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DEPARTMENT OF
ECONOMICS AND STATISTICS
WORKING PAPER SERIES

Quaderni del Dipartimento di Scienze
Economico-Sociali e Matematico-Statistiche

ISSN 2279-7114

TESTING SOURCE INFLUENCE ON AMBIGUITY REACTION: PREFERENCE AND INSENSITIVITY

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Working paper No. 83 - October 2023

Testing Source Influence on Ambiguity Reaction: Preference and Insensitivity

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This study investigated whether different sources of uncertainty exert different influences on both the ambiguity aversion/preference and ambiguity-generated insensitivity to likelihood changes. These two dimensions of ambiguity attitude were measured using matching probabilities for three-fold partitioned events, without needing information about subjective likelihoods. A total of 133 Italian university students were randomly assigned to three different treatment groups. Treatments differed depending on the decision context associated with natural sources of uncertainty (i.e., the Covid-19 pandemic, sovereign interest spread, and football matches) under different national scenarios (i.e., France and Italy). The experimental hypothesis was that each decision context could be characterised by both different degrees of emotional involvement and different knowledge/competence of the participants. Additionally, all the participants faced an artificial source of uncertainty, which was always represented by Ellsberg's three-colour problem. The study found that, within treatments, participants were generally more ambiguity-averse when facing the artificial source of uncertainty than natural sources of uncertainty. However, they were less sensitive to likelihood changes when assessing natural rather than artificial sources of uncertainty. Keeping the national dimension of the decision context constant, the between-treatment comparison showed stronger ambiguity insensitivity for Covid-19 versus Football treatment in France. Overall, these findings provide evidence in favour of source preference (thereby, ambiguity aversion/preference depends on the source of uncertainty) but strong evidence in favour of source sensitivity (thereby, likelihood insensitivity depends on the source of uncertainty).

Keywords: Natural sources of ambiguity, artificial sources of ambiguity, source preference, source sensitivity, Ellsberg paradox

JEL codes: C91, D81

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Supplementary material on line: https://drive.google.com/file/d/1WZheyvzeI8jJPIsLP3gA-aX2Gvh_2NKF/view?usp=sharing

ACKNOWLEDGEMENTS:

We would like to thank participants at the 2022 CIMEO Workshop in Experimental Economics (La Sapienza, Rome), 2022 European Economic Association Meeting (Bologna), 2022 Foundation of Utility and Risk Conference (Ghent), 2023 IAREP-SABE Conference (Nice), 2023 ESA World Meeting (Lyon) for useful comments and suggestions. Mistakes are our own. Michele Santoni acknowledges financial support from MUR under the Department of Excellence 2018-2022 grant agreement "Centre of Excellence in Economics and Data Science" (CEEDS). The authors declare that they have no relevant or material financial interests that relate to the research described in this paper The experiment fully conforms to the ethical standards of the CESARE Laboratory of LUISS University, Rome, Italy, where the experiment was conducted, as certified by the laboratory director in date 15th March 2022.

1. Introduction

The distinction between risk and ambiguity (known versus unknown probabilities) (Keynes, 1921; Knight, 1921) is central in the literature regarding decision making. Since the seminal work of Ellsberg (1961), experimentalists have replicated Ellsberg's thought experiment, finding pervasive ambiguity reaction. Consequently, researchers have attempted to understand the motivations, sources, and conditions under which different individual behaviours originated under risk and uncertainty. In addition, theoreticians have developed models to handle ambiguity by either considering nonadditive probability or limiting the application of the sure-thing principle to specific kinds of acts (for reviews, see Etner et al., 2012, and Trautmann and van de Kuilen, 2015).

Most of the experimental works have focused on the replication of the two- or three-colour Ellsberg urns under different experimental conditions and on the use of different subject pools (for an earlier review, see Cameron and Weber, 1992, and more recently Trautmann and van de Kuilen, 2015). However, since the 1990s, researchers have extended their experimental investigation of ambiguity into the context of so-called 'natural events', which were supposed to better reflect real-life situations that deal with uncertainty (Heath and Tversky, 1991; Fox and Tversky, 1995; Tversky and Fox, 1995; Fox and Tversky, 1998; Kilka and Weber, 2001; and more recently Abdellaoui et al., 2011; Baillon and Bleichrodt, 2015; Baillon et al., 2018). The use of lotteries with unknown probabilities was seen by some researchers as an experimental artefact and, as such, a limited way of representing uncertainty. The underground hypothesis was that individuals may react to this kind of uncertainty differently with respect to uncertain events that they normally face in real life. In particular, the literature of the 1990s assumed and partially proved experimentally that ambiguity reaction was stronger in case of "natural events" (Heath and Tversky, 1991; Fox and Tversky, 1995; Tversky and Fox, 1995; Fox and Tversky, 1998; Kilka and Weber, 2001).

Moreover, while in the original two- or three-colour Ellsberg Paradox and the related experimental works there is a direct conscious comparison between a risky choice and an ambiguous one,[1] when we test ambiguity directly in the context of natural events, this direct comparison of different sources is removed from the picture. To some extent, this rules out all the explanations of ambiguity reaction that assume that subjects depict the Ellsberg urn as second-order probability and then in order to evaluate the lotteries they do or do not apply the reduction principle, since this interpretation of how subjects deal with uncertainty is confined to the Ellsberg urn (artificial source of uncertainty) and cannot be extended to natural sources of uncertainty (see Segal, 1990; Bernasconi and Loomes, 1991; Maffioletti, 1995; Halevy, 2007; Baillon et al., 2022a).

Let us now do the following exercise. Consider different sources of uncertainty: risk, when probabilities are known, and ambiguity, when probabilities are neither known, nor knowable. Inside the reign of unknown probabilities, let us think about the mechanism generating the uncertainty (ambiguity): a lottery device (e.g.,

[1] For the role of the direct comparison between risk and ambiguity in the looming ambiguity reaction see Fox and Tversky (1995), Fox and Weber (2002), and Chow and Sarin (2001).

the Ellsberg urn) or an event (e.g., the variation of a stock index). We call the lottery device an *artificial source of ambiguity* and the event-based lottery a *natural source of ambiguity*. Moreover, inside the family of natural sources of ambiguity, we may ask: is the variation of the stock index as a source of ambiguity treated by individuals equally to the number of deaths during a pandemic? Is the result of a football match equal to the result of a political election? Or do they generate the same attitudes to ambiguity? And for an individual living in London, is the variation of the stock index, or the number of deaths during a pandemic, or the result of a football match generating the same attitude to uncertainty when the respective events occur in London or in Rome?

Hence, the first objective of this study is the comparison between artificial and natural events in uncertainty. More specifically, we have two different sources of uncertainty, which differ by the mechanism that generates ambiguity: the traditional three-colour Ellsberg urn versus a natural event uncertainty, for example the number of Covid-19 positive cases in a certain day. Therefore, are ambiguity attitudes different when using the Ellsberg example or when using a natural event? That is, are individuals facing these two different sources of uncertainty reacting to each of them in the same direction and or with the same strength?

The second objective of this study is to compare different sources of uncertainty within the category of natural events: Covid-19, a football match, and the variation of an interest rate spread. Here, we have different sources of uncertainty, but they are all related to natural events. Hence, we ask, do all the natural sources of uncertainty produce the same attitudes to uncertainty?

The third objective of this study is to see whether the same natural events (the same mechanism of generating uncertainty and the same kind of scenario, e.g., a football match) create the same attitudes when they occur in a more familiar or less familiar environment (i.e., Covid-19, a football match, and the variation of the sovereign interest rate spread each in Italy and in France, respectively). This latest issue relates to another research question present in the literature of decision-making under ambiguity: whether the degree of knowledge of the decision context and the emotions spurred by/associated with it have an influence over ambiguity attitudes. Regarding the former, it has been argued that *preference* towards ambiguity with respect to risk should be observed when participants possess enhanced knowledge. This may imply ambiguity preference or a more moderate ambiguity reaction when facing a natural event about which one has more knowledge than a natural event about which one has less knowledge. Heath and Tversky (1991) have provided early experimental evidence in favour of this *competence effect*. They found that, for a given subjective likelihood of winning, participants preferred betting on natural events for which they considered themselves highly competent than betting on chance devices, while showing a reversed preference when facing natural events for which they felt incompetent. Experimental literature has shown that participants prefer betting on more familiar than less familiar natural events (Keppe and Weber, 1999, for the case of stock exchange indexes and geography.)[2]

[2] Source preference has been associated with a more elevated inverse S-shaped decision weighting function under ambiguity, see Abdellaoui et al. (2011). This feature implies that the sum of decision weights for complementary events is higher for the more familiar than for the less familiar source, see Kilka and Weber (2001).

Another factor that has been used in the literature to explain different attitudes regarding different sources of uncertainty is the presence of emotions. The literature links emotions to source preference and/or source insensitivity. For example, considering risk in the gain domain, Rottenstreich and Hsee (2001) have found that lotteries based on an affect-rich outcome (a coupon for a romantic trip) showed both more pronounced overweighting of low probabilities and underweighting of high probabilities than lotteries based on an affect-poor outcome (i.e., cash), other things being equal. Moreover, insensitivity to probability variations between 1% and 99% was very high for affect-rich lotteries, whereas affect-poor lotteries elicited high sensitivity. To explain their findings, the authors argued that the affect-rich positive outcome provoked a more pronounced curvature of the decision weighting function than the affect-poor outcome, and that immediate emotions of savouring, associated with the former, increased the elevation of the weighting function at each probability level. Both elements imply a different reaction to uncertainty according to the presence of emotion. Turning to ambiguity, Baillon et al. (2016) have shown that the watching of sad rather than joyful video-clips before the assessment of artificial uncertainty sources elicited a more neutral attitude to ambiguity in participants, while Li et al. (2018) have shown that, if the decision context aroused positive emotions under natural sources of uncertainty, participants were both less ambiguity averse and less likelihood insensitive.

How do we measure ambiguity attitudes when different sources and different mechanisms are generating uncertainty? In the 1980s and until the Mid-1990s, ambiguity attitudes were mainly measured through the non-additivity in probabilities, while in the second half of the 1990s and in the early 2000s they were measured by the curvature and elevation of the weighting function.[3] Recent literature has introduced the distinction between the reaction to ambiguity measured through additivity (loosely speaking) and the ability due to properly discriminating likelihood in the presence of ambiguity. Likelihood insensitivity (Abdellaoui et al, 2011) or ambiguity-generated insensitivity (Baillon et al., 2021) represents a second, distinctive, and separate feature of ambiguity.[4] Insensitivity has been interpreted as a cognitive dimension of ambiguity attitudes, which shows how much people fail to discriminate between different likelihood levels, meaning the extent to which they tend to treat all likelihoods as identical. In the previous literature, the source influence was called *source insensitivity* by Fox and Weber (2002). According to Kilka and Weber (2001), source insensitivity means that a participant's reaction to likelihood changes is less pronounced, and they feel less competent/informed/knowledgeable about the decision context. However, the experimental results have been mixed. For example, Tversky and Fox (1995) have found stronger insensitivity for more familiar sources of uncertainty as compared to less familiar sources, whereas Abdellaoui et al. (2011) have detected no significant differences.

[3] The same kind of reasoning has been applied to risk (see Wu and Gonzales, 1999).

[4] Tversky and Fox (1995) have defined insensitivity as lower and upper subadditivity of the decision weights. This implies a curvature distortion of the inverse S-shaped decision weighting function under ambiguity, with the overweighting of unlikely events and underweighting of likely events. Experimentally, this distortion is interpreted as ambiguity proneness for low likelihood events and ambiguity aversion for high likelihood events (Trautmann and van de Kuilen, 2015).

To measure the two independent dimensions of ambiguity reaction (i.e., preference and insensitivity), this study adopted Baillon et al.'s (2021) belief hedges approach. Compared to the traditional approach based on the computation of decision weights under ambiguity, by eliciting matching probabilities, this approach allows the experimenter to measure ambiguity reaction without knowledge of the participants' utility function and their subjective likelihoods or information regarding their attitudes towards risk. Moreover, in implementing this approach from Baillon et al. (2018), we always use a three-fold partition of events for natural and artificial events adopting the same decision frame (Li, 2017, Anantanasuwong et al., 2019, von Gaudecker et al., 2022).

To summarise, following Baillon et al.'s (2021) approach, that considers two independent dimensions of ambiguity reaction (i.e., preference and insensitivity), and using the same decision frame for all the sources of uncertainty (three-fold partition of events), we aim to investigate whether different mechanisms generating uncertainty (artificial vs. natural uncertainty, i.e. three-colour Ellsberg urn vs. natural events) and different sources of natural events (i.e. population positive to Covid-19, football match results, or the variation of an economic variable) generate a different reaction to ambiguity. This reaction can differ both in the additive probability measure (i.e., the b-index in Baillon et al.'s approach), and/or in the sensitivity in discriminating probabilities (i.e., the a-index of insensitivity in Baillon et al.'s approach). Moreover, we aim to identify whether different reaction to ambiguity is correlated with the subject level of knowledge and emotions associated with the decision context. While existing studies measuring source influence have considered competence and emotion as separate determinants of ambiguity attitude, we want to investigate both cognitive and psychological factors simultaneously regarding how they can affect these attitudes.[5] We do not have a priori assumption in the direction of the reaction.

The experiment was conducted at the CESARE Lab, LUISS University, Rome, Italy, in May 2022. The participants were 133 undergraduate and graduate students from LUISS University who were recruited through the laboratory. The participants were randomly assigned to three different treatments (two sessions per treatment). Treatments differed depending on the decision context on which the choice questions were based: the Covid-19 pandemic, economics (sovereign interest rate spread), and football. Within each treatment, participants assessed choice questions referring to both the Italian and French scenarios in addition to facing artificial uncertainty, which was always represented by Ellsberg's three-colour problem. The hypothesis was that different treatments and scenarios could be associated with different knowledge and/or affect-richness in the decision context. More specifically, participants were expected to be more emotionally involved and/or informed when assessing the Italian rather than French scenarios, and to show different degrees of knowledge and involvement across treatments. In turn, these differences would distinguish sources of uncertainty and prompt different ambiguity attitudes. To validate this hypothesis, participants' self-reported emotional involvement and knowledge under both types of scenarios were elicited using a 7-point Likert scale, which

[5] Rubaltelli et al. (2010) have shown that bets on familiar weather conditions were associated with more positive affective reactions than bets on unfamiliar ones when participants evaluated events jointly rather than separately. Consequently, they argued that affection drives knowledge-driven source preference in joint evaluation.

confirmed these expectations. To minimise the possibility of participants hedging over different scenarios, a version of the random incentive system (Johnson et al., 2021) was applied at the beginning of the experiment.

The remainder of this paper is organised as follows. Section 2 describes the ambiguity indexes measuring the ambiguity reaction and insensitivity, and the experimental hypotheses. Section 3 describes the experiments. Section 4 presents the analysis of the experimental data for each treatment. Section 5 focuses on data comparisons among the treatments. Section 6 discusses the results of the experiment in light of the recent literature that adopts the belief hedges approach. Section 7 concludes the study with final remarks. Appendices present further details on the experiment procedure and the statistical analysis.

2. Ambiguity indexes and experimental hypotheses

Following Baillon et al. (2018), for every source of uncertainty (i.e., the Covid-19 pandemic, Economics, and Football – each under the France and Italy scenarios – and Ellsberg), three mutually exclusive and exhaustive non-null single events, denoted by E_i, i=1, 2, and 3, are considered.[6] A composite event E_{ij} represents the union of two single events, $E_i \cup E_j$, with $i \neq j$. For example, in the Football treatment, the single events are victory for the home team (i=1), drawing (i=2), and victory for the away team (i=3). The composite events are E_{13} (victory for either team), E_{12} (the home team does not lose), and E_{23} (the away team does not lose). For any fixed prize (€15 in our case), the matching probability *m* of event *E* is defined as:[7]

Definition 1. *The matching probability m of an event E is the probability making the participant indifferent between receiving €15 under event E and nothing otherwise and receiving €15 with probability m and nothing otherwise.*

Dimmock et al. (2016) have shown that matching probabilities can be used to measure a participant's ambiguous reaction without knowledge of its subjective likelihood, or its risk attitudes, and more generally, its utility function. If a participant is ambiguity-neutral, the sum of the matching probability of a single event E_3 (e.g. the away team wins) and of its complementary event E_{12} (e.g. the home team does not lose) will be equal to unity: $m(E_3) + m(E_{12}) = 1$. However, if the participant is ambiguity-averse, the sum is less than unity: $m(E_3) + m(E_{12}) < 1$. The difference with 1 indicates the degree of ambiguity aversion. Baillon et al. (2021) have interpreted this difference as an ambiguity premium regarding probability, that is, the amount of winning probability a participant is willing to sacrifice to avoid ambiguity. Similarly, if the participant is ambiguity-prone, the sum of the matching probabilities of a single event and its complementary event will be greater than unity: $m(E_3)+ m(E_{12})>1$. Baillon et al. (2021) have defined the b-index of ambiguity aversion as follows:

[6] Baillon et al. (2021) have generalised this approach to more than three single events, providing rigorous theoretical foundations to the indexes of ambiguity reaction presented here.

[7] Matching probabilities are called probability equivalents in the earlier experimental literature (Trautmann and van de Kuilen, 2015).

Definition 2. *The b-index of ambiguity aversion is*

$$b = 1 - \overline{m_c} - \overline{m_s},$$

where $\overline{m_c} = \frac{m(E_{12})+m(E_{13})+m(E_{23})}{3}$ *is the average composite event matching probability, and* $\overline{m_s} = \frac{m(E_1)+m(E_2)+m(E_3)}{3}$ *is the average single event matching probability. If a participant is ambiguity-neutral, b=0; if they are ambiguity-averse, 0<b≤1; and if they are ambiguity-prone, -1≤ b<0.*

The b-index measures the ambiguity reaction as a deviation from the ambiguity neutrality benchmark value of b=0. Ambiguity aversion is observed for positive b-index values, with maximal aversion corresponding to b=1 (meaning that a participant's matching probability is equal to zero for all events). Ambiguity proneness is observed for negative values of the b-index, with maximal proneness corresponding to b=-1 (meaning that the matching probability is equal to unity for all events). The b-index can be interpreted as a motivational component of ambiguity attitudes, measuring how much a participant dislikes or likes ambiguous situations. Hence, it can also be taken as a measure of the willingness to bet under ambiguity. Therefore, from here on we will refer to this component of ambiguity as preference.

The second index of ambiguity reaction captures the extent to which participants are unable to discriminate between different levels of likelihood when facing a given source of ambiguity. This insensitivity to ambiguity has been shown to be distinct and independent of the ambiguity preference component of a participant's ambiguity attitudes (Abdellaoui et al, 2011). Specifically, insensitivity is interpreted as a cognitive component; namely, it reflects the extent to which participants can understand ambiguous situations and react to new information. On the one hand, maximal insensitivity occurs when participants take all events as equally likely. In this situation, the matching probabilities will be the same and the difference between the matching probability of a single event and its composite will be zero. Using the former football example, maximal insensitivity means that a participant's matching probability $m(E_3)$, referred to as the event 'the away team wins', is equal to the matching probability of the composite event $m(E_{12})$, that is, the event 'the home team does not lose'. On the other hand, the maximal sensitivity corresponding to neutrality implies that $m(E_3) = 1/3$ and $m(E_{12}) = 2/3$; hence, $m(E_{12})–m(E_3) = 1/3$. Therefore, Baillon et al. (2018) have defined the index of ambiguity-generated insensitivity (a-index henceforth) by considering the average difference between the matching probability of a composite event and its single event $\overline{m_c} - \overline{m_s}$:

Definition 3. *The a-index of ambiguity-generated insensitivity is*

$$a = 3 \times \left[\frac{1}{3} - (\overline{m_c} - \overline{m_s})\right]$$

If a participant is a-insensitive, 0<a≤1; if they are a-neutral (maximal sensitivity), a=0; and if they are non-insensitive, -1≤a<0.

According to Definition 3, perfect discrimination between single and composite events means $(\overline{m_c} - \overline{m_s}) = \frac{1}{3}$, which implies an a-index value equal to zero, corresponding to ambiguity neutrality. Relative to this benchmark, maximal insensitivity (i.e., full inability to distinguish between likelihood levels by treating them all alike) corresponds to a value of 1 of the a-index instead. This value of unity is obtained because the term in square brackets (i.e., a measure of responsiveness to likelihood changes) is conveniently normalised by a multiplier equal to 3. Note that values of the a-index greater than unity violate weak monotonicity.[8] The a-index can take negative values (implying $(\overline{m_c} - \overline{m_s}) > \frac{1}{3}$). We denote this situation as non-insensitive.[9] Baillon et al. (2021) underscore that negative values of the a-index can be observed experimentally, although they may not be consistent with all theoretical models of ambiguity.

Using both the b-index and a-index to measure ambiguity reaction, the following testable hypotheses are formulated:

Hypothesis 1. *Different sources of ambiguity can give rise to different reaction towards ambiguity.*

Hypothesis 1a. *Artificial sources of ambiguity generate different preference and different sensitivity than natural sources of ambiguity.*

Hypothesis 1b. *Different natural sources of ambiguity may have a different influence on preference and sensitivity.*

Hypothesis 2. *For a given natural source of ambiguity, a more familiar decision context generates both weaker preference and lower insensitivity than a less familiar one.*

Hypothesis 3. *For a given natural source of ambiguity, an affect-rich decision context enhances ambiguity preference and insensitivity.*

Under Hypothesis 1a, on the one hand, one would expect to observe greater deviations from the neutrality benchmark when participants assess natural ambiguity (i.e., generated by the Covid-19 pandemic, Economics, and Football) rather than artificial ambiguity (i.e., generated by the three-colour Ellsberg lotteries). This expectation is based on the results of the 1990's literature. Depicting Ellsberg's urn as second-order probability distribution was supposed to reduce the perceived perception of ambiguity.[10] However, on the other hand, we are aware that in the most recent literature, and especially the literature which uses the b-index to measure ambiguity, the results go in the opposite direction. For this reason, we have used a more general hypothesis, without specifying the direction of the preference.

Hypothesis 1b relates to the difference between natural sources of ambiguity, where emotion and knowledge may have a different impact on the perception of ambiguity.

Hypothesis 2 aims at testing the competence hypothesis. One would expect that participants who are more informed regarding the decision context (i.e., Italy versus France) should prefer betting on the more familiar

[8] Weak monotonicity means $\overline{m_c} \geq \overline{m_s}$. This follows from the set-monotonicity assumption that the "matching probability of a composite event should exceed the matching probability of either one of its two constituents" (Baillon et al., 2018, page 1845).

[9] Anantanasuwong et al. (2019, page 7) have termed this case as "overly sensitive in the likelihood of ambiguous events (i.e., tending to underweight unlikely events)".

[10] Note that at that time most of the experiments were on the two-colour Ellsberg and ambiguity reaction was measured through simple additivity.

event, and they should be able to distinguish better between likelihood levels (see Tversky and Fox, 1995; Kilka and Weber 2001; Fox and Weber, 2002; Keppe and Weber, 1999). Hypothesis 3 is related to the influence of affect-rich events[11] on ambiguity reaction. Since experimental evidences are not clear cut, we do not expect the direction of the impact of affect-rich events to be established a priori.

3. Design and implementation

This section describes the experiment.[12] The experimental design is summarised in Table 1a.

Participants and treatments. N=133 participants (undergraduate and graduate students from LUISS University in Rome, Italy) took part in this experiment. They were randomly assigned to three between-subject treatments.[13] Each treatment was associated with different natural sources of uncertainty with unknown probabilities – regarding Covid-19, Football, and Economics – corresponding to three different natural sources of uncertainty, with unknown probabilities regarding (a) the number of new positive cases of Covid-19 at a fixed date; (b) the result of a football match at the same fixed date; (c) the value of the sovereign interest rate spread at the same fixed date. For each of these sources, the participants were required to evaluate two different scenarios, Italy and France.[14] As the experimental design adopted a three-fold partition of the event space (Section 2), within each treatment, the participants faced six questions for each scenario (France and Italy) concerning event lotteries.[15] For all the natural events, the resolution of the uncertainty occurred on the same date, the 5th of May 2022. Additionally, in each treatment, the participants also faced two other sets of questions: (a) six questions concerning event lotteries based on an Ellsberg scenario. The event on which the lotteries were based concerned the drawing of a ball from a three-colour urn containing 90 balls: 30 red balls and 60 either yellow or blue balls; and (b) one question to elicit the participant's attitude towards risk.[16]

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[11] The seminal paper by Rottenstreich and Hsee (2001) found that participants were more source insensitive to affect-rich outcomes (kisses) than to affect poor ones (money). See also Maffioletti and Santoni (2019).

[12] Further details are provided in Appendix A. The complete version of the instructions, the experiment screenshots in Italian, and the corresponding English translation are in the Supplementary material.

[13] Two sessions were run for each treatment. For the COVID-19 treatment, 22 participants participated in the first session and 20 in the second session. For the Economics treatment, 25 participants participated in the first session and 20 in the second session. For the Football treatment, 24 participants participated in the first session and 20 in the second session.

[14] The maintained hypothesis was that within each treatment, participants were both more knowledgeable and more emotionally involved (i.e., the affect-richness dimension of the event was more salient) when the decision context referred to Italy than to France.

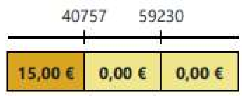
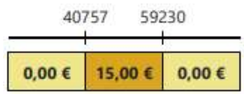
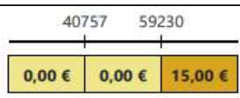
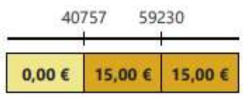
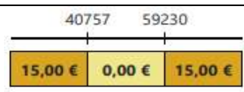
[15] See Tables A1a-A1d in Appendix A for the triple of single and complementary events, their description and visual representation in the experiment for all treatments and scenarios.

[16] This question is not considered in the current paper.

Table 1a. The experimental design

Treatment (between-subject)	Scenario (within-subject)				
		Italy	France	Ellsberg	Risk
	COVID-19	6 questions, one for each partition space	6 questions, one for each partition space	6 questions, one for each partition space	1 question
	FOOTBALL	6 questions, one for each partition space	6 questions, one for each partition space		
	ECONOMICS	6 questions, one for each partition space	6 questions, one for each partition space		

Table 1b. The triple of single and complementary events, their description and representation in the experiment– example for the COVID-19 treatment, Italy scenario

Event		**Description**	**Visual representation**
Single events	E_1	the number of Covid-19 new positive cases in Italy is less than 40757	
	E_2	the number of Covid-19 new positive cases in Italy lies between 40757 and 59230 included	
	E_3	the number of Covid-19 new positive cases in Italy is greater than 59230	
Complementary events	$E_{23} = E_2 \cup E_3$	the number of Covid-19 new positive cases in Italy is greater than or equal to 40757	
	$E_{13} = E_1 \cup E_3$	the number of Covid-19 new positive cases in Italy is less than 40757 or greater than 59230	
	$E_{12} = E_1 \cup E_2$	the number of Covid-19 new positive cases in Italy is less than or equal to 59230	

Note: Events occurring on 5th May 2022.

Choice questions (natural events). For each question, the participants had to choose between the following two lotteries:

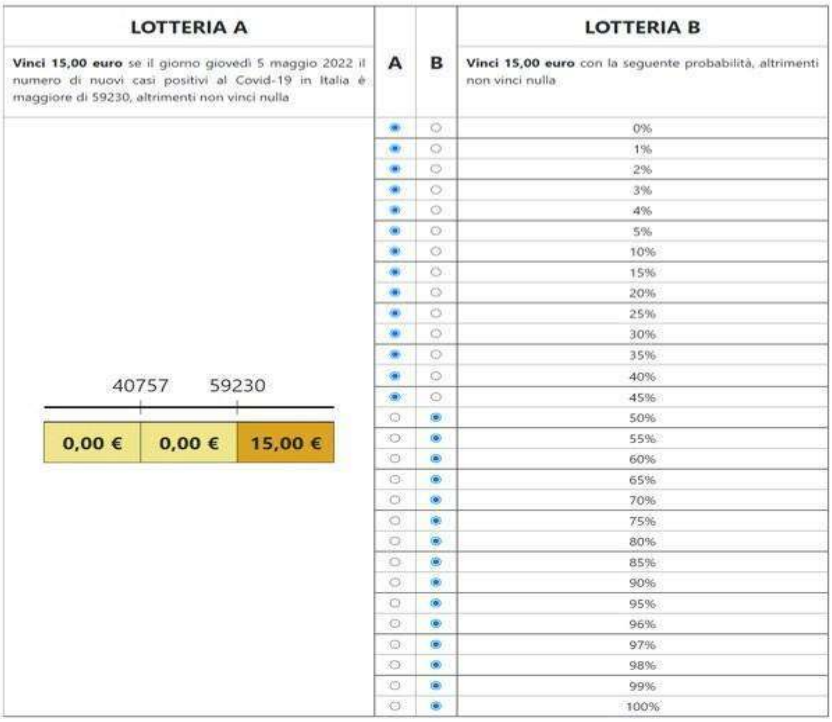
Lottery A: You win €15 if on Thursday the 5th of May 2022, the following event occurs [*description of the natural event depending on treatment and scenario*]; otherwise, you win nothing.

Lottery B: You win €15 with the following probability [*list of probabilities given*]; otherwise, you win nothing.

The participants were asked to indicate which of the two lotteries they preferred from a list of different probability values ranging from 0% to 100% (Figure 1a for an example of a screenshot of the choice list). The midpoint between the two values of p, where the participant switched preference from Lottery A to Lottery B, was taken as the probability of making it indifferent between the two lotteries, that is, their *matching probability*. Hence, for each scenario, six matching probabilities were elicited for all single and complementary events.

Following Baillon et al. (2018), the experimental programme allowed the participant to state their preference for one lottery or the other, for any probability level, by clicking once on a single probability dot. If the participant, as in the example in Figure 1a, clicked on Column B for p=50%, for all p>50%, the option dots for Lottery B were filled (meaning that Lottery B was chosen for all those probabilities), and for all p<50%, the option dots for Lottery A filled (meaning that Lottery A was chosen for all those probabilities). This allowed the participants to make decisions more quickly and ruled out violations of stochastic dominance.

Figure 1a - Screenshot of the choice list for event E_3, Covid-19 treatment, and Italy scenario[17]



Choice questions (Ellsberg scenario). For each question, the participants had to choose between the following two lotteries:

Lottery A: In an opaque urn, there are 90 balls; 30 balls are red, while 60 are either yellow or blue, but you do not know how many are yellow and how many are blue. You draw a ball. You win €15 if you draw a [*colour depending on the event*] ball; otherwise, you win nothing.

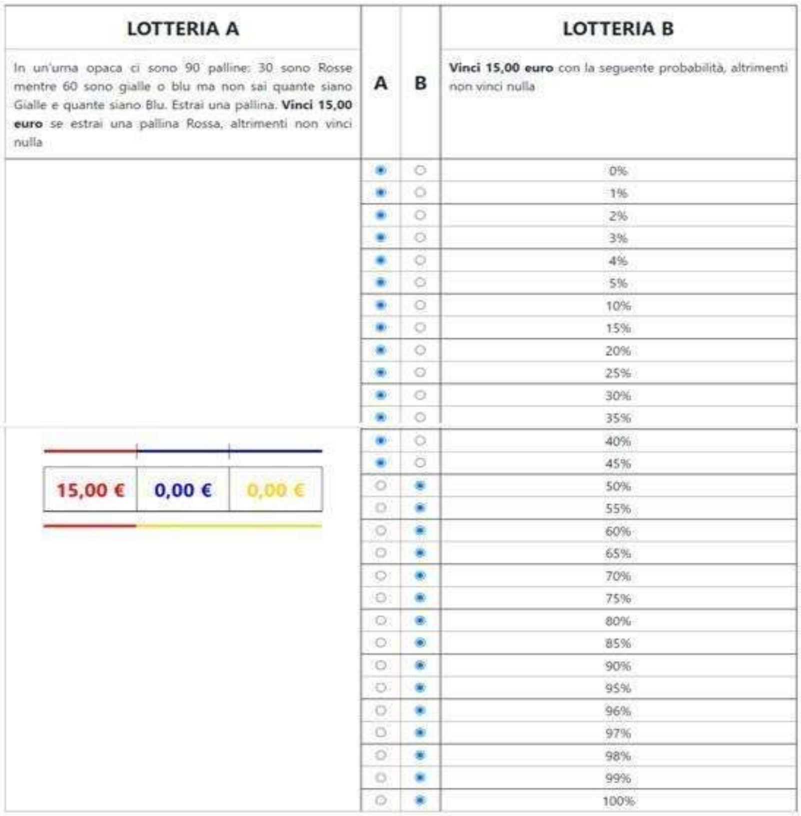
Lottery B: You win €15 with the following probability; otherwise, you win nothing.

The selection procedure was the same as that for natural events. Figure 1b shows an example screenshot.

[17] English translation of Figure 1a: ‘Lottery A: You win €15.00 if, on Thursday the 5th of May 2022, the number of Covid-19 new positive cases in Italy is greater than 59,230, otherwise you win nothing’. ‘Lottery B: You win €15.00 with the following probability, otherwise you win nothing’.

Incentives. We use a random incentive system (RIS) as an incentive mechanism. Different studies have discussed and criticised the RIS as an incentive-compatible mechanism in the elicitation of ambiguity preferences (Oechssler and Roomets, 2014; Bade, 2015; Baillon et al., 2022a, 2022b; Johnson et al., 2022). The main argument against the RIS is that randomisation provides participants with a way to hedge against ambiguity, leading to an underestimation of ambiguity aversion. To mitigate the potential problems related to the incentive compatibility of the RIS system, we followed Baillon et al. (2022a) (and the implementation by Baillon and Placido, 2019, and Li et al., 2020) to perform randomisation before the uncertainty was resolved (and before the decisions were made). Appendix A describes the procedure in detail. Since the uncertainty for all natural events was resolved on Thursday, May 5, participants had to come back the following day, on Friday, May 6, to play out the choice question for real and to be paid.

Figure 1b - Screenshot of the choice list for event E_1, Ellsberg scenario[18]



The participants received a show-up fee of €5, an additional amount of up to €15 on the selected question, and an extra fee of €3 for having to return after the experiment for the payment process.

Procedure. N=42, N=45, and N=46 participants were allocated to the Covid-19, Economics, and Football treatments, respectively. Two sessions were conducted for each treatment group. On average, an experimental

[18] English translation of Figure 1b. 'Lottery A: In an opaque urn, there are 90 balls; 30 balls are Red, while 60 are either yellow or blue, but you do not know how many are Yellow and how many are Blue. You draw a ball. You win €15.00 if you draw a Red ball; otherwise, you win nothing'. 'Lottery B: You win €15.00 with the following probability, otherwise you win nothing'.

session lasted one-and-a-half hours, and the participant earned €19.50. Each experimental session consisted of six parts. In Part 1, instructions were provided. Parts 2, 3, 4, and 5 consisted of six questions concerning the natural events (different according to the treatment) for each of the Italy and France scenarios; six questions concerning the Ellsberg lotteries (the same for all treatments); and one question concerning risk (the same for all treatments). Part 6 presented the participants with two sets of questions concerning demographic information, and knowledge and involvement self-evaluation (i.e., self-reported emotional involvement and self-reported knowledge depending on treatment, both measured on a 7-point Likert scale).[19] The 19 questions in Parts 2, 3, 4, and 5 were the same for all the participants and randomised both by scenario type and order of appearance on the screen.

Methodology. Participants were recruited using ORSEE software (Greiner, 2004). The experiment was conducted in the CESARE laboratory at LUISS University in Rome, Italy, and programmed using the oTree software (Chen et al., 2016).

4. Data analysis by treatment

This section analyses the experimental data by separately considering the three treatments (Covid-19, Economics, Football). This section provides evidence for both source preference and source sensitivity.

4.1 Pooling of data

We conducted two experimental sessions for each treatment group (see footnote 13). Therefore, in order to pool the data, we performed Wilcoxon-Mann-Whitney tests to determine whether the two samples were drawn from the same population within each treatment. In all instances, the tests could not reject the null hypothesis of identical median.[20] Based on this evidence, we pooled data for each treatment.

4.2 COVID 19-treatment

Table 2a reports the summary statistics for the b-indexes and the a-indexes in the Covid-19 treatment when considering pooled data (N=42). Table 2a shows the different rankings across scenarios. At median values, participants show stronger ambiguity aversion (i.e., b>0) in Ellsberg than in the France and Italy scenarios, while they show stronger ambiguity insensitivity (i.e., a>0) in France than in the Italy and Ellsberg scenarios. Table 2b describes the percentage of participants divided according to the value of the b-index: ambiguity aversion (i.e., b>0) prevails, but the percentage of participants across categories (i.e., aversion, neutrality, and proneness) appears to be very similar across scenarios. Table 2c describes the percentage of participants divided according to the a-index value, and it appears that a larger percentage of participants is insensitive to

[19] Appendix A2 presents the questions. The complete questionnaire in Italian and the corresponding English translation are provided in the Supplementary material.

[20] This analysis is available from the authors upon request.

likelihood changes (i.e., a>0) under the France scenario (i.e., 92.85%) than under the Italy (80.9%) and Ellsberg (83.33%) scenarios.

To understand whether the observed differences in the median values of the ambiguity indices were statistically significant, Friedman's two-way analysis of variance by ranks for related samples was performed. The results of this analysis are presented in Table 3.1.

Table 2a. COVID-19 treatment. Ambiguity aversion (b-index) and insensitivity (a-index)

	France			Italy			Ellsberg		
N=42	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**
b-index COVID-19	**0.0333**	0.07753	0.32811	**0.0266665**	0.0529365	0.3434215	**0.1**	0.0884127	0.275945
a-index COVID-19	**0.55**	0.63769	0.48791	**0.5**	0.4633333	0.5756578	**0.385**	0.3688095	0.5502326

Note: b>0 denotes ambiguity aversion; a>0 denotes ambiguity insensitivity. StDv; Standard deviation.

Table 2b. COVID-19 treatment. Distribution of participants by ambiguity aversion index (b-index)

Ambiguity preference	France b-index	Italy b-index	Ellsberg b-index
b>0 (aversion)	61.9% (N=26)	59.5% (N=25)	59.5% (N=25)
b=0 (neutrality)	2.38% (N=1)	4.7% (N=2)	2.38% (N=1)
b<0 (proneness)	35.7% (N=15)	35.7% (N=15)	38% (N=16)
Total COVID-19	100% (N=42)	100% (N=42)	100% (N=42)

Table 2c. COVID-19 treatment. Distribution of participants by ambiguity insensitivity index (a-index)

Ambiguity insensitivity	France a-index	Italy a-index	Ellsberg a-index
a>0 [of which a>1]	92.85% (N=39) [14.28%, N=6]	80.9% (N=34) [11.9%, N=5]	83.33% (N=35) [7.14%, N=3]
a=0 (neutrality)	2.38% (N=1)	0% (N=0)	2.38% [N=1]
a<0	4.76% (N=2)	19% (N=8)	14.28% (N=6)
Total COVID-19	100% (N=42)	100% (N=42)	100% (N=42)

Note: a>1 denotes violation of weak monotonicity.

Table 3.1 COVID-19 treatment. Tests for difference in ambiguity reaction

	Friedman two-way analysis of variance by ranks	Wilcoxon signed-rank test COVID-19 France vs. COVID-19 Italy	Wilcoxon signed-rank test COVID-19 France vs. Ellsberg	Wilcoxon signed-rank test COVID-19 Italy vs. Ellsberg
b-index COVID-19	Fr=1.321 p-value=0.517	-------------	-----------------------	--------------------
a-index COVID-19	Fr=6.072** p-value=0.048	z = 1.818 adj p-value=0.21	z = 2.326* adj p-value=0.0573	z = 0.044 adj p-value=0.99

Note 1: Null hypothesis of equal medians. ***significant at 1%, **significant at 5%; * significant at 10% levels.
Note 2: adj p-value=Bonferroni-adjusted p-value.

The first test was run under the null hypothesis that the median b-index was the same across the three scenarios, versus the alternative hypothesis that at least two medians were different. The Friedman test did not reject the null hypothesis (Fr=1.321, p =0.517). We performed the same test for the a-index. In the latter case, the Friedman test rejected the null hypothesis at the 5% significance level (Fr=6.072, p =0.048). Since at least two medians were different, we ran a set of Wilcoxon signed-rank tests for dependent samples by pairing the scenarios. These tests are reported in Columns 3–5 of Table 3.1, where the Bonferroni adjustment of p-values was used because of multiple pairwise comparisons. The Wilcoxon test rejected the null hypothesis of equal medians at the 10% significance level for the a-index for the Covid-19 France versus Ellsberg scenario comparison.

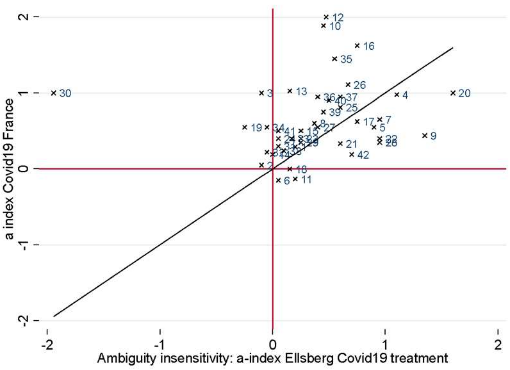
To investigate the sign of this difference, we run a Page test of ordered alternatives, where the alternative hypothesis is specified according to the descriptive evidence in Table 2a. The Page test, reported in Table 3.2, rejected the null hypothesis of equal medians at the 5% significance level (z=2.128; Bonferroni-adjusted p-value=0.0334). We take this result as evidence of source sensitivity. At median values, participants were more insensitive to likelihood changes when evaluating prospects based on natural sources of uncertainty on less familiar events, like the Covid-19 France scenario, than an artificial source of uncertainty, such as the Ellsberg scenario. A visual representation of the source insensitivity based on descriptive data is shown in Figure 2. For each participant, Figure 2 plots the a-index computed under the French scenario against the corresponding index computed under the Ellsberg scenario. More than two-thirds of the points lie in both the first and second quadrants, above the 45-degree line, implying stronger a-insensitivity under France than under the Ellsberg scenarios at the individual level.

Table 3.2 Covid-19 treatment. Page test for ordered alternatives

	Null hypothesis H_0	Alternative hypothesis H_1	Page L-statistics	Test significance
a-index	$ma_{Ellsberg}= ma_{Italy}= ma_{IFrance}$	$ma_{Ellsberg}< ma_{Italy} < ma_{France}$	523.5	z=2.128** p-value=0.0167 adj p-value= 0.0334

Note 1: ***significant at the 1% level, **significant at the 5% level, * significant at the 10% level.
Note 2: Adj p-value=Bonferroni-adjusted p-value.
Note 3: The Page test under the alternative hypothesis $ma_{Italy}< ma_{Ellsberg} < ma_{France}$ yields the same statistics.

Figure 2. COVID-19 France vs Ellsberg scenario a-index of ambiguity insensitivity



Note: a>0 a-insensitivity; a=0 a-neutrality; a<0: non-insensitivity; a>1: violation of weak monotonicity

The underlying assumption of the research Hypothesis 1b (page 7), is that perceived ambiguity should be negatively correlated with emotional involvement and knowledge. In particular, we expect Italian scenarios to be perceived as more familiar than French scenarios and consequently to cause a weaker reaction to uncertainty. In order to test this, we asked participants to self-evaluate their degree of emotional involvement and knowledge on a 7-point Likert scale.[21] Tables 4a and 4b summarise the descriptive statistics: they show stronger emotional involvement and knowledge, respectively, when assessing Italy than France scenarios at median values, as we expected. More than 95% of participants reported higher involvement and higher knowledge of Covid-19 in Italy than France. The Wilcoxon signed-rank tests confirmed these results.

Table 4a. COVID-19 treatment: Emotional involvement (N=42)

France Involvement			Italy Involvement			Difference in Involvement			Wilcoxon
Median	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**z=5.669*** **
2	2.095238	1.461865	**5.5**	4.88095	1.533407	**3**	2.785714	1.371055	p-value=0.00

Note 1: Self-assessed emotional involvement on a 7-point Likert scale.
Note 2: Difference in involvement is the difference between self-assessed involvement in Italy and in France.
Note 3: Wilcoxon sign-rank test under the null-hypothesis that emotional involvement is the same for the two scenarios.

Table 4b. COVID-19 treatment: Knowledge (N=42)

France Knowledge			Italy Knowledge			Difference in Knowledge			Wilcoxon
Median	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**z=5.663*** **
2	1.928571	1.176868	**4**	4.166667	1.480222	**2**	2.238095	1.143583	p-value=0.00

Note 1: Self-assessed knowledge on a 7-point Likert scale.
Note 2: Difference in knowledge is the difference between self-assessed knowledge in Italy and in France.
Note 3: Wilcoxon sign-rank test under the null-hypothesis that knowledge is the same for the two scenarios.

To test whether differences in emotional involvement and knowledge between scenarios affected a-insensitivity,[22] we ran random effects estimates of the a-index, where the repeated measures under the three scenarios were used as individual observations for each participant.[23] This analysis is presented in Appendix B (Table B1; standard errors are clustered by subjects). First, we regressed the a-index on a categorical variable for the scenario (France and Italy), taking Ellsberg's scenario as the baseline and on a constant. It turned out that both the France and Italy scenario categories have positive signs, but only the estimated coefficient for France was statistically significant at the 5% level. This means that participants were, on average, more ambiguity-insensitive when evaluating natural than artificial sources of uncertainty, but this effect was statistically significant when considering the French scenario relative to the Ellsberg scenario only. These results are consistent with the Page test of Table 3.2. The results were also confirmed when adding as controls observed individual characteristics, measures of cognitive perception and familiarity with experiments, a

[21] Appendix A2 reports the questions.

[22] We did not investigate for the b index, as long as no significant differences were detected from Table 3.1.

[23] Hence, considering a panel data set of 42×3 observations.

session dummy variable, and measures of differential involvement and knowledge.[24] Regarding the latter, no statistically significant effect on the a-index was detected when using both the difference between involvement and the difference between knowledge for Italy and France. However, when we normalised these differences by the self-assessed level of involvement/knowledge for France at the individual level, "differential knowledge" was positively correlated with the a-index at the 5% significance level.[25]

4.3 Economics treatment

Table 5a presents the descriptive statistics for the b-index and a-index in the Economics treatment (N=45). The pattern shows, at median values, more ambiguity aversion (b>0) for the Ellsberg scenario than for the France scenario and more ambiguity insensitivity (a>0) for the France scenario than for Italy and Ellsberg ones. The percentage of participants divided according to the b-index value shows a stronger prevalence of ambiguity aversion when participants assess the Ellsberg scenario (Table 5b), whereas the percentage of participants by ambiguity insensitivity (Table 5c) is similar across the scenarios. To test whether the ambiguity indices were significantly different across scenarios, we performed Friedman's two-way analysis of variance by ranks for related samples. When the Friedman test was statistically significant, it was followed by pairwise Wilcoxon sum rank tests with Bonferroni adjustment of p-values to account for multiple testing. Table 6.1 summarises the results of this analysis.

Regarding the b-index, the Friedman test rejected the null hypothesis of equal median at the 1% significance level (Fr=9.706, p=0.008). Pairwise Wilcoxon signed-ranked tests, with Bonferroni adjustment of the p-values, rejected the null hypothesis at the 5% significance level for the Italy versus Ellsberg comparison only (z=-2.4, adjusted p-value=0.045).

Table 5a. Economics treatment. Ambiguity aversion (b-index) and insensitivity (a-index)

	France			Italy			Ellsberg		
N=45	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**
b-index Econ	0	0.0377524	0.2466263	0.0166667	0.0366295	0.234147	0.1	0.1015556	0.26206
a-index Econ	0.48	0.4334815	0.594635	0.33	0.4156667	0.5574257	0.15	0.2224444	0.4998132

Note: b>0 denotes ambiguity aversion; a>0 denotes ambiguity insensitivity. StDv, Standard deviation.

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[24] We used as controls: age; a categorical variable for gender as one participant was non-binary: the baseline was male gender; a categorical variable for region of residence: the baseline was residence in the South and Islands; cognitive perception (i.e., self-evaluation of ease of experiment dummy: the dummy was equal to zero if the experiment was perceived as being easy, and equal to one, otherwise); familiarity/general knowledge with past experiments (i.e., a categorical variable measuring intermediate or high experience with experiments: the baseline was no experience); a session dummy variable. In all specifications, we found that participants who perceived the experiment to be difficult were significantly more ambiguity-insensitive than participants who found it easy, pointing to the role of general cognitive attitudes; age, non-binary gender, and residence in the North were associated with lower ambiguity insensitivity at statistically significant levels (1% for the former two variables and 10% for the region of residence). See Appendix B for details of the analysis.

[25] The regression result did not change qualitatively, when we estimated the a-index jointly with the b-index using SUR, see Table B1 in Appendix B.

Table 5b. Economics treatment. Distribution of participants by ambiguity aversion index (b-index)

Ambiguity preference	France b-index	Italy b-index	Ellsberg b-index
b>0 (aversion)	48.88% (N=22)	51.11% (N=23)	71.11% (N=32)
b=0 (neutrality)	4.44% (N=2)	6.67% (N=3)	4.44% (N=2)
b<0 (proneness)	46.67% (N=21)	42.22% (N=19)	24.44% (N=11)
Total Economics	100% (N=45)	100% (N=45)	100% (N=45)

Table 5c. Economics treatment. Distribution of participants by ambiguity insensitivity index (a-index)

Ambiguity insensitivity	France a-index	Italy a-index	Ellsberg a-index
a>0 [of which a>1]	68.88% (N=31) [15.55%, N=7]	75.55% (N=34) [13.33%, N=6]	73.33% (N=33) [6.67%, N=3]
a=0 (neutrality)	4.44% (N=2)	2.22% (N=1)	0% [N=0]
a<0	26.67% (N=12)	22.22% (N=10)	26.67% (N=12)
Total COVID-19	100% (N=45)	100% (N=45)	100% (N=45)

Note: a>1 denotes violation of weak monotonicity.

Table 6.1. Economics treatment. Test for difference in ambiguity reaction

	Friedman two-way analysis of variance by ranks	**Wilcoxon signed-rank test Economics France vs. Economics Italy**	**Wilcoxon signed-rank test Economics France vs. Ellsberg**	**Wilcoxon signed-rank test Economics Italy vs. Ellsberg**
b-index	Fr= 9.706*** p-value=0.008	z = -0.209 adj p-value=1	z = 2.054 adj p-value=0.12	z = -2.404** adj p-value=0.0453
a-index	Fr= 5.806* p-value=0.055	z = 0.073 adp-value=1	z = 2.534** adp-value=0.0312	z = 2.709** adp-value=0.018

Note 1: Null hypothesis of equal medians. ***significant at 1%, **significant at 5%; * significant at 10% levels.
Note 2: adj p-value=Bonferroni-adjusted p-value.

This finding is taken as evidence of source preference. Regarding the a-index, the Friedman test rejected the null hypothesis of equal medians across the scenarios at the 10% significance level (Fr=5.806, p-value=0.055). The pairwise Wilcoxon signed-rank tests rejected the null hypothesis for both the France and Ellsberg comparisons (z=2.534**, adjusted p-value=0.0312) and for the Italy versus Ellsberg comparison (z=2.709, adjusted p-value=0.018). This finding is considered evidence of source insensitivity.

Based on this evidence, we ran Page tests for ordered alternatives, where alternative hypotheses based on the rankings of Table 5a were specified assuming more ambiguity aversion and less ambiguity insensitivity for the Ellsberg scenarios vis-à-vis natural uncertainty source scenarios. The results of these tests are presented in Table 6.2. For the b-index, the Page test rejected the null hypothesis of equal medians in favour of the alternative of higher ambiguity aversion under the Ellsberg scenario than under the Italy scenario than under the France one (Page test z=2.951, adjusted p-value=0.0032). Likewise, the Page test for the a-index rejected the null hypothesis of equal medians in favour of the alternative of higher a-insensitivity for the Italy than for the France and Ellsberg scenarios. These findings support the hypotheses of source preference and source sensitivity. Visual representations, based on descriptive data, of source preference and source sensitivity are shown in Figures 3.1 and 3.2. Figure 3.1 plots the b-index for Italy versus Ellsberg scenario: two-thirds of participants show stronger ambiguity aversion for the Ellsberg scenario (i.e., 30 observations lie below the 45-degree line in Figure 3.1). Figure 3.2 plots the a-index for France versus Ellsberg (a) and Italy versus Ellsberg (b). These plots show stronger a-insensitivity for natural than artificial sources of uncertainty: two-thirds of observations (i.e., N = 29 for France vs. Ellsberg; N = 28 for Italy vs. Ellsberg) lie above the 45-degree line in Figure 3.2.

Table 6.2 Economics treatment. Page test for ordered alternatives

	Null hypothesis H_0	Alternative hypothesis H_1	Page L-statistics	Test significance
b-index	$mb_{Ellsberg}= mb_{Italy}= mb_{IFrance}$	$mb_{France}< mb_{Italy} <mb_{Ellsberg}$	568	z=2.951*** p-value=0.0016 adj p-value=0.0032
a-index	$ma_{Ellsberg}= ma_{Italy}= ma_{Ifrance}$	$ma_{Ellsberg}< ma_{France} <ma_{Italy}$	560	z=2.108** p-value=0.0175 adj p-value= 0.035

Note 1: ***significant at the 1% level, **significant at the 5% level, * significant at the 10% level.
Note 2: adj p-value=Bonferroni-adjusted p-value.
Note 3: Page test under the alternative hypothesis $mb_{Italy} <mb_{France}< mb$: z= 2.266, adj p-value=0.0023
Note 4: Page test under the alternative hypothesis $ma_{Ellsberg} <<ma_{Italy}. <ma_{France}$: z=2.003, adj p-value=0.0452

Figure 3.1 Economics treatment: b-index of ambiguity aversion, Italy versus Ellsberg.

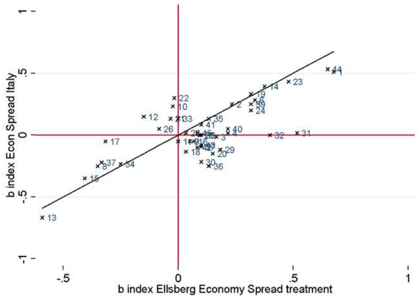
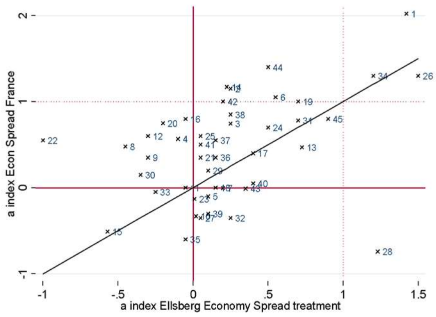
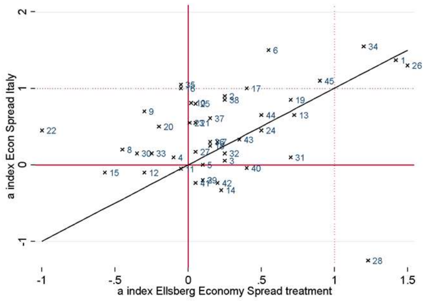


Figure 3.2 Economics treatment: a-index of ambiguity insensitivity.



(a) France vs Ellsberg



(b) Italy vs Ellsberg

Considering self-assessment data, subjects reported low levels of involvement and knowledge (Tables 7a and 7b). However, significant differences at median values between the Italy and France scenarios were detected for both involvement (Wilcoxon sign-rank test: z=3.898, p-value=0.00, Table 7a, and knowledge (Wilcoxon sign-rank test: z=3.366, p-value=0.0008, Table 7b), validating one of our research hypotheses.

Table 7a. Economics treatment: Emotional involvement (N=45)

France Involvement			Italy Involvement			Difference in Involvement			Wilcoxon
Median	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**z=3.898*****
1	1.622222	1.153825	**2**	2.288889	1.531817	**0**	**0.6666667**	**1**	p-value=0.00

Note 1: Self-assessed emotional involvement on a 7-point Likert scale.
Note 2: Difference in involvement is the difference between self-assessed involvement in Italy and in France.
Note 3: Wilcoxon sign-rank test under the null-hypothesis that emotional involvement is the same for the two scenarios.

Table 7b. Economics treatment: Knowledge (N=45)

France Knowledge			Italy Knowledge			Difference in Knowledge			Wilcoxon
Median	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**z=3.366*****
1	1.622222	1.19257	**1**	2.044444	1.413499	**0**	0.4222222	0.8390712	p-value=0.0008

Note 1: Self-assessed knowledge on a 7-point Likert scale.
Note 2: Difference in knowledge is the difference between self-assessed knowledge in Italy and in France.
Note 3: Wilcoxon sign-rank test under the null-hypothesis that knowledge is the same for the two scenarios.

To further test for source preference, using a panel dataset of 45×3 observations, we regressed the b-index on a categorical variable for the scenario (France and Italy), using Ellsberg's as a baseline. The results are reported in Table B2 of Appendix B. Both the France and Italy scenarios entered with a negative sign, implying that participants were, on average, less ambiguity-averse when assessing real-world uncertainty than Ellsberg's. This result is consistent with the findings of the Page test in Table 6.2. However, only the Italian scenario was statistically significant at the 5% significance level.

Next, we regressed the b-index on additional variables, using the same methodology as in the previous analysis of Covid-19 treatment. The details are presented in Table B2 of Appendix B. The size, sign, and statistical significance of the Italian scenario's categorical variables remained unaffected. Measures capturing differences in knowledge and in involvement were not statistically different from zero. The only control variable that was statistically significant at the 10% level is the high-experience category, which had a positive sign. This implies that, on average, highly experienced participants (i.e., participants who participated in more than five past experiments) were more ambiguity-averse than participants without experience in past experiments.

The same type of analysis was performed to test source sensitivity (see Table B2 in Appendix B). The France and Italy scenarios entered with a positive sign, and the estimated coefficients were statistically significant at the 5% level. This means that the participants were, on average, more ambiguity-insensitive in evaluating real-world scenarios than the Ellsberg scenario. This result is again consistent with the findings of the Page test in Table 6.2. No control variable turned out to be statistically significant in the regression.[26]

To recap, the analysis for the Economics treatment suggests differences in ambiguity reaction (both ambiguity preference and ambiguity insensitivity) between natural (i.e. France and Italy scenarios) and artificial source of uncertainty (i.e. Ellsberg scenario). Page tests for ordered alternatives (see Table 6.2) and random effects estimates suggest that for the natural source of uncertainty subjects exhibited both less ambiguity aversion and more ambiguity insensitivity (in the latter case, similar to the Covid-19 treatment) than for the artificial source. However, no role was detected for differential knowledge or involvement in explaining either source preference or source sensitivity.

4.4 Football treatment

Table 8a shows the descriptive statistics for the b-index and a-index in the Football treatment (N=46). At median values, one observes for this treatment stronger ambiguity aversion when evaluating the Ellsberg scenario than the France scenario than the Italy scenario, and stronger ambiguity insensitivity when evaluating the Italy scenario than the France scenario than the Ellsberg one. Regarding the percentage distribution of participants across categories, in the Ellsberg scenario, approximately three-quarters of participants (N=34) were ambiguity-averse, whereas for the France and Italy scenarios, this was true for approximately half of the samples (N=25 and N=23, respectively, Table 8b). Regarding a-insensitivity, the percentage distribution of participants was rather similar across categories, with a slightly more pronounced prevalence of insensitivity in the Italy scenario (Table 8c). Consistent with the descriptive analysis, the Friedman two-way analysis of variance by ranks was strongly significant for the b-index (Fr=12.211, p-value=0.002), with the pairwise Wilcoxon signed-rank test showing the source of the difference among medians in the comparison of the Italy versus Ellsberg scenarios (adjusted p-value=0.0219). For the a-index the Friedman test was significant only at 10% significance level. Pairwise Wilcoxon signed-rank tests did not detect any statistically significant differences. The results of these tests are presented in Table 9.1. These findings provide evidence of source preference.

Page tests for order alternatives were significant for both the b-index and the a-index. Table 9.2 illustrates this with at least one strict inequality across the medians. For the b-index we interpret the results of the Page test as evidence of weaker ambiguity aversion for natural sources of uncertainty than for artificial sources of

[26] The regression results did not change qualitatively, when we estimated the a-index jointly with the b-index using SUR, see Table B3 in Appendix B.

uncertainty. For the a-indexes the Page test is statistically significant, with more insensitivity for Italy and France than for Ellsberg. This is also suggested by Figure 4.2, which plots the a-indeces for France versus Ellsberg (a) and Italy versus Ellsberg (b).[27] Figure 4.1 plots the b-index for France versus Ellsberg (a) and for Italy versus Ellsberg (b) and descriptively confirms that participants exhibit higher ambiguity aversion for Ellsberg than for France and Italy.[28]

Table 8a. Football treatment. Ambiguity aversion (b-index) and insensitivity (a-index)

	France			Italy			Ellsberg		
N=46	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**
b-index Foot	**0.0166667**	0.0458696	0.1932081	**0.0083333**	0.0491304	0.2589789	**0.1**	0.0966486	0.1601017
a-index	**0.325**	0.321123	0.431836	**0.375**	0.4383696	0.4543604	**0.25**	0.30625	0.621303

Note: StDv, Standard deviation

Table 8b. Football treatment. Distribution of participants by ambiguity aversion index (b-index)

Ambiguity preference	France b-index	Italy b-index	Ellsberg b-index
b>0 (aversion)	54.35% (N=25)	50% (N=23)	73.91% (N=34)
b=0 (neutrality)	6.52% (N=3)	10.87% (N=5)	4.35% (N=2)
b<0 (proneness)	39.13% (N=18)	39.13% (N=18)	21.74% (N=10)
Total Football	100% (N=46)	100% (N=46)	100% (N=46)

Table 8c. Football treatment. Distribution of participants by ambiguity insensitivity index (a-index)

Ambiguity insensitivity	France a-index	Italy a-index	Ellsberg a-index
a>0 [of which a>1]	69.5% (N=32) [8.69%, N=4]	73.91% (N=34) [13.04%, N=6]	69.5% (N=32) [10.87%, N=5]
a=0 (neutrality)	2.17% (N=1)	2.17% (N=1)	0% [N=0]
a<0	28.26% (N=13)	23.91% (N=11)	30.43% (N=14)
Total COVID-19	100% (N=46)	100% (N=46)	100% (N=46)

Note: a>1 denotes violation of weak monotonicity.

Table 9.1. Football treatment. Test for difference in ambiguity reaction

	Friedman two-way analysis of variance by ranks	Wilcoxon signed-rank test Football France vs. Football Italy	Wilcoxon signed-rank test Football France vs. Ellsberg	Wilcoxon signed-rank test Football Italy vs. Ellsberg
b-index	Fr=12.211*** p-value=0.002	z=0.962 adj p-value=1	z=-1.923 adj p-value=0.126	z=-2.649** adj p-value=0.0219
a-index	Fr=5.091* p-value=0.078	z=-1.667 adj p-value=0.2889	z=0.4947 adj p-value=1	z=1.584 adj p-value=0.3429

[27] Less than two-thirds of the observations lie above the 45-degree line.

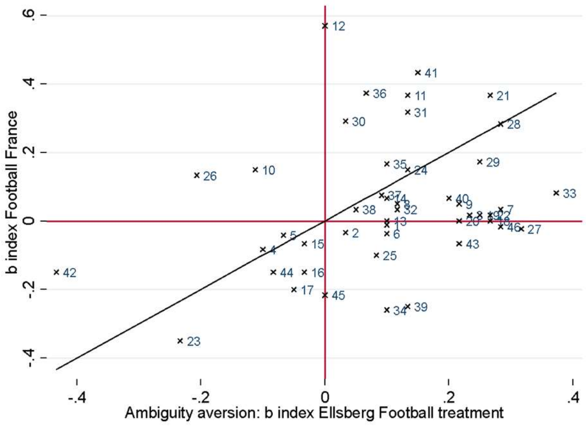
[28] Approximately two-thirds of observations (N=35 for France and N=34 for Italy) lie below the 45-degree line.

Table 9.2. Football treatment. Page test for ordered alternatives

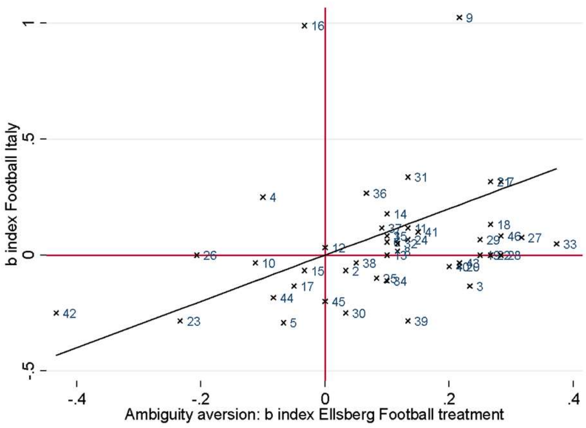
Football	Null hypothesis H_0	Alternative hypothesis H_1	Page L-statistics	Test significance
b-index	$mb_{Ellsberg} = mb_{Italy} = mb_{France}$	$mb_{Italy} < mb_{France} < mb_{Ellsberg}$	584	z=3.336*** p-value=0.00
a-index	$ma_{Ellsberg} = ma_{Italy} = ma_{France}$	$ma_{Ellsberg} < ma_{France} < ma_{Italy}$	572	z=2.085** p-value=0.0185

Note 1: ***significant at the 1% level, **significant at the 5% level, * significant at the 10% level.

Figure 4.1 Football treatment: b-index of ambiguity aversion.

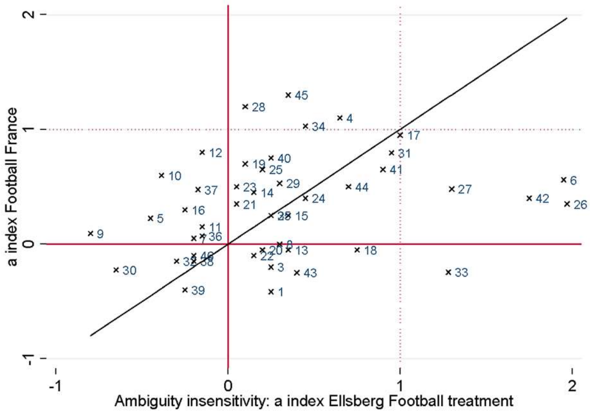


(a) France vs Ellsberg

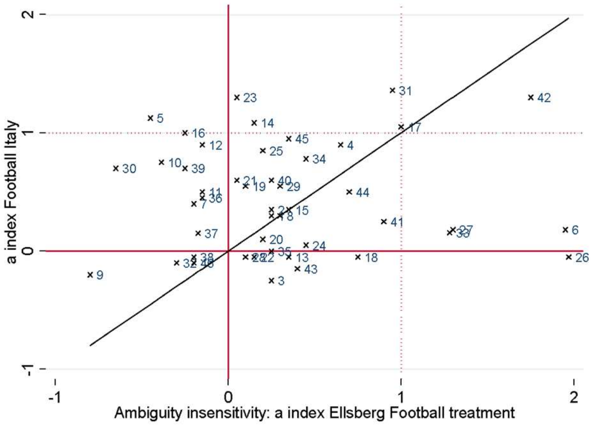


(b) Italy vs Ellsberg

Figure 4.2 Football treatment: a-index of ambiguity insensitivity.



(a) France vs Ellsberg



(b) Italy vs Ellsberg

Considering the self-assessed data, it turns out that self-assessed emotional involvement and knowledge are both significantly higher when considering the Italy than France scenarios at median data (Wilcoxon sign rank z=4.895, p-value=0.00, Table 10a; and z=5.289 p-value=0.00, Table 10b, respectively), with a median difference in involvement and in knowledge equal to two and 1.5, respectively. These results are again consistent with our a priori hypothesis.

Table 10a. Football treatment: Emotional involvement (N=46)

France Involvement			Italy Involvement			Difference in Involvement			Wilcoxon
Median	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**z=4.895*** **
1	1.217391	0.786357	**3**	3.304348	2.448306	**2**	**2.086957**	**2.229361**	p-value=0.00

Note 1: Self-assessed emotional involvement on a 7-point Likert scale.
Note 2: Difference in involvement is the difference between self-assessed involvement in Italy and in France.
Note 3: Wilcoxon sign-rank test under the null-hypothesis that emotional involvement is the same for the two scenarios.

Table 10b. Football treatment: Knowledge (N=46)

France Knowledge			Italy Knowledge			Difference in Knowledge			Wilcoxon
Median	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**z=5.289*** **
1	1.695652	1.473764	3	3.543478	2.410224	1.5	1.84782	1.849533	p-value=0.00

Note 1: Self-assessed knowledge on a 7-point Likert scale.
Note 2: Difference in knowledge is the difference between self-assessed knowledge in Italy and in France.
Note 3: Wilcoxon sign-rank test under the null-hypothesis that knowledge is the same for the two scenarios.

As usual, we ran random effects estimates of the b-index and a-index separately by regressing each index first on categorical variables for scenario and a constant, then on differential knowledge, differential involvement, and the full set of controls. The results are shown in Table B4 Appendix B. In the used specification, the scenario variable is specified as an Ellsberg's dummy (taking the value of 1 for Ellsberg scenario' s observations, and the value of zero otherwise): the estimated coefficient takes on a positive sign and is significant at the 10% level, implying more ambiguity aversion with artificial than natural sources of uncertainty. Adding controls did not alter the results (see Appendix B for details). Self-assessed measures of knowledge and involvement were not statistically significant.

For the a-index, we used a scenario categorical variable with Italy as the baseline (Table B4 in Appendix B). The participants were, on average, less ambiguity-insensitive under the France than Italy scenario. The Ellsberg scenario category was not statistically significant. This result was unaffected by the addition of controls.

We consider the results of this section to be weak evidence of source effects. Participants were more ambiguity-averse when assessing Ellsberg lotteries than when assessing Italy and France football lotteries. However, they were less sensitive when evaluating Italy than France prospects.

We summarise the results of the separate analysis of the three treatments. First, ambiguity aversion (b-index) was stronger under Ellsberg uncertainty than natural sources of uncertainty in both the Economics and Football treatments. No such evidence was found in the Covid-19 treatment. Second, as far as the a-index is concerned, in each treatment participants always exhibited higher insensitivity for the Italy and the France scenario than for the Ellsberg one. The paper's results clearly support the hypotheses of source preference and source sensitivity. Despite this general result, there are also differences among the treatments. More specifically, although participants were always more emotionally involved and more informed regarding Italy than France, no clear ranking emerged among scenarios. For example, a-insensitivity was stronger for the France scenario in the Covid-19 treatment, whereas it was stronger in the Italy scenario in both the Economics and Football treatments. Regression analysis (presented in Appendix B) suggested that subjective measures of emotional involvement did not appear to influence ambiguity reactions directly, whereas those of information on the decision context had an effect on ambiguity aversion in the Covid-19 treatment (i.e., with higher differential knowledge reducing aversion) and ambiguity insensitivity in the Covid-19 and Football treatments (i.e., with higher differential knowledge increasing a-insensitivity). Table 11 summarises the main results in Section 4.

Table 11. Source preference and source sensitivity

Treatment	Source preference	Source sensitivity	Remarks
COVID-19	**NO**	**YES** Ambiguity insensitivity ranking France>Italy>Ellsberg	Ambiguity aversion decreasing in differential knowledge (5% level) Ambiguity insensitivity increasing in differential knowledge (5% level)
Economics	**YES** Ambiguity aversion ranking Ellsberg>France>Italy	**YES** Ambiguity insensitivity ranking Italy>France>Ellsberg	--------------------------------
Football	**YES** Ambiguity aversion ranking Ellsberg>France>Italy	**YES** Ambiguity insensitivity ranking Italy>France>Ellsberg	Ambiguity insensitivity increasing in differential knowledge (10% significance level)

Note 1: Source preference denotes statistically significant differences between the b-indices of ambiguity aversion within treatments.
Note 2: Source sensitivity denotes statistically significant differences between the a-indices of ambiguity insensitivity within treatments.
Note 3: Remarks refer to regression analysis presented in Appendix B, Tables B1 and B4, respectively

5. Data analysis between treatment

This section compares the ambiguity reaction considering Covid-19 (N=42), Economics (N=45), and Football (N=46) treatments. To make this comparison, we considered each treatment to be an independent sample. Consequently, we run a Kruskal-Wallis one-way analysis of variance by rank test under the null hypothesis that the three samples came from populations with the same median. If the null hypothesis is rejected, at least one pair of samples has different medians. The KW test was run by comparing the b-index and a-index across treatments while keeping the scenario constant. Hence, we compared the Covid-19 confirmed positive cases in France with the Economics sovereign interest spread for France with the Football Conference League match for a French team, and similarly for Italy and Ellsberg scenarios. Of course, only the Ellsberg scenario was the same across treatments. Hence, the results of the KW test across treatments for the other two scenarios must be considered with caution, as long as they only have the same decision context, namely France and Italy, but not the type of scenario that was specific to each treatment. Regarding the b-index, the KW tests could not reject the null hypothesis of equal medians across all treatments. We take this result as evidence that ambiguity aversion was not affected by the different treatments in our experiment, given a common decision context (France, Italy, Ellsberg scenarios).

Turning to the a-index, the KW tests could not reject the null hypothesis of equal medians in the Italian and Ellsberg decision contexts. However, the KW test rejected the null hypothesis for the French decision context at the 5% significance level. The results are shown in Table 12.1. Following the rejection of the KW tests for the a-indexes for the France decision context, in order to ascertain the source of this difference, Table 12.2 shows the result of pairwise comparisons of treatments using the Dunn test with Bonferroni adjustment of p-values. The statistically significant test was found to be the one for Covid-19 treatment vs Football treatment ($z = 2.689007$ and adjusted p-value = 0.0215). Hence, the French decision context showed different degrees of ambiguity insensitivity at median values in the two real-world treatments that were characterised by higher perceived differential knowledge and involvement relative to the Economics treatment.

The KSW test with post-hoc Dunn test suggests differences in ambiguity insensitivity between Covid-19 and Football in the French scenario. In Appendix B, Table B5 regresses the a-index for the pooled data on a categorical variable treatment, where the baseline category is Covid-19, and on a set of regressors, including differential knowledge, differential involvement, sociodemographic variables (age, gender, and region), ease of experimentation, and experience with the experiment. Recall the differential knowledge and involvement are treatment specific. Table B5 confirms that participants reacted differently to the Covid-19 and Football treatments when facing France scenarios. More specifically, a-insensitivity was higher for Covid-19 than for Football treatment, and this effect was significant at the 1% significance level. As for other determinants of a-insensitivity, higher differential knowledge led to higher a-insensitivity and not being male, whereas older participants and participants with residence in the North were less a-insensitive. The absence of across-treatment effects when participants evaluated the Ellsberg scenario suggests that the evaluation of Ellsberg lotteries was not affected by the general decision context (Covid-19, Economics, and Football). We interpret this finding as evidence that the participants evaluated prospects in isolation within each treatment, which was one of the aims of our incentive scheme.

Table 12.1 Kruskall-Wallis test for difference in ambiguity preference and ambiguity insensitivity among treatments

	France: COVID-19 vs Econ vs Football	Italy: COVID-19 vs Econ vs Football	Ellsberg: COVID-19 vs Econ vs Football
b-index	chi2(2)= 0.441 p-value = 0.802	chi2(2)= 0.337 p-value = 0.845	chi2(2) = 0.21 p-value = 0.9005
a-index	**chi2(2) = 7.249**** **p-value= 0.0267**	chi2(2) = 0.123 p-value= 0.9405	chi2(2) = 4.053 p-value = 0.1318

Note: The null hypothesis is equal median. ***significant at 1%, **significant at 5%; * significant at 10% levels. Exact p-values.

Table 12.2 Dunn test for difference in ambiguity insensitivity

	Dunn test a-index COVID-19 vs Economy	Dunn test a-index COVID-19 vs Football	Dunn test a-index Economy vs Football
France scenarios	z=1.514028 (adj p-value= 0.3901)	z=2.689007 (adj p-value= 0.0215)**	z=1.187853 (adj p-value= 0.7047)

Note: Bonferroni adjustment for p-values. ***p<0.01, **p<0.05; * p<0.1.

6. Discussion

In this section, we discuss our results, and we compare them with the existing literature.

A few papers (Li, 2017, Anantanasuwong et al., 2019, von Gaudecker et al, 2022, Henkel, 2022, Gutierrez and Kemel, 2021) have adopted Baillon et al.'s (2018, 2021) belief-hedges method to measure ambiguity attitudes. Anantanasuwong et al (2019) used an online survey with no incentivised subjects, while incentivised subjects were used by von Gaudecker et al (2022) always in a large scale survey. In Henkel (2022) and Gutierrez and Kemel (2021), subjects participated in an incentivised lab experiment, while Li (2017) ran a field experiment with linguistic students in China.

In spite of the different methodologies adopted and the different sample sizes, the results of these papers are consistent in finding that on average ambiguity preference (generally aversion) is independent of the source of uncertainty, whereas likelihood insensitivity is source dependent. In all of these papers, however, except for Gutierrez and Kemel (2021), the natural source of uncertainty was in the same domain (i.e. Li (2017) used a linguistic domain, Anantanasuwong et al., 2019 and von Gaudecker et al, 2022 economic domains, while Henkel, 2019 weather domain).[29]

Our study is the first – in the framework of the belief-hedges approach of source preference and source insensitivity - that uses three natural sources of uncertainty in three different domains (Covid-19, Economics and Football). Moreover, we consider for each source of natural uncertainty a more familiar source (Italy) and a less familiar one (France). Last but not least, we also use an artificial source (Ellsberg's three-colour lottery) in a within-subject design, so that we can compare participants' behaviour towards ambiguity when facing natural versus artificial uncertainty in exactly the same set up. In addition, by introducing some questions over knowledge and emotional involvement, we are able to check whether the dependence of ambiguity attitudes on sources might be caused by the different knowledge or emotion that can characterise different natural sources of ambiguity.

As far as our results are concerned, we find evidence, as in the above quoted papers, that ambiguity preference (generally aversion) is in most cases independent of the source of uncertainty (Hypothesis 1b), whereas a-insensitivity is source-dependent for the natural sources of uncertainty (Hypothesis 1b). However, when we compare the artificial source of uncertainty with the natural one (whatever we used), surprisingly we find more ambiguity aversion and less insensitivity for the artificial sources (Hypothesis 1a). Hence, artificial sources of uncertainty are clearly treated differently from natural ones, and this may depend on different effects that knowledge and emotion can have on these two very different sources of uncertainty. This fact deserves further investigation that we leave to future research.

As far as the behaviour within a specific source of uncertainty between a more and a less familiar one, we find, generally speaking, a trend in behaviour in the direction of the more familiar source of uncertainty generating weaker reaction both in preferences and insensitivity (Hypothesis 2). This is certainly related (see Tables 4b, 7b, and 10b) to the different level of knowledge involving the Italy versus the France scenario. Our results go in the same direction of Gutierrez and Kemel (2021), who explicitly address the issue of source preference and sensitivity in two pairs of sources that arguably differ in familiarity (i.e., local and foreign temperature; approval ratings of local and foreign heads of state and government). Our and their results confirm the evidence of the experimental literature in the late 1990s and early 2000s (see Kilka and Weber, 2001; Tversky and Fox, 1995 and Fox and Weber, 2002).

Overall, our results suggest that ambiguity aversion/proneness represents a preference of individuals, which is not affected much by the source of uncertainty as far as natural sources are concerned, whereas likelihood insensitivity is source dependent and can be influenced by knowledge of the decision context (Hypothesis 2).

[29] See Kilka and Weber, 2001; Tversky and Fox, 1995, and Fox and Weber 2002.

In this respect, our findings are in line with the above quoted literature. However, the novelty of our results is that differences in ambiguity reaction in terms of preferences or aversion and not only in ambiguity insensitivity may arise when comparing different domains of uncertainty, in particular natural sources versus artificial sources, for which participants may have different degrees of emotional involvement and knowledge.

However, we do have in mind that our paper and the ones quoted above following Baillon et al. (2018) use a three partition of the space in the experimental tasks.[30] Using different partitions of the states has been shown to lead to different attitudes towards ambiguity. In particular, there is experimental evidence that attitudes can go from aversion to preference as far as the partitions of the state space increase (Maffioletti and Santoni 2019).[31] The increase of ambiguity aversion according to the increase in the number of the partitions was predicted by *support theory* (Tversky and Koehler, 1994 and Rottenstreich and Tversky, 1997). As a consequence, it will be interesting to design an experiment using Baillon et al.'s model to test support theory, but we will leave that to further research.

7. Conclusion

This study tests the hypotheses of source preference and source sensitivity under ambiguity. It adopts Baillon et al.'s (2018; 2021) belief hedges approach to measure ambiguity reaction (i.e., preference and likelihood insensitivity). This approach allows the experimenter to measure ambiguous attitudes without knowledge of subjective likelihoods. The experimental results provide weak evidence in favour of source preference: participants showed, on average, stronger ambiguity aversion when facing artificial uncertainty rather than natural uncertainty, for which they had superior knowledge of the decision context and/or higher emotional involvement. However, this finding was expected across the different sources of natural uncertainty. As for source sensitivity, the experimental data showed a consistently higher likelihood insensitivity to natural uncertainty than to artificial uncertainty.

The prevalence of source sensitivity and some evidence of the impact of knowledge and, to a lesser extent, emotional involvement related to the decision context on likelihood insensitivity (i.e., for Covid-19 and Football) suggests policy implications that are in line with those already identified by Li (2017) and Anantanasuwong et al. (2019), among others. These implications include the following: to facilitate people's choice under uncertainty, policy action is likely to be more effective in targeting a-insensitivity (the cognitive component of ambiguity attitudes) than ambiguity aversion (the preference component of ambiguity attitudes). Specifically, by providing more information regarding the decision context, which may also affect its

[30] A threefold partition of the space state is not necessary in the theoretical model of Baillon et al (2021). They specify that the only elements that are necessary for the application of their model are *at least* a threefold partition of the set space and probabilities of the events that are not close to one or zero.

[31] In this case, ambiguity preference was measured by binary complementarity and ternary additivity following Baillon and Bleichrodt (2015), with subjects going from subadditivity to superadditivity as space partition increased from two to four.

emotional salience, policymakers can facilitate people's decisions to get a new vaccine, adopt a new technology, start a new business, or participate in financial markets.

Although this study considers the role of emotional involvement in affecting ambiguity attitudes, one of its limits is that it does not control for the valence of emotions (i.e. negative or positive) nor for the fact that knowledge of the decision context and emotions related to it may be highly correlated in some domains (i.e., more informed people tend also to be more emotionally involved, as suggested by our data; or, on the contrary, information reduces emotional involvement, as suggested by Schwartz, 2012), while they may be independent of each other in other domains. The presumption that emotions would merely shape ambiguity reaction (Li, 2017) and not likelihood insensitivity should be further investigated.

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APPENDIX A

A1. *Procedure*.

Two sessions were run for each treatment. In each session, all subjects started the experiment at the same time. Each experimental session was composed of six parts:

Part 1: Instructions. After the subjects were seated at separated computer terminals, the instructions appeared on the screen, at the same pace for all subjects, while the experimenter read them aloud. An extract of the Instructions was given to each subject on paper with examples for each set of choice questions, together with a pen and a blank piece of paper (see the Supplementary material for the experiment's complete instructions and screenshots). Questions could be asked to the experimenter at any moment and talking was not allowed. After the instructions were read and before the decision process started, the instructions for payment were given.

The experimenter showed the participants 4 different envelopes containing: (1) 19 sheets of paper each one containing one of the 19 choice questions; (2) 29 tickets each numbered with one of the 29 probabilities of the choice options; (3) 20 tickets each numbered with one of the 20 different pairwise choices of the risk scenario; (4) the composition of the Bingo Blower used as a device for the drawing of the coloured ball in the Ellsberg scenario. One participant drew the choice problem and the three tickets, and inserted them in an envelope, which she cross-signed and which was opened the day after the resolution of the uncertainty (the 6th of May 2022). It was explained to the subjects that the day after the uncertainty was resolved, one subject would have opened the cross-signed envelope and read out its content: the decision problem, the probability, the row number of the risk scenario, and the composition of the Ellsberg urn. It was made clear to the subject that three possible different cases could apply:

(1) a choice problem of the natural event had to be played out for real. Then, the ticket with the probability would be read out. All subjects who for that probability had chosen Lottery A based on the event would be paid out according to the result of the event. Each subject who had chosen Lottery B for that probability would play out the lottery on that probability. They would choose a ticket from an envelope containing numbers 1-100. If the number drawn was between 1 and the probability, they won the €15 prize. If the number was higher than the probability, they would get nothing.

(2) One of the Ellsberg scenarios had to be played out for real. It was explained to the participants that the Bingo Blower would have been used to draw a ball, with the indicated composition. Then, the ticket with the probability and the ticket with the composition of the coloured balls would be read out. All subjects who for that probability had chosen Lottery A based on the drawing of the coloured ball would use the Bingo Blower with the indicated composition to draw one coloured ball (a photo of the Bingo Blower is given in Figure A1)[32]. The subjects were paid according to the result of the ball drawing. The subjects who had chosen Lottery B for that probability would play out the lottery on that probability as explained above in (1).

[32] The composition of the Bingo Blower was the following: 30 red balls, and 30 yellow and 30 blue balls. The red balls were fully painted. The yellow and blue balls of unknown composition were only marked with their respective colour,

(3) The risk scenario had to be played out for real. The row number of the choice option would be read out. The subjects that for that option had chosen the sure amount of money would be paid that amount. The subjects who had chosen the 50-50 lottery would draw a ticket, winning €15 in case a number between 1 and 50 was drawn, and 0 otherwise.

In the invitation to the experiment, it was specified that the subjects would have got 3 euros in addition to the participation fee for having to come back to play the lottery and being paid.

After the instruction part was over, the experiment started.

Parts 2, 3, 4, and 5: Choice questions. In each treatment, the three sets of six questions (Italy, France, and Ellsberg scenario) and the one question for the risk scenario (19 choice questions overall) appeared on the screen for each subject in random order, both by scenario type and by question order. A complete list of the description of the events in Lottery A for the different treatments and scenario types are given in the following Tables A1a-A1d.

Figure A1 – The Bingo Blower in action

so that when the Bingo Blower was in motion the colour of the balls could not be distinguishable and balls of different colours could not be counted.

Table A1a. The triple of single and complementary events, their description and representation – COVID-19 treatment

Event	Description And Visual representation				
	Italy			France	
Single events	E_1	the number of Covid-19 new positive cases in Italy is less than 40757	40757 59230; 15,00 € | 0,00 € | 0,00 €	the number of Covid-19 new positive cases in France is less than 35850	35850 49482; 15,00 € | 0,00 € | 0,00 €
	E_2	the number of Covid-19 new positive cases in Italy lies between 40757 and 59230 included	40757 59230; 0,00 € | 15,00 € | 0,00 €	the number of Covid-19 new positive cases in France lies between 35850 and 49482 included	35850 49482; 0,00 € | 15,00 € | 0,00 €
	E_3	the number of Covid-19 new positive cases in Italy is greater than 59230	40757 59230; 0,00 € | 0,00 € | 15,00 €	the number of Covid-19 new positive cases in France is greater than 49482	35850 49482; 0,00 € | 0,00 € | 15,00 €
Complementary events	E_{23}	the number of Covid-19 new positive cases in Italy is greater than or equal to 40757	40757 59230; 0,00 € | 15,00 € | 15,00 €	the number of Covid-19 new positive cases in France is greater than or equal to 35850	35850 49482; 0,00 € | 15,00 € | 15,00 €
	E_{13}	the number of Covid-19 new positive cases in Italy is less than 40757 or greater than 59230	40757 59230; 15,00 € | 0,00 € | 15,00 €	the number of Covid-19 new positive cases in France is less than 35850 or greater than 49482	35850 49482; 15,00 € | 0,00 € | 15,00 €
	E_{12}	the number of Covid-19 new positive cases in Italy is less than or equal to 59230	40757 59230; 15,00 € | 15,00 € | 0,00 €	the number of Covid-19 new positive cases in France is less than or equal to 49482	35850 49482; 15,00 € | 15,00 € | 0,00 €

Note: Events occurring on 5th May 2022.

Table A1b. The triple of single and complementary events, their description and representation – Economics treatment

Event	Description And Visual representation				
	Italy			France	
Single events	E_1	the value of the Spread BTP Italy-BUND 10 years is less than 185.3	185.3 194.7 15,00 € | 0,00 € | 0,00 €	the value of the Spread OAT France-BUND 10 years is less than 49.7	49.7 54.8 15,00 € | 0,00 € | 0,00 €
	E_2	the value of the Spread BTP Italy-BUND 10 years lies between 185.3 and 194.7 included	185.3 194.7 0,00 € | 15,00 € | 0,00 €	the value of the Spread OAT France-BUND 10 years lies between 49.7 and 54.8 included	49.7 54.8 0,00 € | 15,00 € | 0,00 €
	E_3	the value of the Spread BTP Italy-BUND 10 years is greater than 194.7	185.3 194.7 0,00 € | 0,00 € | 15,00 €	the value of the Spread OAT France-BUND 10 years is greater than 54.8	49.7 54.8 0,00 € | 0,00 € | 15,00 €
Complementary events	E_{23}	the value of the Spread BTP Italy-BUND 10 years is greater than or equal to 185.3	185.3 194.7 0,00 € | 15,00 € | 15,00 €	the value of the Spread OAT France-BUND 10 years is greater than or equal to 49.7	49.7 54.8 0,00 € | 15,00 € | 15,00 €
	E_{13}	the value of the Spread BTP Italy-BUND 10 years is less than 185.3 or greater than 194.7	185.3 194.7 15,00 € | 0,00 € | 15,00 €	the value of the Spread OAT France-BUND 10 years is less than 49.7 or greater than 54.8	49.7 54.8 15,00 € | 0,00 € | 15,00 €
	E_{12}	the value of the Spread BTP Italy-BUND 10 years is less or equal to 194.7	185.3 194.7 15,00 € | 15,00 € | 0,00 €	the value of the Spread OAT France-BUND 10 years is less or equal to 54.8	49.7 54.8 15,00 € | 15,00 € | 0,00 €

Note: Events occurring on 5th May 2022.

Table A1c. The triple of single and complementary events, their description and representation – Football treatment

Event	Description And Visual representation				
	Italy			France	
Single events	E_1	AS Rome wins at home against Leicester City in regular time in the UEFA Conference League second-leg semi-final	AS Rome wins / Draw / Leicester City wins: 15,00 € | 0,00 € | 0,00 €	Marseille wins at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	Marseille wins / Draw / Feyenoord wins: 15,00 € | 0,00 € | 0,00 €
	E_2	AS Rome draws at home against Leicester City in regular time in the UEFA Conference League second-leg semi-final	AS Rome wins / Draw / Leicester City wins: 0,00 € | 15,00 € | 0,00 €	Marseille draws at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	Marseille wins / Draw / Feyenoord wins: 0,00 € | 15,00 € | 0,00 €
	E_3	Leicester City wins away against AS Rome in regular time in the UEFA Conference League second-leg semi-final	AS Rome wins / Draw / Leicester City wins: 0,00 € | 0,00 € | 15,00 €	Feyenoord wins away against Marseille in regular time in the UEFA Conference League second-leg semi-final	Marseille wins / Draw / Feyenoord wins: 0,00 € | 0,00 € | 15,00 €
Complementary events	E_{23}	AS Rome does not win at home against Leicester City in regular time in the UEFA Conference League second-leg semi-final,	AS Rome wins / Draw / Leicester City wins: 0,00 € | 15,00 € | 15,00 €	Marseille does not win at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	Marseille wins / Draw / Feyenoord wins: 0,00 € | 15,00 € | 15,00 €
	E_{13}	AS Rome does not draw at home against Leicester City in regular time in the UEFA Conference League second-leg semi-final	AS Rome wins / Draw / Leicester City wins: 15,00 € | 0,00 € | 15,00 €	Marseille does not draw at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	Marseille wins / Draw / Feyenoord wins: 15,00 € | 0,00 € | 15,00 €
	E_{12}	Leicester City does not win away against AS Rome in regular time in the UEFA Conference League second-leg semi-final	AS Rome wins / Draw / Leicester City wins: 15,00 € | 15,00 € | 0,00 €	Feyenoord does not win away against Marseille in regular time in the UEFA Conference League second-leg semi-final	Marseille wins / Draw / Feyenoord wins: 15,00 € | 15,00 € | 0,00 €

Note: Events occurring on 5th May 2022.

Table A1d. The triple of single and complementary events, their description and representation – Ellsberg scenario (same for all treatments)

Event	Description And Visual representation		
Single Events	E_1	you extract a Red ball	15,00 € | 0,00 € | 0,00 €
	E_2	you extract a Blue ball	0,00 € | 15,00 € | 0,00 €
	E_3	you extract a Yellow ball	0,00 € | 0,00 € | 15,00 €
Complementary events	E_{23}	you extract a Blue or Yellow ball	0,00 € | 15,00 € | 15,00 €
	E_{13}	you extract a Red or Yellow ball	15,00 € | 0,00 € | 15,00 €
	E_{12}	you extract a Red or Blue ball	15,00 € | 15,00 € | 0,00 €

Part 6: Demographic and Self-evaluation questions

After all the subjects had submitted their decisions, they were asked some demographic questions (age, gender, course, general experience with experiments, perceived easiness of the decision task) and some questions concerning their emotional involvement and their knowledge concerning the event, different according to the treatment they were allocated to (see A2 below), and the experiment was over.

Payment. The day after the uncertainty was resolved (the 6th of May 2022), all subjects came back to the lab in 6 different groups at different timings, according to the session of the experiment they participated in. In each group, one subject volunteered to open the envelope sealed during the experimental session, and the payment process occurred as explained above in Part 1 *Instructions*. Each subject was paid a € 5 participation fee, the €15 prize in case they won, and an additional fee of €3 for having to come back after the experiment for the payment process.

A2. Questions

Demographic questions (same for all treatments). The participant was asked to either state a value or choose one of the listed options):

Age

Gender (options: Male, Female, I prefer not to answer)

Faculty (options: Economics, Law, Political Science, Other)

What year are you in?

Area of origin (options: North, Centre, South and Islands, Foreign country)

Did you find the experiment easy? (options: Yes, No)

Number of experiments you took part in until today (options: None, Between 1 and 5, More than 5)

Self-evaluation questions

Covid treatment (the participant was asked to choose just one out of seven options, by marking one out of seven ovals, ranging from 1 (Not at all) to 7 ('Always' or 'Very much'))

Do you keep yourself informed about the Covid-19 pandemic in Italy?

Do you feel emotionally involved with the Covid-19 pandemic in Italy?

Do you keep yourself informed about the Covid-19 pandemic in France?

Do you feel emotionally involved with the Covid-19 pandemic in France?

Economics treatment (the participant was asked to choose just one out of seven options, by marking one out of seven ovals, ranging from 1 (Not at all) to 7 ('Always' or 'Very much'))

Do you keep yourself informed about the trend of the value of the spread BTP Italia – BUND 10 years?

Do you feel emotionally involved with the trend of the value of the spread BTP Italia – BUND 10 years?

Do you keep yourself informed about the trend of the value of the spread OAT France – BUND 10 years?

Do you feel emotionally involved with the trend of the value of the spread OAT France – BUND 10 years?

Football treatment (The participant was asked to either state a value or answer ‘Yes’ or ‘No’, or choose one out of seven options, by marking one out of seven ovals, ranging from 1 (Not at all) to 7 (‘Always’ or ‘Very much’))

Do you follow the UEFA Conference League of football?

Do you follow the Serie A Italian league of football?

Are you a football fan of any Serie A Italian league of football team?

Which Serie A team do you support?

How much are you a fan of the Serie A football team you support?

Do you follow the Ligue 1 French league of football?

Are you a football fan of any Ligue 1 French league of football team?

Which French Ligue 1 team do you support?

How much are you a fan of the French Ligue 1 football team you support?

APPENDIX B: REGRESSION ANALYSIS

As already described in Appendix A.2, at the end of the experiment, subjects answered to a questionnaire as regards demographic characteristics, namely their age (in years), gender (male, female or no-binary gender), and region of residence in Italy (i.e., North, Centre or South and the Islands); cognitive perception and familiarity with experiments, namely easiness of the experiment (i.e., easy vs. difficult) and experience with past experiments (i.e., none, between 1 and 5 experiments, more than 5 experiments). For each treatment (Covid-19, Economics and Football) subjects were asked two questions to self-assess their knowledge (on the Covid-19 pandemic in Italy and in France), on the interest rate spread in Italy and France, and on the outcome of the second-leg semi-finals of the UEFA Football Conference League, one match involving an Italian team (i.e., AS Roma), and the other involving a French team (i.e., Olympique Marseille). Similarly, they were asked two questions to evaluate their self-assessed emotional involvement for an Italy and a France scenario in relation to each specific treatment. In each case, self-assessments were measured on a 7 point Likert scale (starting from 1: no knowledge/no involvement; to 7: highest/knowledge/involvement). Actually, the experimental design presumed that, within each treatment, subjects were both more informed and more involved as regards Italy than France. This assumption was validated by Wilcoxon signed rank tests (see the main text for details) confirming our a priori of greater involvement and information of subjects in the Italy than France scenarios.

Based on this information, we run random effects regressions, separately for the b-index and the a-index, treating each index computed for each scenario as a different observation for each subject (hence, using a panel dataset of Nx3 observations, where N=42 for Covid-19, N=45 for Economics, and N=46 for Football). For each ambiguity index, we estimated the following baseline model:

$$\text{Ambiguity index}_{is} = \alpha + \lambda_1 \text{ Scenario Italy} + \lambda_2 \text{ Scenario France} + \varepsilon_s$$

Then, we added the full set of controls, implying the following model:

$$\text{Ambiguity index}_{is} = \alpha + \lambda_1 \text{ Scenario Italy} + \lambda_2 \text{ Scenario France} + \beta \text{Differential Knowledge}_i + \gamma \text{Differential Involvement}_i + \delta \text{Easiness}_i + \zeta \text{ Experience}_i + \eta \text{Gender}_i + \theta \text{Region of residence}_i + \kappa \text{Session}_i + \varepsilon_s \tag{B.1}$$

In Equation (B.1) ambiguity index= {b-index, a-index}; i=1…N denotes subjects. In most regressions (if not specified in the main text otherwise), the Ellsberg scenario was used as baseline. Hence the categorical variable scenario measured potential differences in ambiguity reaction when subjects evaluated Italy or France scenarios vs Ellsberg's. In the unrestricted model of Eq. (B.1), each index was regressed on a set of individual-specific variables. This set includes two self-evaluation variables related to the decision context: *Differential knowledge* and *Differential involvement*. Using the answers to the Likert scale questions, differential knowledge for each subject was computed as the difference between the self-reported level of information for Italy and the corresponding subjective valuation for France, divided by the latter. This variable aimed at measuring whether a subject felt to have superior information about the decision context (i.e. either Covid-19, or Economics sovereign interest spread, or Football) in the Italy than France scenario. Differential involvement for each subject was computed as the proportionate difference between the self-reported degree of emotional involvement for each decision context in Italy and France. Note that both differential involvement and differential knowledge amplify upwards any self-assessed difference in involvement and knowledge, respectively, the lower is the reference level in the France scenario. Namely, the same numerical difference between levels of involvement, say, translates into a higher index of differential involvement when the reference level is lower. As an alternative measure, we also used the simple difference between self-assessed involvement, and similarly for self-assessed knowledge. However, as long as these latter measures were never statistically significant in our regressions and did not change the sign or significance of the covariates, we do not report them here.

The covariates are a cognitive variable termed *Easiness*, i.e., a dummy variable equal to zero if the subject found the experiment easy, and equal to 1 if s/he found it difficult; *Experience,* i.e., a categorical variable equal to 0 if subjects declared no experience with past experiments, equal to 1 if they had intermediate experience having participated to 1 to 5 past experiments; equal to 2 if they had high experience, i.e. participation to more than five past experiments); demographic variables: *Age* (in years), *Gender* (i.e., a categorical variable equal to 0 if male, equal to 1 if female; and equal to 2 if no-binary gender (one subject in the sample) and *Region of residence* (i.e., a categorical variable equal to 1 if subjects resided in Southern Italy and the Islands; equal to 2 if they resided in Central Italy, and equal to 3 if they resided in Northern Italy); a Session dummy. The additive error term ε_s is assumed to be normally distributed and captures decision errors that may affect the computation of the ambiguity indeces.

As long as the b-index and a-index are computed from the same data, we always computed the Breusch-Pagan test for independence of errors between equations. When the test rejected the null hypothesis of independence, we ran SUR estimates of the unrestricted models.

The results of our estimates for the Covid-19 treatment are presented in Table B1. When considering the full set of regressors, differential knowledge entered with a positive sign, while differential involvement entered with a negative sign. However, the estimated coefficients of the former variable were statistically significant at the 1% significance level, whereas that of the latter variable were significant at the 10% level. We interpret the differential knowledge result as being driven by relative ignorance of the French decision context, which enhanced a-insensitivity, especially when participants evaluated the French scenario.[33]

Regarding the latter result, we propose the following mechanism. As long as the participants were more involved in Covid-19 in Italy than in France (see Table 4a in the main text) and given that involvement in Italy was positively correlated with involvement in France (corr. 0.58, p = 0.01), it is likely that more emotionally involved participants evaluated real-world prospects more carefully. According to extant literature (Baillon et al., 2016; Schwartz, 2012), this would indeed be the case if the decision context elicited negative emotions (e.g., sadness or fear). However, we can only speculate that this was the driving mechanism given that we did not measure the sign (i.e., positive or negative) of emotional involvement.

[33] An OLS regression showed a *positive,* statistically significant at the 5% level association between the *a-index for France* and differential knowledge, controlling for observed individual characteristics, cognitive perception, and general knowledge. This analysis is available on request from the authors.

Table B1. COVID-19 treatment. Ambiguity insensitivity (a-index) and ambiguity aversion (b-index)

	(1) a-index RE estimates	(2) a-index RE estimates	(3) a-index RE estimates	(4) a-index SUR estimates	(5) b-index SUR estimates
France Scenario	0.269 ** (0.105)	0.269 ** (0.111)	0.269 ** (0.109)	0.269*** (0.103)	-0.011 (0.037)
Italy Scenario	0.095 (0.123)	0.095 (0.129)	0.095 (0.127)	0.094 (0.120)	-0.036 (0.050)
Differential Knowledge		0.106 ** (0.033)	0.104 *** (0.035)	0.106 ** (0.031)	-0.084 ** (0.036)
Differential Involvement		-0.044 * (0.025)	-0.050 * (0.027)	-0.044 (0.023)	-0.005 (0.023)
Easiness		0.433 *** (0.106)	0.446 *** (0.099)	0.433*** (0.099)	-0.058 (0.105)
Experience					
Intermediate		-0.052 (0.104)		-0.052 (0.097)	0.026 (0.098)
High		-0.121 (0.112)		-0.121 (0.104)	-0.249* (0.140)
Age		-0.020 *** (0.003)	-0.021 *** (0.003)	-0.02*** (0.003)	0.008 (0.005)
Gender					
Female		-0.073 (0.091)	-0.071 (0.091)	-0.072 (0.085)	-0.032 (0.064)
Non-binary		-0.609 *** (0.126)	-0.496 *** (0.078)	-0.609** (0.118)	0.171 (0.133)
Region Of Residence					
Centre Italy		0.100 (0.087)		0.100 (0.082)	-0.194 *** (0.070)
Northern Italy		-0.206 (0.129)	-0.255 ** (0.113)	-0.206 (0.121)	-0.110 (0.099)
Session Dummy		-0.070 (0.081)	-0.049 (0.084)	-0.067 (0.075)	0.02 (0.069)
Intercept	0.369 *** (0.086)	0.781 *** (0.164)	0.793 *** (0.138)	0.781*** (0.153)	0.189 (0.170)
Wald χ^2	7.54	459.65	397.60		
Breusch–Pagan				3.233 (p-value=0.0721)	
Number Of Observations	126	126	126	126	126
Number Of Participants	42	42	42	42	42

Note 1: *** p<.01, ** p<.05, * p<.1. Standard errors adjusted for clusters in participants.
Note 2: a-index of ambiguity insensitivity, b-index of ambiguity aversion; pooled data.
Note 3: Columns 1 to 3 present random effects estimates of the a-index. Column 1 presents the baseline model, Column 2 the unrestricted model, while Column 3 the parsimonious model derived by using a general-to-specific approach. Columns 4 and 5 present the SUR model of the a-index and the b-index using the unrestricted model specification of Column 2.

Regarding control variables, Column 3 shows that participants who found the experiment difficult were significantly more ambiguity-insensitive than participants who found it easy, pointing to the role of general cognitive attitudes. Finally, notice that age, non-binary gender, and residence in the North were associated with lower ambiguity insensitivity at statistically significant levels (1% for the former two variables and 10% for the region of residence).

For robustness, we considered a Seemingly Unrelated Regression model by estimating simultaneously, with the full set of regressors, and using panel-type data, the a-index, and the b-index. The Breusch–Pagan test rejected the null hypothesis that the residuals of the two regressions were independent (BP: chi2 (1)=3.233, p-value=0.072), justifying the SUR approach. Columns 4 and 5 of Table B1 present the results for the a- and b-indices, respectively. As for the a-index, all the results in Column 2 are confirmed, but for differential involvement, they become statistically insignificant. This suggests that the effect of this variable detected in Columns 2 and 3 is likely driven by collinearity with other regressors. Regarding the b-index, it is worth noting the statistically significant and negative association with differential knowledge at the 5% significance level. As long as participants were more informed about Covid-19 in Italy than in France and given that knowledge of Covid-19 in Italy was positively correlated with that in France (corr. 0.66, p-value 0.01), the former result is likely to be driven by higher willingness to bet associated with higher knowledge, other things being equal.[34]

Turning to the Economics treatment, Table B2, Column 1, reports the results with errors clustered at the individual level. Both the France and Italy scenarios entered with a negative sign, implying that participants were, on average, less ambiguity-averse when assessing real-world uncertainty than Ellsberg's. This result is consistent with the findings of the Page test in Table 6.2 of the main text. However, only the Italian scenario was statistically significant at the 5% significance level. Next, we regressed the b-index on additional variables, as in the previous analysis of Covid-19 treatment. These variables include *differential knowledge* (the proportionate difference between self-reported knowledge in Italy and France regarding interest rate spreads), *differential involvement* (the corresponding proportionate difference between self-reported emotional involvement), and controls[35]. Column 2 of Table B2 reports the results.

[34] An OLS regression showed a *negative*, statistically significant at the 5% level, association between the *b-index for France* and differential knowledge, controlling for observed individual characteristics, cognitive perception, and general knowledge. This analysis is available on request from the authors.

[35] The controls are as follows: individual characteristics (age; a categorical variable for gender as one participant was non-binary: the baseline was male gender; a categorical variable for region of residence: the baseline was residence in the South and Islands), cognitive perception (i.e. self-evaluation of ease of experiment dummy: the dummy was equal to zero if the experiment was perceived as being easy, and equal to one otherwise), familiarity/general knowledge with past experiments (that is, a categorical variable measuring intermediate or high experience with experiments: the baseline was not experienced), and a session dummy variable.

Table B2 Economy spread. Random effects GLS estimates of ambiguity aversion and ambiguity insensitivity

	(1) b-index	(2) b-index	(3) b-index	(4) a-index	(5) a-index	(6) a-index
France Scenario	-0.064	-0.059	-0.064	0.211 **	0.207 **	0.211 **
	(0.043)	(0.043)	(0.044)	(0.090)	(0.092)	(0.091)
Italy Scenario	-0.065 **	-0.065 **	-0.065 **	0.193 **	0.193 **	0.193 **
	(0.027)	(0.028)	(0.028)	(0.094)	(0.098)	(0.095)
Differential Knowledge		-0.012			-0.106	
		(0.032)			(0.074)	
Differential Involvement		0.001			0.036	
		(0.034)			(0.101)	
Easiness		-0.109			-0.020	
		(0.076)			(0.186)	
Experience Intermediate		0.029			-0.073	
		(0.073)			(0.240)	
High		0.185 *	0.213 ***		-0.149	
		(0.111)	(0.067)		(0.267)	
Age		-0.008	-0.023		-0.025	-0.028
		(0.023)	(0.019)		(0.039)	(0.030)
Gender Female		-0.046	-0.060		0.259	0.215*
		(0.079)	(0.066)		(0.174)	(0.134)
Non-binary		-0.093	-0.065		-0.194	-0.103
		(0.079)	(0.055)		(0.179)	(0.139)
Region Of Residence Centre Italy		0.015			0.175	
		(0.069)			(0.146)	
Northern Italy		-0.217			0.169	
		(0.196)			(0.336)	
Session Dummy		-0.045	-0.056		-0.033	-0.013
		(0.061)	(0.059)		(0.152)	(0.137)
Intercept	0.102 ***	0.347	0.686 *	0.222 ***	0.659	0.736
	(0.039)	(0.498)	(0.416)	(0.075)	(0.979)	(0.750)
Wald χ^2	5.85	44.42	19.51	6.31	19.01	14.09
Number Of Observations	135	135	135	135	135	135
Number Of Participants	45	45	45	45	45	45

Note 1: *** p<.01, ** p<.05, * p<.1. Standard errors adjusted for clusters in participants.
Note 2: b-index of ambiguity aversion; a-index of ambiguity insensitivity, pooled data.
Note 3: Columns 1 and 3 present the baseline models; Columns 2 and 5 present the unrestricted models, while Columns 3 and 6 present the parsimonious models derived with a general-to-specific approach.

The size, sign, and statistical significance of the Italian scenario's categorical variables remained unaffected. Differential knowledge and differential involvement entered with negative and positive signs, respectively, but the estimated coefficients were not statistically different from zero. The only control variable that was statistically significant at the 10% level is the high-experience category, which had a positive sign. This implies that, on average, highly experienced participants (i.e., participants who participated in more than five past experiments) were more ambiguity-averse than participants without experience in past experiments. Column 3 of Table B2 reports the estimates of the restricted model obtained using the general-to-specific approach, starting from the unrestricted model in Column 2. Column 3 always controls for age, gender (even when these variables are not statistically significant), and session. The restricted model confirms the previous analysis: the coefficient of the Italian scenario variable remained significant at the 5% level, with a negative sign and the same size; the high-experience categorical variable entered with a positive sign, while the size of the estimated coefficient became larger and gained statistical significance.

The same type of analysis was performed to test source sensitivity. Column 4 of Table B2 reports the regression of the a-index on the categorical dummy variable for the scenario and a constant (i.e., the baseline model). Column 5 illustrates the regression of the a-index on the scenario categorical variable, differential knowledge, differential involvement, and the full set of controls, and Column 6 reports the restricted model derived from a general-to-specific approach. Column 4 shows that both the France and Italy scenarios entered with a positive sign, and that the estimated coefficients were statistically significant at the 5% level. This means that the participants were, on average, more ambiguity-insensitive in evaluating real-world scenarios than the Ellsberg scenario. This result is again consistent with the findings of the Page test in Table 6.2. Columns 5 and 6 of Table 7.1 confirm the previous results. Neither differential knowledge nor differential involvement nor other controls were statistically significant at conventional levels (in Column 6, women are estimated to be more a-insensitive than men but at the 10% significance level).

As long as the residuals of the regression on the b-index were correlated with the residuals of the regression on the a-index according to the Breusch–Pagan tests (chi2(1))=8.144, p-value=0.0043 for the unrestricted models),[36] we re-estimated the models in Columns 2 and 5 of Table B2, using the Seemingly Unrelated Regression estimator. The results are depicted in Table B3. This table confirms the results of the previous analyses.

[36] A SUR estimation was also run for the baseline models. The results are available from the authors on request.

Table B3 Economy spread. Seemingly Unrelated Regression of ambiguity aversion and ambiguity insensitivity

	(1) b-index		(2) a-index	
France Scenario	-0.063		0.213	**
	(0.042)		(0.088)	
Italy Scenario	-0.065	**	0.193	**
	(0.027)		(0.092)	
Differential Knowledge	-0.016		-0.101	
	(0.029)		(0.070)	
Differential Involvement	0.001		0.035	
	(0.031)		(0.093)	
Easiness	-0.080		-0.059	
	(0.069)		(0.177)	
Experience				
Intermediate	0.056		-0.108	
	(0.067)		(0.221)	
High	0.245	**	-0.230	
	(0.098)		(0.239)	
Age	-0.017		-0.013	
	(0.019)		(0.034)	
Gender				
Female	-0.075		0.298	*
	(0.071)		(0.161)	
Non-binary	-0.118	*	-0.160	
	(0.072)		(0.157)	
Region Of Residence				
Centre Italy	0.033		0.151	
	(0.061)		(0.135)	
Northern Italy	-0.022		-0.095	
	(0.109)		(0.193)	
Session Dummy	-0.063		-0.008	
	(0.057)		(0.139)	
Intercept	0.530		0.412	
	(0.424)		(0.879)	
Breusch–Pagan χ^2	8.144 (p-value=0.0043)			
Number Of Observations	135		135	
Number Of Participants	45		45	

Note 1: *** p<.01, ** p<.05, * p<.1. Standard errors adjusted for clusters in participants. Note 2: b-index of ambiguity aversion; a-index of ambiguity insensitivity; pooled data.

Finally, using the Football treatment data, we ran random effects estimates of the b-index and a-index separately by regressing each index first on categorical variables for scenario and a constant, then on differential knowledge, differential involvement, and the full set of controls.[37] Table B4 illustrates this where Column 1 presents the baseline model. Here, we control for scenarios by using an Ellsberg dummy variable, taking the value of 1 if the observation refers to the Ellsberg scenario, and the value of zero otherwise (i.e. for both Italy and France scenarios). It turns out that the estimated coefficient for the Ellsberg dummy takes on a positive sign and is significant at the 10% level, implying more ambiguity aversion with artificial than natural sources of uncertainty. Column 2 specifies the unrestricted model and shows no role in both differential knowledge and involvement. The restricted model in Column 3 confirms the size and significance of the Ellsberg dummy variable. It also shows that ambiguity aversion was larger, on average, for female participants,

[37] The Breusch–Pagan test could not reject the null hypothesis of error independence between the b-index and a-index regressions for the unrestricted models using the same base for the categorical scenario variable (chi2(1)=0.18, p-value=0.6717). Therefore, we did not perform SUR estimates.

residents in the South and islands, and participants finding the experiment difficult, whereas it was significantly smaller for more experienced participants, other things being equal.

For the a-index, Columns 4–6 of Table B4 controls scenarios by using a categorical variable with Italy as the baseline. The participants were, on average, less ambiguity-insensitive under the France than Italy scenario. No significant difference was detected for Ellsberg vs Italy. This result is unaffected by the addition of differential knowledge, differential involvement, or the full set of controls. Column 6 shows that differential knowledge entered with a positive coefficient that was significant at the 10% significance level. This result is likely driven by how differential knowledge affects insensitivity in France.[38] As for other controls, residents in northern Italy and participants who found the experiment more difficult were less insensitive, whereas participants with high experience of the experiments were more insensitive.

[38] An OLS regression of differential knowledge and other controls on the a-index for France shows an estimated coefficient for the former variable that is positively signed and statistically significant at the 1% significance level. This analysis is available from the authors on request.

Table B4 Football. Random effects GLS estimates of ambiguity aversion and ambiguity insensitivity

	(1) b-index		(2) b-index		(3) b-index		(4) a-index		(5) a-index		(6) a-index	
France Scenario	NA		NA		NA		-0.117	*	-0.117	*	-0.117	*
							(0.067)		(0.069)		(0.069)	
Ellsberg Scenario§o	0.049	*	0.049		0.049	*	-0.132		-0.132		-0.132	
	(0.029)		(0.030)		(0.0297)		(0.114)		(0.118)		(0.117)	
Differential knowledge			-0.017						0.048		0.042	*
			(0.015)						(0.032)		(0.026)	
Differential Involvement			0.015						-0.007			
			(0.011)						(0.024)			
Easiness			0.182	***	0.175	***			-0.524	***	-0.519	***
			(0.057)		(0.052)				(0.130)		(0.120)	
Experience												
Intermediate			0.037						-0.008			
			(0.057)						(0.105)			
High			-0.062		-0.104	**			0.276		0.286	*
			(0.077)		(0.052)				(0.172)		(0.151)	
Age			0.009		0.007				-0.036		-0.035	
			(0.009)		(0.009)				(0.022)		(0.022)	
Gender												
Female			0.078	**	0.062	*			0.083		0.089	
			(0.033)		(0.032)				(0.093)		(0.089)	
Region Of Residence												
Centre Italy			-0.088	***	-0.089	***			0.007			
			(0.032)		(0.034)				(0.098)			
Northern Italy			-0.130	**	-0.122	**			-0.365	***	-0.371	***
			(0.066)		(0.057)				(0.131)		(0.112)	
Session Dummy			-0.030		-0.035				0.093		0.093	
			(0.039)		(0.034)				(0.099)		(0.085)	
Intercept	0.048	*	-0.165		-0.077		0.438	***	1.150	**	1.124	**
	(0.027)		(0.224)		(0.208)		(0.067)		(0.483)		(0.457)	
Wald χ²	2.88		54.49		49.82		3.20		41.04		37.66	
Number Of Observations	138		138		138		138		138		138	
Number Of Participants	46		46		46		46		46		46	

Note 1: *** p<.01, ** p<.05, * p<.1. Standard errors adjusted for clusters in participants.
Note 2: b-index of ambiguity aversion; a-index of ambiguity insensitivity, pooled data.
Note 3: Columns 1 and 3 present the baseline models; Columns 2 and 5 present the unrestricted models; and Columns 3 and 6 present the parsimonious models derived with a general-to-specific approach.
Note 4: § In columns (1) to (3) Ellsberg scenario is a dummy variable, taking the value of 1 for observations under this scenario, and the value of zero otherwise (i.e. both Italy and France scenarios). In columns (4) to (5), scenario is specified as a categorical variable, using the Italy scenario as baseline

In Section 5 of the main text, we compare our results across treatments. One finding of the KSW test with post-hoc Dunn test is the presence of difference in ambiguity insensitivity between Covid-19 and Football in the French scenario. Table B5 regresses the a-index for the pooled data of the France scenarios across treatments on a categorical variable treatment, where the baseline category is Covid-19, and on a set of regressors, including differential knowledge, differential involvement, sociodemographic variables (age, gender, and region), ease of experimentation, and experience with the experiment. It turns out that subjects were on average less insensitive in the Football France treatment than in the Covid-19 France treatment.

Table B5. OLS estimates of a-index France

	1		2		3	
	a-index France		a-index France		a-index France	
Treatment						
Economics	-0.204	*	-0.138		-0.141	
	(0.116)		(0.127)		(0.125)	
Football	-0.317	***	-0.302	***	-0.306	***
	(0.099)		(0.093)		(0.092)	
Differential Knowledge			0.074	*	0.077	**
			(0.040)		(0.033)	
Differential Involvement			0.013			
			(0.031)			
Age			-0.016	***	-0.015	***
			(0.006)		(0.005)	
Gender						
Female			0.174	*	0.153	*
			(0.090)		(0.087)	
Non-binary			0.218	*	0.284	**
			(0.119)		(0.135)	
Region of residence						
Centre			0.088			
			(0.095)			
North			-0.232		-0.298	**
			(0.149)		(0.141)	
Easiness			0.070			
			(0.145)			
Experience						
Intermediate			-0.148			
			(0.112)			
High			-0.148			
			(0.136)			
Intercept	0.638	***	0.858	***	0.796	***
	(0.075)		(0.212)		(0.165)	
R-squared	0.06		0.17		0.15	
Number of observations	133		133		133	
*** p<.01, ** p<.05, * p<.1						