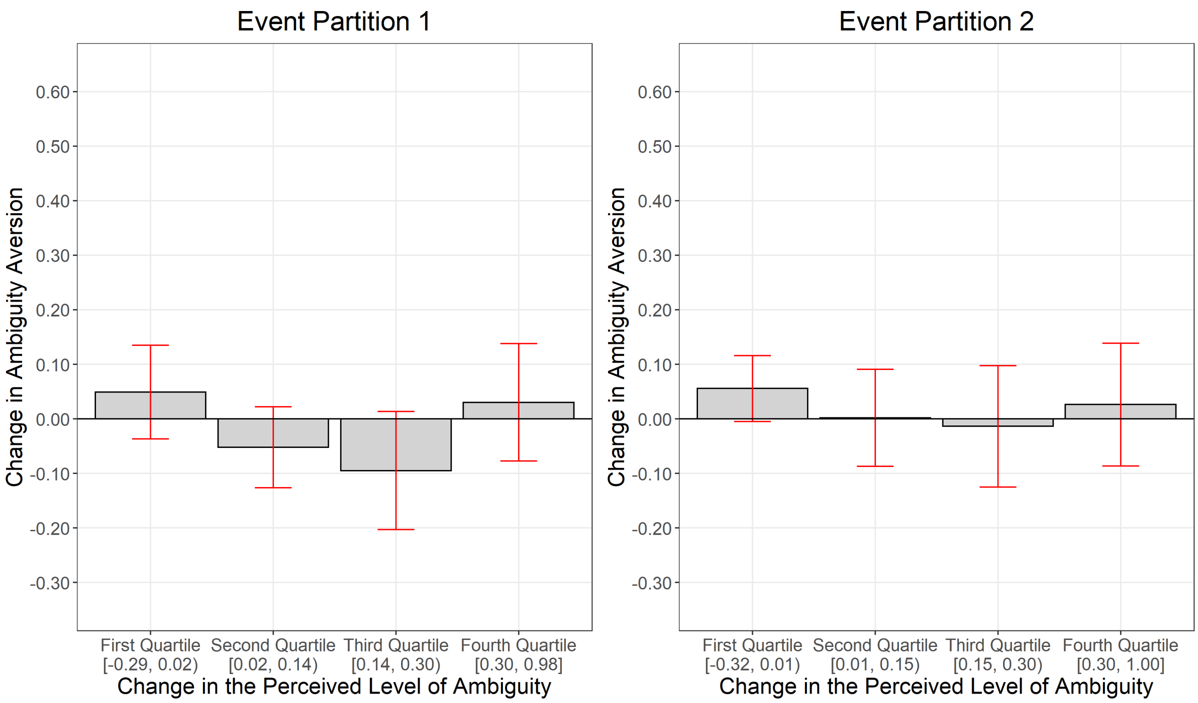



Figure B.7: Average value of the ambiguity aversion index for four bins of changes in perceived ambiguity. Each bin correspond to a quartile. The corresponding cutoff values are displayed on the x-axis description. Error bars show 95% confidence intervals.

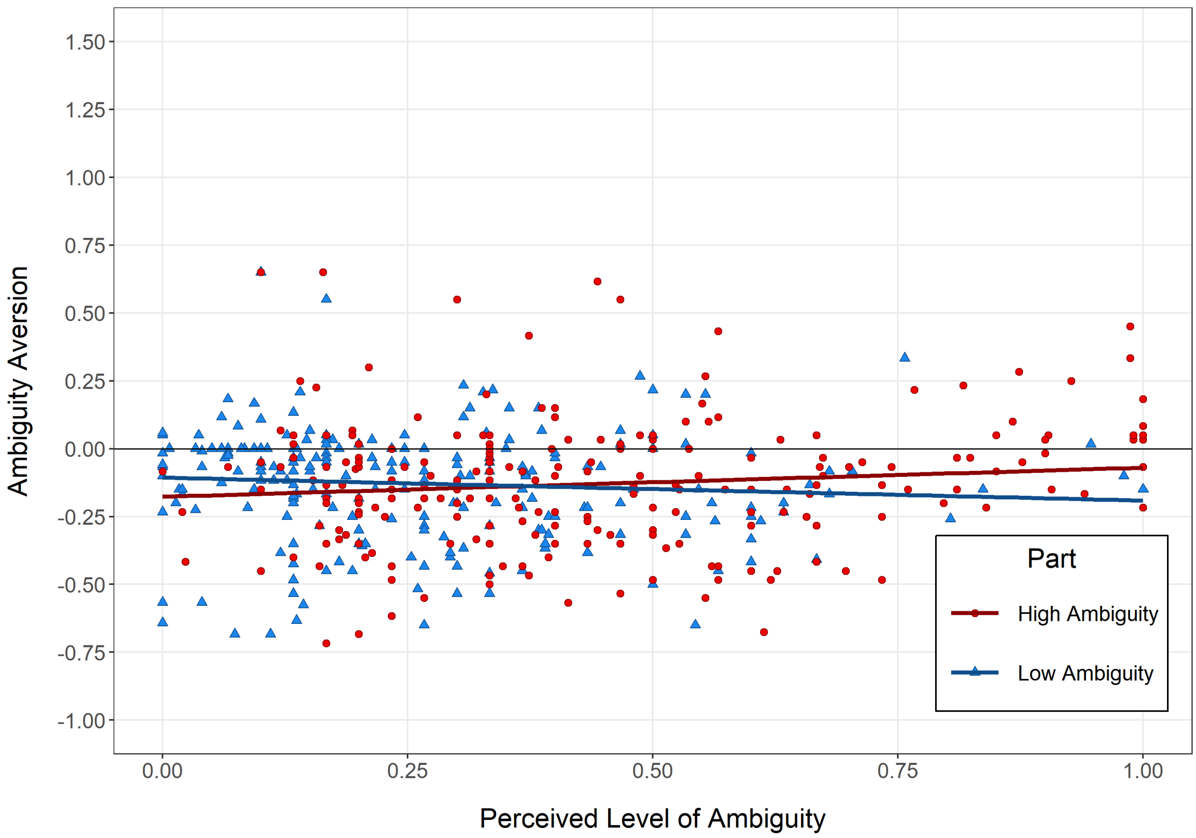



Figure B.8: Scatter plot of the relationships between the index capturing perceived ambiguity and ambiguity aversion. The dots represent a combination of the two indices from a subject for each part, with the *Low* and *High Ambiguity* parts colored differently, so each subject appears four times in the plot. Each line represents an OLS-regression of the a-insensitivity index on the ambiguity aversion index.

## C 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). Regarding Hypothesis 2, the correlation between $\Delta\overline{p}$ and $\Delta a$ 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.

Assessing Hypothesis 3, 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 C.1 replicates Table 3 of the main text using the full sample.

Table C.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 4.4 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 *Low Ambiguity* parts.

# D Experimental Instructions

## D.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.

## D.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]

## D.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]