Testing Source Influence on Ambiguity Reaction: Preference and Insensitivity

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Abstract

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. Our experiment was held in Rome, and we ran six sessions with three different treatments associated with diverse natural sources of uncertainty (i.e., the COVID-19 pandemic, sovereign interest spread, and football matches) considering different national scenarios (France and Italy). The experimental hypothesis was that each decision context could be characterised by 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 the original Ellsberg's three-colour problem framed in the same way as the natural source of uncertainty. The study found that, within treatments, participants were generally more ambiguity-averse (they did not like uncertainty) when facing the artificial source than natural sources of uncertainty. However, they were less sensitive to likelihood changes (i.e., cognitively less able to assess changes in probability levels) for natural than artificial sources. Our findings provide partial evidence in favour of source preference with stronger ambiguity aversion for the Ellsberg scenario than the natural ones in two out of three natural sources; hence, our paper shows that ambiguity aversion/preference depends on the source of uncertainty. Moreover, our results provide strong evidence in favour of source sensitivity; thereby, ambiguity-generated insensitivity is influenced by the inner characteristics of the different natural sources 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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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 Camerer 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 reflect better 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). A few researchers have considered lotteries with unknown probabilities 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 first subjects depict the ambiguous Ellsberg urn as a second-order probability distribution 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) it can hardly be extended to natural sources of uncertainty (see Segal, 1990; Bernasconi and Loomes, 1992; 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., the Ellsberg urn) or an event (e.g., the variation of a stock index). We call the lottery device an *artificial source*

[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).

of ambiguity and the event-based lottery a *natural source of ambiguity*.[2] 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, the variation of an interest rate spread, and a football match. 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? Is there any characteristic or property of a natural source that may help us to predict the possible reaction?

In order to test this aspect, we chose three different natural sources that differ in terms of emotional involvement. Based on the psychological literature (Loewenstein et al., 2001, Rick and Loewenstein, 2008: 138–139, Slovic and Västfjäll, 2010, Bechara, 2011, and more recently Västfjäll et al., 2016) our intuition is that, if natural sources of uncertainty are characterised by different emotional involvement in terms of valence and intensity, this may affect judgment and decision and in particular the perception of uncertainty and the ability to form probabilities. According to our prior, the three natural sources of uncertainty (COVID-19, the variation of a sovereign interest rate spread, and a football match) differ quite significantly. By keeping in mind that our subject pool was composed by students in economics and law, we expect that the economic index should involve little emotion, the football match should imply a higher level of emotional involvement, at least for the supporters/rival fans of the considered teams,[3] while the COVID-19 frame should involve a far more spread and intensity in emotions (with past mixed with present integral affect/emotion).[4] Emotion and in particular integral affect may have a diversified influence over the preference to uncertainty and the ability to understand variation in probability. Few previous studies examined the effects of emotions on source preference and/or source insensitivity. For example, Rottenstreich and Hsee (2001) found that risky lotteries based on an affect-rich outcome (a coupon for a romantic trip) showed both more pronounced overweighting

[2] See for this distinction Li et al. (2018, 2020).
[3] We put control questions over this in our experiment.
[4] The experiment was run at the beginning of May 2022, and the COVID-19 emergency was declared to have finished on the 30th of April 2022. The media still gave the number of contagions every day at the opening of every news. Students had experienced three semesters of lectures at a distance and masks and vaccinations were still compulsory in Italy.

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. Baillon et al. (2016) showed that watching sad rather than joyful video clips (i.e., incidental emotion) before assessing artificial uncertainty sources elicited a more neutral attitude to ambiguity in participants. Li et al. (2018) showed that, if the decision context aroused positive emotions when assessing a natural source of uncertainty, participants were less ambiguity averse and less ambiguity-generated insensitive.

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, the variation of the sovereign interest rate spread, and a football match each in Italy and 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 influences ambiguity attitudes. It has been argued that a *preference* towards ambiguity is more probable to be observed when participants possess enhanced 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 rather 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 (see Keppe and Weber, 1999, for the case of stock exchange indexes and geography).[5]

How do we measure ambiguity attitudes when different sources and different mechanisms generate uncertainty? In the 1980s and until the Mid-1990s, ambiguity attitudes were mainly measured through the non-additivity in probabilities. In the second half of the 1990s and in the early 2000s, they were measured by the curvature and elevation of the weighting function.[6] 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.[7] Insensitivity has been interpreted as a cognitive dimension of ambiguity attitudes, which shows

[5] 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 (Kilka and Weber, 2001).

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

[7] 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

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 a participant's reaction to likelihood changes is less pronounced when they feel less competent/informed/knowledgeable about the decision context.

This study adopted Baillon et al.'s (2021) belief hedges approach to measure the two independent dimensions of ambiguity reaction (i.e., preference respect to ambiguity -aversion or proneness-and insensitivity generated by ambiguity). 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 used a three-fold partition of events for natural and artificial events adopting the same decision frame (Li, 2017, Anantanasuwong et al., 2024, von Gaudecker et al., 2022).

To summarise, following Baillon et al.'s (2021) approach, which considers two independent dimensions of ambiguity reaction (i.e., preference: ambiguity aversion/proneness; and ambiguity-generated 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, the variation of an economic variable, or a football match result) generate a different reaction to ambiguity. This reaction can differ both in the additive probability measure (i.e., the *b-index* or in words ambiguity aversion in Baillon et al.'s approach), and/or in the inability in discriminating probabilities (ambiguity- generated insensitivity i.e., the a-index of insensitivity in Baillon et al.'s approach).[8] 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.[9] We do not have a priori assumption in the direction of the reaction.

The experiment was conducted in Rome in May 2022 (see Section 3 below for details on the experimental design and procedure). The participants were randomly assigned to three different treatments (two sessions per treatment). The 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, while also in addition to facing artificial uncertainty, which was always represented by Ellsberg's three-colour problem.

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).

[8] From here on we will use ambiguity aversion/ b-index indifferently and ambiguity-insensitivity /a-index indifferently.

[9] 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.

Since our background hypothesis was that different treatments and scenarios could be associated with different knowledge and/or affect-richness in the decision context, we measured emotional involvement and knowledge with a self-reported 7-point Likert-type scale, which confirmed our expectations. We used a version of the random incentive system (Johnson et al., 2021) to avoid hedging.

The remainder of this paper is organised as follows. Section 2 describes the ambiguity indexes measuring the ambiguity aversion and ambiguity-generated insensitivity, and the experimental hypotheses. Section 3 describes the experiments. Section 4 presents the analysis of the experimental data for each treatment (within-subjects data analysis). Section 5 focuses on data comparisons among the treatments (between-subjects data analysis). 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.[10] 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:[11]

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.*

We use the matching probability elicitation following Baillon et al. (2018). This method (see Dimmock et al. 2016) allows us to measure a participant's ambiguous reaction without knowledge of its subjective likelihood, its risk attitudes, and, more generally, its utility function. Although it is more cognitively burdensome for the subjects than the elicitation of certainty equivalents, given that subjects must choose between two lotteries with the same outcomes, their evaluation of utility and the comparison with risk are no longer a problem. Moreover, since an event's matching probability and its complement are elicited, the distinction between aversion to ambiguity and subjects' belief is cancelled out. 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

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

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

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 probability 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:

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 equals 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 ambiguity-generated insensitivity has been shown to be distinct and independent of the ambiguity preference component of a participant's ambiguity attitudes (Abdellaoui et al, 2011). Specifically, ambiguity-generated insensitivity is interpreted as a cognitive component, reflecting the extent to which participants can understand ambiguous situations and react to new information. On the one hand, maximal ambiguity-generated insensitivity occurs when participants consider all events 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. If using the former football example, maximal ambiguity-generated 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 perfect ability to discriminate likelihoods 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, 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., complete inability to distinguish between likelihood levels by treating them all alike) corresponds to a value of 1 of the a-index. 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.[12] The a-index can take negative values (implying $(\overline{m_c} - \overline{m_s}) > \frac{1}{3}$). We denote this situation as non-insensitive.[13] Baillon et al. (2021) underscored that negative values of the a-index can be observed experimentally. However, 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 ambiguity aversion and different ambiguity-generated insensitivity than natural sources of ambiguity.*

Hypothesis 1b. *Different natural sources of ambiguity may have a different influence on aversion and ambiguity-generated insensitivity.*

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

Hypothesis 3. *For a given natural source of ambiguity, an affect-rich decision context influences ambiguity preference (aversion/proneness) and ambiguity-generated insensitivity.*

Under Hypothesis 1a, on the one hand, one would expect to observe more significant 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 1990s literature. Depicting Ellsberg's urn as a second-order probability distribution was supposed to reduce the perceived perception of ambiguity.[14] 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 aversion/proneness, 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 ambiguity reaction measured through both ambiguity-generated

[12] 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).

[13] Anantanasuwong et al. (2024) have termed this case as "overly sensitive to changes in likelihood, implying underweighting of unlikely events" (online p. 7).

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

insensitivity and ambiguity aversion/preference.

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 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[15] 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.[16] 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-subjects treatments.[17] Each treatment was associated with different natural sources of uncertainty with unknown probabilities – regarding COVID-19, Economics, and Football – 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 value of the sovereign interest rate spread at the same fixed date; and (c) the result of a football match at the same fixed date.

Why did we choose these natural scenarios? We needed different scenarios characterized by different sources of uncertainty. We were looking for scenarios that could be solved in terms of uncertainty at the same time to allow comparison in terms of resolution of uncertainty between treatments. (We did not want the resolution of uncertainty to influence the measure of ambiguity.) The chosen sources of uncertainty had to be salient at the period chosen for the lab experiments. In addition, we were looking for scenarios that could elicit different kinds of emotions. Emotions can be characterized by valence and arousal. Hence, the interest spread and the number of positive cases of COVID-19 have likely negative valence, but also different arousal (weaker for the interest spread than for COVID-19 according to our expectations). In contrast, football can elicit strong or weak arousal depending on whether the subject is a fan, and positive or negative valence depends on whether they are supporters or haters of one of the teams. We expect that these characteristics might affect the valuation of uncertainty as far as ambiguity aversion and ambiguity-generated insensitivity are concerned. While we expected both weaker ambiguity aversion and lower ambiguity-generated insensitivity for more familiar sources of uncertainty than for less familiar ones, we did not have an expectation in one direction for affect decision context. In fact, the psychological literature pointed out how the effect of emotion can be complex: it might depend on valence and arousal. In particular, when negative emotions are involved, a weak arousal can

[15] See also Maffioletti and Santoni (2019).

[16] 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.

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

help to decide rationally, while, if the arousal is too extreme people are unable to make proper decisions (Loewenstein and Lerner, 2003).

For each source, the participants were required to evaluate two different scenarios, Italy and France.[18] All natural and artificial sources of uncertainty used in the experiment adopted a three-fold partition of the event space (Section 2*). It is important to notice that the space event for each source of uncertainty was split into three single events and that the intervals considered to define the single event were chosen in a way that our prior of the occurrence of each single event was (as for the traditional three-colour Ellsberg paradox) equal to one third (i.e., each single event was equiprobable).* To do so, we looked at the past frequency (i.e., the average of the last two weeks) for all the events and determined the space and the single events accordingly.[19] Hence for all the natural sources of uncertainty, familiar and unfamiliar ones, and the three-colour Ellsberg the partition of the events was the same as their prior probabilities).

The fact that each single event partition was designed to have the same probability prior helped us control the effect of the different emotions and the different knowledge elicited by the different scenarios. (That was true for all the natural sources of uncertainty, familiar and unfamiliar ones).

Within each treatment, the participants faced six questions for each scenario (France and Italy) concerning event lotteries (for an example, see Table 1b).[20] 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.[21]

Table 1a. The experimental design

Treatment (between-subjects)	**Scenario (within-subjects)**				
		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		

Choice questions (natural events). For each question, the participants had to choose between the following two lotteries (see Table 1b for an example):

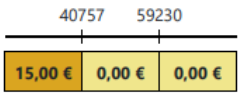
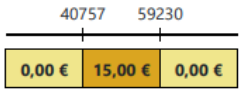
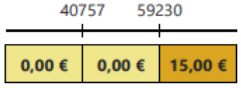
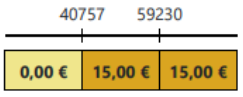
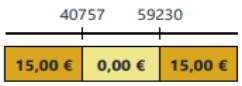
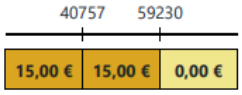
[18] The maintained hypothesis was that participants were both more knowledgeable and more emotionally involved within each treatment (i.e., the affect-richness dimension of the event was more salient) when the decision context referred to Italy than to France.

[19] Our expectation of equiprobable results for the football matches was based on the final score at the end of regular time of the second-leg semi-finals of the UEFA Conference League. Betting odds comforted our priors.

[20] 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.

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

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	

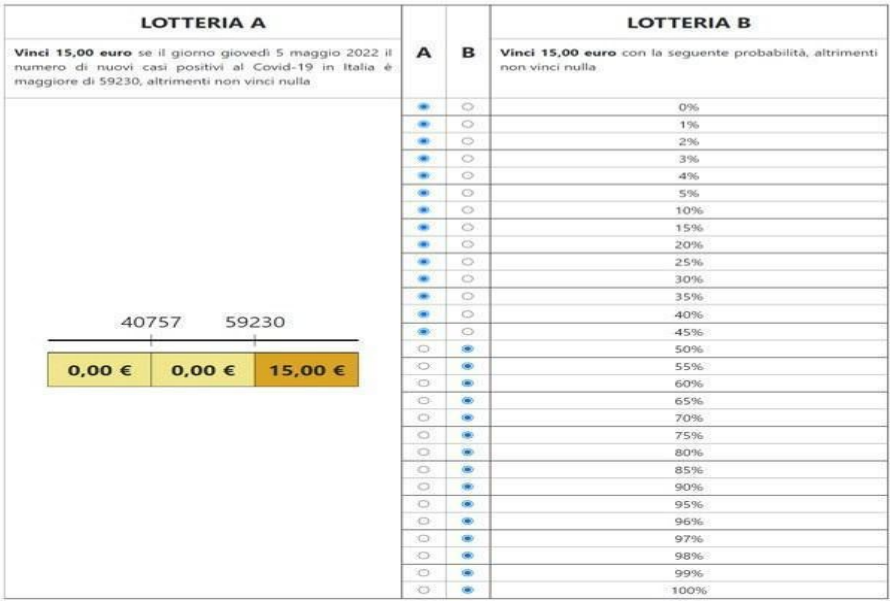
Note: Events occurring on the 5th of May 2022.

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 them 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 were 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[22]



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.

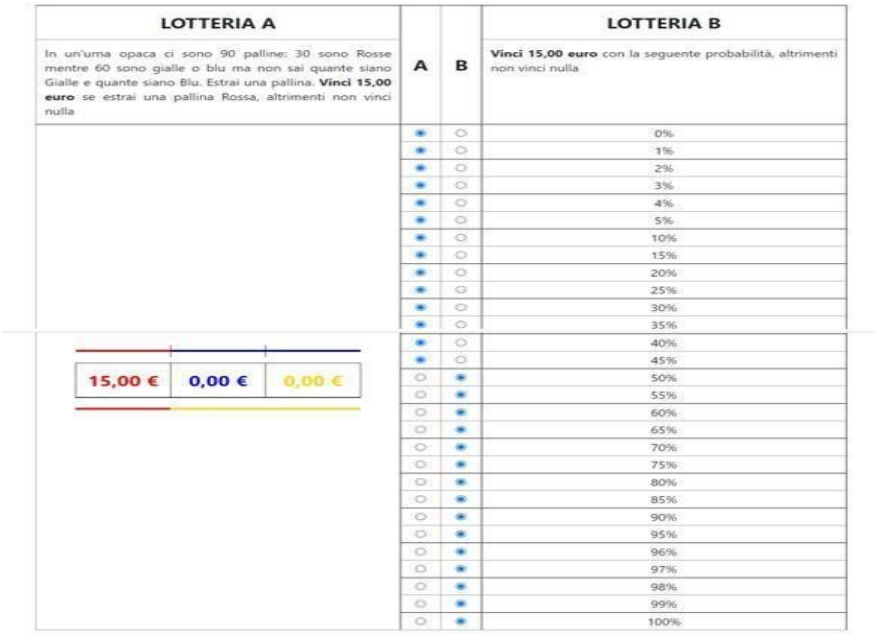
The selection procedure was the same as that for natural events. Figure 1b shows an example screenshot.

Incentives. We used 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, 2019; Bade, 2015; Baillon et al., 2022a, 2022b; Johnson et al., 2021). The main argument against the RIS is that randomisation allows participants 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 the 5th of May participants had to come back the following day, on Friday, the 6th of May, to play out the choice question for real and to be paid.

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.

[22] 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'.

Figure 1b - Screenshot of the choice list for event E_1, Ellsberg scenario[23]



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 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-type scale).[24] 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. Part 6 was always presented at the end of the experiment.

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. Within-subjects data analysis by treatment

This section presents the within-subjects data analysis by treatment (COVID-19, Economics, Football). We use descriptive statistics and non-parametric tests in the main section. We discuss the regression model in

[23] 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'.

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

Appendix B, presenting the main results in the text. The section provides evidence for source preference (different ambiguity aversion depending on different sources) and source ambiguity-generated insensitivity, as well as some evidence of the influence of knowledge and emotion on them. The exposition of the results is structured as follows.

We analyse the behaviour of individuals facing natural (familiar/unfamiliar) and artificial sources of uncertainty for given treatment (i.e., COVID-19, Economics, Football) by looking at whether the three different scenarios (i.e., France, Italy, Ellsberg) produced different levels in the b or a-indices (preferences-aversion or proneness- and ambiguity-generated insensitivity). Then, we study whether the different levels of emotion and knowledge can explain these differences.

Before proceeding with the detailed analysis, we briefly summarise a few results.

First, according to our expectations, COVID-19, the economic index and football showed differences in knowledge and emotional involvement, with the more familiar scenario (Italy) generally implying stronger emotional involvement and higher knowledge (Tables 4a, 7a, and 10a, for emotion and 4b, 7b and 10b for knowledge).

Second, within each treatment, the data show a different attitude towards the artificial and the natural sources of uncertainty: this involves differences in the a-index in all cases (Tables 3.1, 3.2; 6.1, 6.2, and 9.1, 9.2) and differences in the b-index only in two out of three treatments (Tables 6.1, 6.2, and 9.1, 9.2). However, when we compare all three natural sources of uncertainty together (see the between-subjects analysis of Section 5), we find differences in the a-index in the unfamiliar scenario (France) but little evidence in the familiar one (Italy), even if emotion and knowledge are different.

4.1 Pooling of data

We conducted two experimental sessions for each treatment group (see footnote 17). 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.[25] 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 (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-generated 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 ambiguity-generated insensitive

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

to 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 ambiguity-generated insensitivity (a-index)

	France			Italy			Ellsberg		
N=42	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**
b-index COVID-19	0.033	0.078	0.32811	0.027	0.053	0.3434	0.1	0.088	0.2759
a-index COVID-19	0.55	0.638	0.4879	0.5	0.463	0.5757	0.385	0.369	0.5502

Note: b>0 denotes ambiguity aversion; a>0 denotes ambiguity-generated 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-generated 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. 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=1

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 (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.

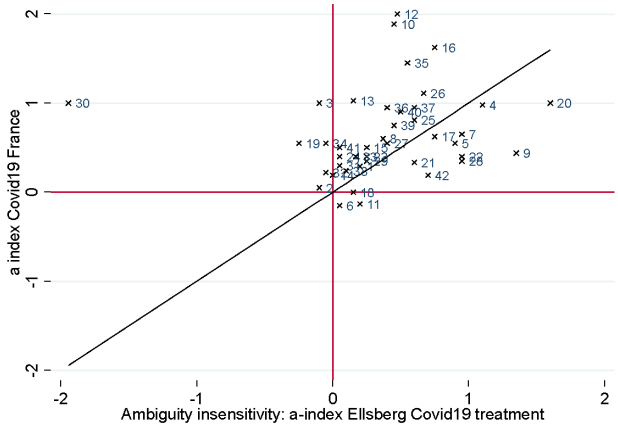
To investigate the sign of this difference, we run a Page test of ordered alternatives, where the alternative hypothesis is specified according to the descriptive evidence in Table 2a. The Page test (Table 3.2) rejected the null hypothesis of equal medians at the 5% significance level (z=2.128; Bonferroni-adjusted p-value=0.0334). We take this result as evidence of source ambiguity-generated insensitivity. 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 ambiguity-generated insensitivity based on descriptive data is shown in Figure 2, which plots for each participant 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 ambiguity-generated 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	$ma_{Ellsberg} = ma_{Italy} = ma_{France}$	$ma_{Ellsberg} < ma_{Italy} < ma_{France}$	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-generated 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 Hypotheses 2 and 3 (page 8) is that ambiguity reaction should be influenced by emotional involvement and knowledge. In particular, we expect Italian scenarios to be perceived as more familiar than French scenarios, consequently causing a weaker reaction to uncertainty. Moreover, we expect Italian scenarios to elicit more emotional involvement than French scenarios with no a-

priori effect on uncertainty reaction. To test this, we asked participants to self-evaluate their degree of emotional involvement and knowledge about the Italy and France decision contexts on a 7-point Likert-type scale.[26] As it can be noted looking at the descriptive statistics (Tables 4a and 4b), emotion and knowledge go in the supposed directions with greater involvement and higher knowledge in Italy than in France. In fact, more than 95% of participants reported higher involvement and knowledge of COVID-19 in Italy than in France (not shown in Table 4). 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	2.095	1.4619	5.5	4.881	1.5334	3	2.786	1.3711	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 signed-rank test under the null-hypothesis that emotional involvement is the same for the two scenarios. ***significant at 1%.

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	1.929	1.177	4	4.167	1.4802	2	2.238	1.1436	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 signed-rank test under the null-hypothesis that knowledge is the same for the two scenarios. ***significant at 1%.

To test whether differences in emotional involvement and knowledge between scenarios affected ambiguity-generated insensitivity,[27] we ran OLS estimates of the a-index as the dependent variable, where we used the repeated measures under the three scenarios as individual observations for each participant.[28] This analysis is presented in Appendix B (Table B1). Standard errors were clustered by subjects. First, we regressed the a-index on a categorical variable for the scenario (France and Italy), taking Ellsberg as the reference category. It turned out that both the France and Italy scenario categories had positive signs, but only the estimated coefficient for France was statistically significant (p=0.015). This result means that participants were, on average, more ambiguity-generated insensitive when evaluating natural than artificial sources of uncertainty. However, the effect was statistically significant only for the French scenario relative to Ellsberg's (Column 1). These results are consistent with the Page test of Table 3.2.[29]

Second, we constructed a binary measure of individual differential knowledge, defined as the difference between the self-reported degree of information about the COVID-19 pandemic in Italy and France divided by the self-reported degree of information in France. The binary variable took on a value of unity if differential knowledge was above the sample median (equal to 1 using the Likert-scale responses) and zero otherwise. We built a similar binary variable for individual differential involvement, but using self-reported measures of the degree of emotional involvement regarding the Covid-19 pandemic (with a median equal to 2 from the Likert-

[26] Appendix A2 reports the questions.
[27] We did not investigate the b-index as long as no significant differences were detected from Table 3.1.
[28] Hence, considering a panel data set of 42×3 observations.
[29] We repeated the analysis using France as the reference group, finding that both the Italy scenario dummy (p=0.092) and Ellsberg's (p=0.015) were statistically significant and had negative signs, suggesting more a-insensitivity for France than Italy scenarios as well (see Table B1, Column 2).

scale responses).[30] The estimated coefficient for binary differential knowledge had a statistically significant (p=0.03) positive sign**.** In contrast, the binary variable for differential emotional involvement had a negative sign but was not statistically significant (p=0.6, Table B1 Column 3). The results remained robust when we added demographic variables (age, gender, region of residence), a dummy for the self-perceived difficulty of the experiment (easy or difficult), a categorical variable for general experience with experiments (intermediate and high vs. no experience), and the fixed effect of the experimental session (Table B1, Column 4).[31]

How can we interpret these results? Subjects with differential knowledge above the median have relatively superior information for the more familiar decision context than the less familiar one. Why this should be associated with higher ambiguity-generated insensitivity is unclear. However, we shall provide a tentative explanation for this correlation in Section 5 below.[32]

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-generated insensitivity (a>0) for the France scenario than for Italy and Ellsberg ones. When we divide the participants according to the value of the b-index, our data show a stronger prevalence of ambiguity aversion when participants assessed the Ellsberg scenario (Table 5b). However, the distribution of participants by ambiguity-generated insensitivity (Table 5c) is similar across the scenarios. Table 6.1 summarises the results of Friedman's two-way analysis of variance by ranks for related samples and the pairwise Wilcoxon signed-rank tests. Regarding the b-index, the Friedman test rejected the null hypothesis of equal median at the 1% significance level (Fr=9.284, p=0.01). Pairwise Wilcoxon signed-ranked tests rejected the null hypothesis at the 5% significance level for the Italy versus Ellsberg comparison only (z=-2.41, Bonferroni adjusted p-value=0.045). The finding is taken as evidence of the fact that different sources generated different preferences towards ambiguity.

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

	France			Italy			Ellsberg		
N=45	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**
b-index Econ	0	0.038	0.2466	0.017	0.037	0.2342	0.1	0.102	0.2621
a-index Econ	0.48	0.434	0.5946	0.33	0.416	0.5574	0.15	0.2224	0.5

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

[30] Note that both differential emotional involvement and differential knowledge amplify upwards any self-assessed difference in emotional involvement and knowledge, respectively, the lower the reference level in the France scenario. Namely, the same numerical difference between levels of involvement, for example, translates into a higher index of differential involvement when the reference level is lower.

[31] The binary variables of differential knowledge and differential emotional involvement were uncorrelated.

[32] Table B1, Columns 5 and 6, in Appendix B presents and discusses the results of a Seemingly Unrelated Regression for the a-index and b-index when differential knowledge and differential involvement replaced the corresponding binary variables. In this case, our results show that ambiguity-generated insensitivity was lower when differential emotional involvement was higher (p-value=0.063). In contrast, ambiguity aversion was negatively correlated with differential knowledge (p-value=0.024), which implies a higher willingness to bet associated with relatively superior knowledge of the familiar scenario.

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-generated 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 Economics	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. Italy	Wilcoxon signed-rank test Economics France vs. Ellsberg	Wilcoxon signed-rank test Economics Italy vs. Ellsberg
b-index	Fr= 9.284*** p-value=0.01	z = -0.209 adj p-value=1	z = -2.049 adj p-value=0.12	z = -2.410** adj p-value=0.045
a-index	Fr= 5.806* p-value=0.055	z = 0.073 adj p-value=1	z = 2.534** adj p-value=0.031	z = 2.709** adj p-value=0.018

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

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 ambiguity- generated 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-generated insensitivity for the Ellsberg scenarios vis-à-vis natural uncertainty source scenarios (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 scenario than for the France and Ellsberg scenarios. These findings support the hypotheses of source preference and source ambiguity-generated insensitivity. Based on descriptive data, visual representations of source preference and source-generated insensitivity are shown below. Figure 3.1 plots the b-index for Italy versus Ellsberg scenario: two-thirds of participants show stronger ambiguity aversion for the Ellsberg scenario.[33] Figure 3.2 plots the a-index

[33] N=30 observations lie below the 45-degree line.

for France versus Ellsberg (a) and Italy versus Ellsberg (b). These plots show stronger ambiguity-generated insensitivity for natural than artificial sources of uncertainty.[34]

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	$mb_{Ellsberg} = mb_{Italy} = mb_{France}$	$mb_{France} < mb_{Italy} < mb_{Ellsberg}$	568	z=2.951*** p-value=0.0016 adj p-value=0.0032
a-index	$ma_{Ellsberg} = ma_{Italy} = ma_{France}$	$ma_{Ellsberg} < ma_{France} < ma_{Italy}$	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 $mb_{Italy} < mb_{France} < mb_{Ellsberg}$: z= 2.266, adj p-value=0.023
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.

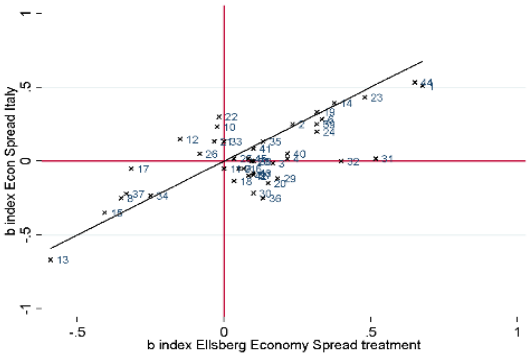
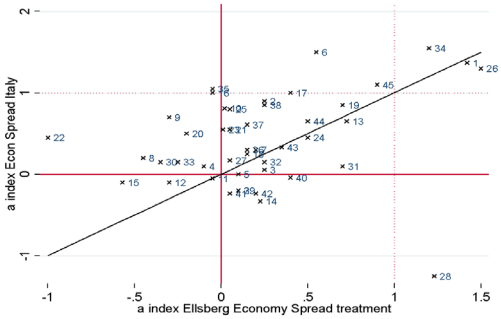


Figure 3.2 Economics treatment: a-index of ambiguity-generated insensitivity.

(a) France vs. Ellsberg



(b) Italy vs. Ellsberg

Considering self-assessment data, subjects reported low levels of involvement (Table 7a) and knowledge (Table 7b). However, significant differences at median values between the Italy and France scenarios were detected for both involvement (Wilcoxon signed-rank test: z=3.898, p-value=0.00), and knowledge (Wilcoxon signed-rank test: z=3.366, p-value=0.0008), validating one of our research hypotheses. Moreover, it should be noted that if we compare these results with the COVID-19 ones (Tables 4a and 4b), even though there is a significant difference in the variable between France and Italy, the emotional involvement was much higher in the COVID-19 than in the Economics treatments, as we expected (see also Section 5 below).

[34] Two-thirds of observations (N = 29 for France vs. Ellsberg; N = 28 for Italy vs. Ellsberg) lie above the 45-degree line.

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	1.622	1.1538	**2**	2.289	1.5318	**0**	0.667	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 France.
Note 3: Wilcoxon signed-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	1.622	1.1926	**1**	2.044	1.4135	**0**	0.422	0.8390	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 France.
Note 3: Wilcoxon signed-rank test under the null-hypothesis that knowledge is the same for the two scenarios.

Because the residuals of the regression on the a-index were correlated with those of the regression on the b-index, we used Seemingly Unrelated Regression for the panel dataset of 45×3 observations. We clustered errors at the individual level. First, we regressed the ambiguity indices on a categorical variable for the scenario (France and Italy), using Ellsberg's as the reference category. Table B2 of Appendix B reports the results. Both the France and Italy scenarios entered with a negative sign in the regression for the b-index, implying that participants were, on average, less ambiguity-averse when assessing natural uncertainty than Ellsberg's. However, only the Italian scenario was statistically significant at the 5% significance level (p=0.015; Table B2, Column 1). The France and Italy scenario dummies entered with a positive sign in the regression for the a-index, and the estimated coefficients were statistically significant at the 5% level (p=0.016 and p=0.036, respectively, Column 4).[35] Both results are consistent with the findings of the Page tests in Table 6.2. Next, we added binary variables for differential knowledge and differential emotional involvement (taking on the value of one if the Likert-scale response was above the treatment median, and zero otherwise) referred to the sovereign interest rate spreads and then the same individual controls we used to analyse the COVID-19 treatment (Columns 2-3 and 5-6 of Table B2). In either case, the estimated impact of binary differential knowledge and differential involvement on the two ambiguity indexes was not statistically different from zero, and the estimated size, sign and significance of the scenario dummies were not altered.[36]

To recap, the analysis for the Economics treatment suggests differences in ambiguity reaction (both ambiguity aversion and ambiguity-generated insensitivity) between natural (i.e. France and Italy scenarios) and artificial sources of uncertainty (i.e. Ellsberg scenario). In contrast, the evidence of differences between natural sources was weaker. Page tests for ordered alternatives (Table 6.2) and SUR estimates suggest that for the natural source of uncertainty, subjects exhibited both less ambiguity aversion and more ambiguity-generated insensitivity (in the latter case, like the COVID-19 treatment) than for the artificial source. However, no role was detected for the binary measures of differential knowledge and differential emotional involvement in explaining either source preference or source ambiguity-generated insensitivity.

[35] If using Italy as the reference scenario, we did not detect differences with the France scenario, but only with Ellsberg's.
[36] When we experimented using binary measures for Italy only, the b-index was negatively correlated with knowledge (p=0.086), and the a-index was positively correlated with emotional involvement (p=0.051), see section 5 for an interpretation. This analysis is available from the authors on request.

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 stronger ambiguity aversion when evaluating the Ellsberg than the France than the Italy scenarios, and stronger ambiguity-generated insensitivity when evaluating the Italy scenario than the France than the Ellsberg ones. Regarding the 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 distribution of participants was rather similar across categories, with a slightly more pronounced prevalence of ambiguity-generated 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. (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, with at least one strict inequality across the medians (Table 9.2). For the b-index we interpret these results as evidence of weaker ambiguity aversion for natural than artificial sources of uncertainty. For the a-indexes, the Page test is statistically significant, with more ambiguity-generated insensitivity for Italy and France than for Ellsberg. This is also suggested by Figure 4.2, which plots the a-indexes for France versus Ellsberg (a) and Italy versus Ellsberg (b).[37] 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.[38]

As expected, the descriptive statistics show a strong emotional involvement in Football (weaker than for COVID-19 but stronger than for Economics) and higher knowledge in the Italian scenario (less than for COVID-19 but more than for Economics; see also Section 5 below). Emotional involvement and knowledge are both significantly higher when considering Italy than France scenarios at median data (Wilcoxon signed-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. Again, these results are consistent with our *a priori* hypothesis.

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

	France			Italy			Ellsberg		
N=46	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**	**Median**	**Mean**	**StDv**
b-index	0.017	0.046	0.193	0.008	0.049	0.259	0.1	0.097	0.16
a-index	0.325	0.321	0.4318	0.375	0.438	0.4544	0.25	0.306	0.6213

Note: StDv, Standard deviation

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

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

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-generated 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 Football	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

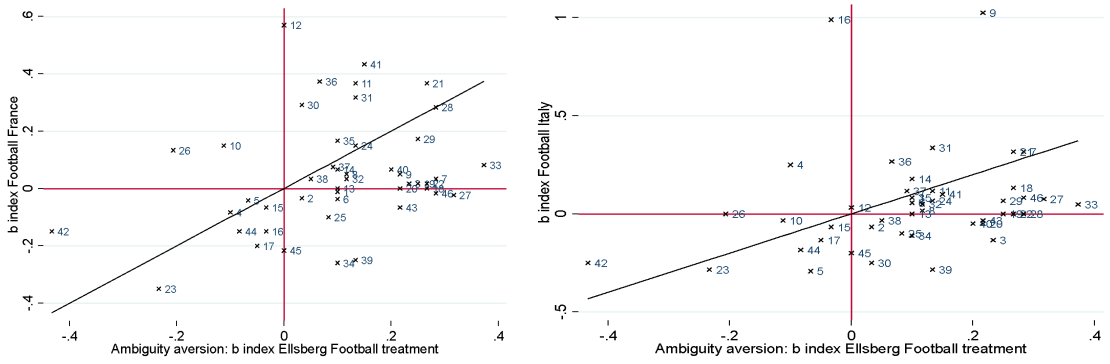
	Friedman two-way analysis of variance by ranks	Wilcoxon signed-rank test Football France vs. Football Italy	Wilcoxon signed-rank test Football France vs. Ellsberg	Wilcoxon signed-rank test Football Italy vs. Ellsberg
b-index	Fr=12.211*** p-value=0.002	z=0.962 adj p-value=1	z=-1.923 adj p-value=0.163	z=-2.649** adj p-value=0.022
a-index	Fr=5.091* p-value=0.078	z=-1.667 adj p-value=0.289	z=0.683 adj p-value=1	z=1.584 adj p-value=0.343

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*** adj p-value=0.00
a-index	$ma_{Ellsberg} = ma_{Italy} = ma_{France}$	$ma_{Ellsberg} < ma_{France} < ma_{Italy}$	572	z=2.085** adj p-value=0.037

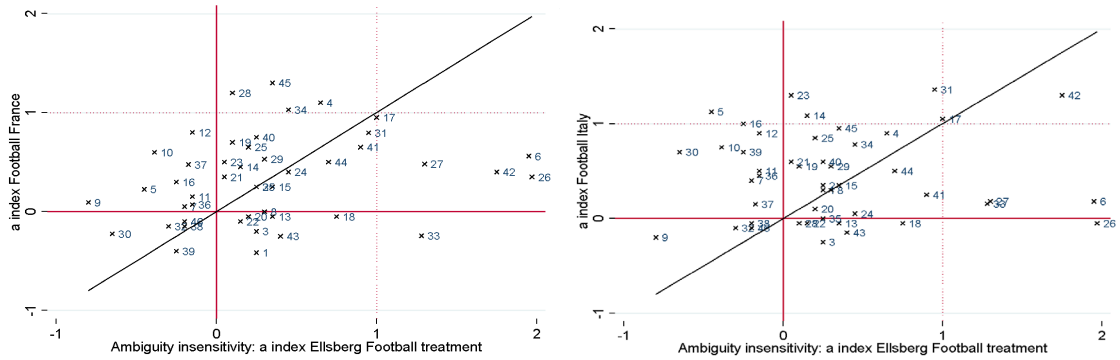
Note 1: ***significant at the 1% level, **significant at the 5% level, * significant at the 10% level.
Note 2: adj p-value=Bonferroni-adjusted p-value.

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-generated insensitivity.



(a) France vs. Ellsberg (b) Italy vs. Ellsberg

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	1.217	0.7864	3	3.304	2.4483	2	2.087	2.2294	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 France.
Note 3: Wilcoxon signed-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	1.696	1.4738	3	3.543	2.4102	1.5	1.848	1.8495	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 France.
Note 3: Wilcoxon signed-rank test under the null-hypothesis that knowledge is the same for the two scenarios.

To explain the previous findings, we ran OLS estimates of the b-index and a-index separately by regressing each index first on the scenario dummies, then adding binary measures of differential knowledge and differential emotional involvement referred to football, at last on the full set of individual controls (see Table B3 in Appendix for details).[39] We used a dummy variable for Ellsberg (taking the value of one for Ellsberg's observations and zero otherwise) to control for scenarios in the regression for the b-index (Table B3, Columns 1-3): the estimated coefficient had a positive sign and was significant at the 10% level (p=0.097), which implies more ambiguity aversion with artificial than natural sources of uncertainty. The binary measures of differential knowledge and differential emotional involvement were not statistically significant. Adding individual controls did not alter the main results, although the Ellsberg dummy became statistically not significant at the margin (p=0.109).

We used Italy as the reference scenario in the regression for the a-index (Table B3, Columns 4-6). The participants were, on average, less ambiguity-generated insensitive when evaluating the France than Italy scenarios (p=0.085). The Ellsberg dummy was not statistically significant. The result was unaffected by the addition of binary differential knowledge and binary differential emotional involvement, and standard individual controls. However, when we excluded Ellsberg's scenario observations, we found a statistically

[39] We did not use SUR, since the Breusch-Pagan test did not detect a correlation in the residuals of the two regressions.

significant positive correlation between binary differential knowledge and the a-index (p=0.017, Table B3, Column 7).[40]

We consider the results of this section to be weak evidence of source effects. Participants were more ambiguity-averse when assessing Ellsberg lotteries than Italy and France football lotteries. However, they were less ambiguity-generated insensitive when evaluating France than Italy's prospects. Regression analyses partially confirmed the scenario effects and detected a weak positive correlation between the degree of differential knowledge and the a-index.

4.5 Summary

We summarise the results of the within-subjects analysis. Considering the findings of the nonparametric tests, 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. Regarding the a-index, participants always exhibited higher insensitivity for the natural than Ellsberg scenarios. The paper's results support the hypotheses of source preference (in particular, stronger aversion for artificial sources of uncertainty given the equal frame) and source ambiguity- generated insensitivity (between familiar and unfamiliar natural sources for all the natural sources of uncertainty). Despite this general result, there are also differences among the treatments. For example, a-insensitivity was stronger for France than Italy in the COVID-19 treatment. However, it was stronger for Italy than France in the Economics and Football treatments.

We reported results from OLS and SUR regressions (presented in detail in Appendix B) to explain the observed within-subjects differences in ambiguity aversion and ambiguity-generated insensitivity. This analysis provided weaker evidence that ambiguity aversion was stronger when subjects faced Ellsberg than natural sources of uncertainty in the Economics and Football treatments. However, it fully confirmed that ambiguity-generated insensitivity was source dependent and higher for natural than Ellsberg uncertainty. No clear-cut familiarity effect was detected, consistently with the results of the nonparametric analysis. Overall, the results support our Hypothesis 1. However, they do not fully support Hypothesis 2, which is that familiarity with the decision context leads to a less pronounced ambiguity reaction (p. 7).

Possible explanations for our findings rely upon the role played by both knowledge and affect-richness of the decision context. As expected, the data showed that the subjects were more involved and familiar with Italy than France scenarios. However, the different treatments showed differences in emotional arousal and information. One purpose of the regression analysis was to establish whether subjective measures of knowledge and emotional involvement could be correlated with the two ambiguity indexes. We found that

[40] Because football may elicit emotions of both negative and positive valence (which we did not measure), we replaced differential involvement with a categorical variable, distinguishing between non-fans, fans of AS Roma (the Italian team considered in the Italy scenario), and fans of other Italian teams (predominantly AS Roma's rival teams). In the sample without Ellsberg's scenario observations, fans of other Italian teams were significantly more ambiguity-generated insensitive than non-fans (p=0.042) when controlling for both the scenario and the binary measure of differential knowledge. However, when we added individual controls, the correlation became statistically not significant (p=0.15). This analysis is available from the authors on request.

subjects with differential knowledge (a measure of the relative familiarity of the Italian vs. French decision contexts) above the median exhibited more ambiguity-generated insensitivity than subjects at or below the median in the COVID-19 treatment and, to a lesser extent, in the Football treatment. We do not have a clear interpretation of the positive correlation between differential knowledge and ambiguity-generated insensitivity. We suspect it may be related to some type of confirmation bias involved in providing information when emotional involvement is at work (as further discussed in Section 5). However, despite the fact that the three treatments implied different degrees of emotional involvement (as previously discussed), our measures did not capture any direct influence on ambiguity in any treatment.

Table 11 summarises the main results of Section 4.

Table 11. Ambiguity aversion according to sources and source ambiguity-generated insensitivity

Treatment	Source ambiguity aversion	Source ambiguity- generated insensitivity	Remarks
COVID-19	**NO**	**YES** Ambiguity-generated insensitivity ranking France>Italy>Ellsberg	Ambiguity-generated insensitivity increasing in binary differential knowledge (p=0.003)
Economics	**YES** Ambiguity aversion ranking Ellsberg>France>Italy	**YES** Ambiguity- generated insensitivity ranking Italy>France>Ellsberg	----------
Football	**YES** Ambiguity aversion ranking Ellsberg>France>Italy	**YES** Ambiguity- generated insensitivity ranking Italy>France>Ellsberg	Ambiguity- generated insensitivity increasing in binary differential knowledge (p=0.017) when excluding Ellsberg's observations

Note 1: Source ambiguity aversion denotes statistically significant differences between the b-indices of ambiguity aversion within treatments (Page tests).
Note 2: Source sensitivity denotes statistically significant differences between the a-indices of ambiguity-generated insensitivity within treatments (Page tests).
Note 3: Remarks refer to the regression analysis presented in Appendix B, Tables B1 (COVID-19) and B3 (Football).

5. Between subjects Data analysis (between treatment)

This section compares the ambiguity reaction considering the COVID-19 (N=42), Economics (N=45), and Football (N=46) treatments as independent samples. Consequently, we ran 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. First, we ran the KW to verify whether self-reported differential knowledge and differential emotional involvement differed between treatments, as suggested by data comparison. The KW test rejected at the 1% level the null hypothesis of equal medians for both variables (H=29.48 for differential knowledge and H=24.73 for differential emotional involvement). Next, we ran Dunn tests with Bonferroni adjustment of p-values to detect the source of these differences (see Table 12). We found that median differential knowledge was significantly higher in the COVID-19 than Economics treatments and significantly lower in the Economics than Football treatments at the 1% significance level. However, the test could not reject the null hypothesis of no differences between COVID-19 and Football.

For differential emotional involvement, the Dunn test showed a similar trend: stronger differential emotional involvement for COVID-19 vs. Economics and Football vs. Economics; no statistically significant difference between COVID-19 and Football.[41] We take this result as supporting our *a priori* hypothesis of negative valence, but different arousal, between COVID-19 and Economics.

Table 12. Testing for differences in differential knowledge and differential emotional involvement between treatments

	KRUSKAL-WALLIS TEST	Dunn test COVID-19 vs. ECONOMICS	Dunn test COVID-19 vs. FOOTBALL	Dunn test ECONOMICS vs. FOOTBALL
Differential knowledge	H=29.479*** p-value=0.00	z=5.3324*** adj p-value=0.00	z= 1.8996 adj p-value=0.17	z= -3.523*** adj p-value=0.00
Differential emotional involvement	H=24.763*** p-value=0.00	z= 4.9311*** adj p-value=0.00	z= 1.9928 adj p-value=0.14	z= -3.0174*** adj p-value=0.01

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.

Second, we ran the KW test for the b-index and a-index, while keeping the (national) scenario constant. Therefore, we compared the ambiguity indeces for COVID-19, Economics and Football given the France scenario, and similarly given the Italy scenario and Ellsberg's. Regarding the b-index, the KW test could not reject the null hypothesis of equal medians across treatments (H=0.34, p-value=0.85 for the Italy scenario; H=0.44, p-value=0.8 for the France scenario; H=0.21, p-value=0.9 for Ellsberg). We take this result as evidence that, for a given scenario type, ambiguity aversion was not affected by the different treatments.

Turning to the a-index, the KW tests could not reject the null hypothesis of equal medians in the Italian (H=0.123, p-value= 0.94) and Ellsberg (H=4.05, p-value=0.13) decision contexts. However, the KW test rejected the null hypothesis for the French decision context at the 5% significance level. Consequently, we computed pairwise Dunn tests with Bonferroni adjustment of p-values. Table 13 shows higher ambiguity-generated insensitivity exclusively in the COVID-19 vs. Football treatments (z = 2.689, adjusted p-value = 0.0215). The absence of treatment effects for Ellsberg suggests that the evaluation of Ellsberg lotteries was unaffected 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 13. Testing for differences in ambiguity-generated insensitivity under France scenario

	KRUSKAL-WALLIS TEST	Dunn test COVID-19 vs. ECONOMICS	Dunn test COVID-19 vs. FOOTBALL	Dunn test ECONOMICS vs. FOOTBALL
a-index France scenario	H=7.249** p-value=0.027	z=1.514 adj p-value=0.39	z= 2.689** adj p-value=0.022	z= 1.187 adj p-value=0.71

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.

To further investigate the determinants of ambiguity-generated insensitivity, we regressed by OLS the a-index for the France scenarios on a categorical variable for treatment, where the reference category was COVID-19, using the pooled dataset (N=133). Standard errors were clustered by individuals. The results are

[41] When testing self-assessed knowledge and emotional involvement by scenarios, we found the same pattern for Italy. In contrast, differences between treatments for France were weaker, but for COVID-19 vs. Football, see Table B4 in Appendix B.

reported in Table B5 in Appendix B. The analysis shows that ambiguity-generated insensitivity was lower in Football than in COVID-19 treatments (p=0.002) and in Economics than in COVID-19 treatments (p=0.08, Table B5, Column 1). When we added, first, the binary variables for differential knowledge and emotional involvement (Column 2), equal to one if the observation was above the relevant treatment median and zero otherwise, then the full set of individual controls (Column 3), the Football category remained statistically significant in both regressions (p<0.01), while the Economics category only in the latter (p=0.09).

In contrast, the binary measure of differential knowledge entered with a positive sign and was statistically significant only in the former (p=0.08), but not in the latter regression (p=0.12), while the binary measure of differential involvement was never statistically significant. Because of the positive correlation between dummies (p=0.24), we also repeated the regression for the a-index with the full set of controls dropping binary differential emotional involvement. In this case, binary differential knowledge gained significance at the margin (p=0.106, see Table B4, Column 4).

One possible interpretation of the previous findings is that differential knowledge might correlate with the arousal of emotions. If this is the case, the more emotion I feel, the more I want to know about the situation I have to decide on. However, the increased information due to strong emotions might not correspond to increased individual cognitive abilities (in fact, this relation needs to be properly investigated in an ad hoc experiment) since I might look only for the information that supports my point of view. The positive correlation of the a- indexes with the binary measure differential knowledge (also documented in Section 4) may suggest this. As the psychological literature has pointed out during the COVID-19 period regarding anti-vax positions**,** since acquiring information can be driven by emotion and available media are often biased, subjects' information can be tainted by confirmation bias. Consequently, keeping oneself informed may decrease the ability to evaluate and decide correctly, not increase it. However, since the binary measures of differential emotional involvement were never statistically significant in our regressions, this is a tentative interpretation, even if only supported by the descriptive analysis.

Given the national scenarios, we ran separate OLS regressions of the a-index and b-index, controlling for treatment and other individual characteristics, on binary measures of national knowledge and emotional involvement. Each binary variable was equal to unity if the observation was above the treatment median and zero otherwise. Because the national binary variables were positively correlated,[42] we used them alternatively in the regressions. Table 14 shows the main results. As expected, treatment effects were statistically significant only in the regression for the a-index given the France scenarios. The binary measures of knowledge and emotional involvement in France did not affect the reaction to ambiguity (Columns 1 to 4). Given the Italy scenarios, ambiguity aversion was negatively correlated with binary knowledge (p=0.026, Column 5), whereas ambiguity-generated insensitivity positively correlated with binary emotional involvement (p=0.016, Column 8). These results may help shed some light on previous findings.

[42] The correlation between the binary measures of knowledge and emotional involvement was 0.48 in Italy and 0.58 in France.

First, they suggest that superior knowledge of the familiar decision context may increase the willingness to bet. In Table 14, subjects with self-assessed knowledge above the treatment median (Column 5) exhibit lower ambiguity aversion in the familiar decision context. Second, they suggest that stronger involvement in the familiar decision context may raise ambiguity-generated insensitivity (Column 8). If stronger involvement leads to information acquisition, and if information acquisition is conditioned by confirmation bias, a positive correlation may exist between the a-index and measures of knowledge driven by emotions.

Table 14. OLS regressions of ambiguity aversion (b-index) and ambiguity-generated insensitivity (a-index) for given national scenarios

	(1) b-index France scenarios	(2) b-index France scenarios	(3) a-index France scenarios	(4) a-index France scenarios	(5) b-index Italy scenarios	(6) b-index Italy scenarios	(7) a-index Italy scenarios	(8) a-index Italy scenarios
Economics treatment	-0.049 (0.068)	-0.049 (0.068)	-0.227** (0.121)	-0.238** (0.12)	-0.006 (0.063)	-0.025 (0.068)	-0.087 (0.131)	-0.036 (0.125)
Football treatment	-0.035 (0.059)	-0.034 (0.061)	-0.307*** (0.01)	-0.303*** (0.103)	0.008 (0.063)	-0.003 (0.064)	-0.04 (0.117)	-0.017 (0.115)
Binary knowledge in France	-0.004 (0.054)		-0.091 (0.114)					
Binary emotional involvement in France		0.005 (0.062)		0.029 (0.119)				
Binary knowledge in Italy					-0.105** (0.0467)		0.084 (0.089)	
Binary emotional involvement in Italy						-0.033 (0.048)		0.232** (0.095)
Individual Controls	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Intercept	0.223* (0.13)	0.221* (0.132)	0.958*** (0.21)	0.94*** (0.208)	0.167 (0.156)	0.162 (0.172)	0.809*** (0.255)	0.634*** (0.231)
Number of obs	133	133	133	133	133	133	133	133

Note 1: *** p<0.01, ** p<0.05, * p<0.1. Standard errors adjusted for clusters in participants appear in brackets.
Note 2: b-index of ambiguity aversion, a-index of ambiguity-generated insensitivity.
Note 3: Binary Knowledge and Binary Emotional Involvement in France and Italy are equal to one if the Likert-scale response is above the treatment median and zero otherwise.
Note 3: Individual controls include: age, dummies for gender, region of residence, perceived easiness/difficulty of the experimental task, experience with past experiments, experimental session.
Note 4: Reference treatment is COVID-19.

6. Discussion

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

A few papers (e.g., Li, 2017, Anantanasuwong et al., 2024, von Gaudecker et al, 2022, Henkel, 2024, Gutierrez and Kemel, 2024, Watanabe and Fujimi, 2024) have adopted Baillon et al.'s (2018, 2021) belief-hedges method to measure ambiguity attitudes. Anantanasuwong et al. (2024) used the DHS online survey with weakly incentivised subjects, while incentivised subjects were used by von Gaudecker et al (2022) always in a large-scale survey, and by Watanabe and Fujimi (2024) in a medium-scale survey. In Henkel (2024) and Gutierrez and Kemel (2024), 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 consistently find 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 (2024) (who consider investment in a familiar and unfamiliar source of uncertainty), the natural source of uncertainty was in the same domain (i.e., Li (2017) used a linguistic domain, Anantanasuwong et al., 2024 and von Gaudecker et al, 2022 economic domains, while Henkel, 2024, and Watanabe and Fujimi (2024) weather domains).[43]

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 natural domains (COVID-19, Economics and Football), by using a more familiar (Italy) and a less familiar source (France) in each of the three domains. Moreover, 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 (and with the same prior probabilities for each single event). In addition, by introducing some questions about 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 emotions that can characterise different natural sources of ambiguity.

We found 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 ambiguity-generated 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 ambiguity-generated insensitivity for the artificial sources (Hypothesis 1a) contrary to Watanabe and Fujimi (2024) that found more ambiguity aversion toward the natural source than the artificial source.[44] These differences might be driven by the use of a 10-colour version of the Ellsberg paradox (the composition of the event space can have a strong influence on the evaluation of probabilities assigned as defined by support theory), as in Dimmock et al., 2016, but used in a different way, so that in Dimmock this problem does not occur, and by considering events and their complement that were quite different in term of symmetry.[45] 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.

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

[44] Abstracting from the different methodologies (e.g., lab experiment vs. web survey) and different incentive schemes (i.e., randomised incentive system before decisions were made vs. small monetary incentive) adopted, their findings refer to the gain domain. In the loss domain, Watanabe and Fujimi (2024) found that participants were more ambiguity-generated -insensitive to the natural source than artificial source. However, they were ambiguity seeking, with similar levels between sources.

[45] Partitions of the event space different from the original Ellsberg paradox (i.e., using two or three colours) have been seen to involve different theoretical problems (see Siniscalchi, 2009; Machina, 2014) and different experimental behaviour (i.e., less ambiguity aversion or ambiguity preferences; see Trautmann and van de Kuilen, 2015: 103-104), rather than a three-colour version as in our case. However, it is quite clear why Watanabe and Fujimi (2024) choose those partitions, which were functional to their paper's aim: the testing of the reflection effect.

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 ambiguity-generated 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 (2024), 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. In contrast,-ambiguity-generated insensitivity is source dependent and can be influenced by knowledge of the decision context (Hypothesis 2). In this respect, our findings align 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-generated 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. If the natural sources are characterized by different arousal and valence in emotions, these characteristics may determine the different reaction to ambiguity. Such reaction might be caused by the interaction between knowledge and emotion, so that if emotion determines the willingness to acquire more knowledge, this acquired knowledge might be more influenced by confirmation bias, leading subjects to a poor decision. The relation between emotion, knowledge and confirmation bias and the role it plays in individual ambiguity reactions deserves further investigation, since emotion can induce motivated knowledge, but knowledge can be affected by bias (see, in completely different contests, Charness and Chetan, 2017, and Martel et al., 2020).

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.[46] 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).[47] 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). Consequently, 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.

[46] 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.

[47] 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.

7. Conclusion

This study tests the hypotheses of source preference and source ambiguity-generated insensitivity 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. As for source ambiguity-generated insensitivity, the experimental data showed a consistently higher ambiguity-generated insensitivity to natural uncertainty than to artificial uncertainty.

The prevalence of source ambiguity- generated insensitivity and some evidence of the impact of knowledge and, to a weaker extent, emotional involvement related to the decision context on ambiguity-generated insensitivity suggests policy implications that are in line with those already identified by Li (2017) and Anantanasuwong et al. (2024), and Watanabe and Fujimi (2024) among others. These implications include the following: to facilitate people's choice under uncertainty, policy action is likely to be more effective in targeting ambiguity-generated 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, policymakers can facilitate people's decisions to get a new vaccine, adopt a new technology, implement risk-mitigating behaviour, start a new business, or participate in financial markets. However, we also showed that emotional involvement can affect the level of perceived uncertainty. As a consequence, for a given level of knowledge and a given level of objective uncertainty the valence and the strength of the emotional involvement embedded in the source of uncertainty may make a difference (helping us to predict a certain ambiguity preference for example). Our paper tries to give a first understanding of this implication, but more accurate research should be taken in this respect. In fact one of the limits of our paper 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 preference (Li, 2017) and not ambiguity-generated 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)[48]. 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).

(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.

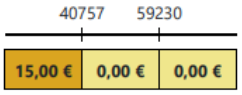
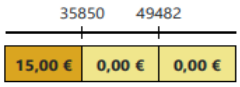
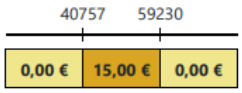
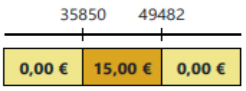
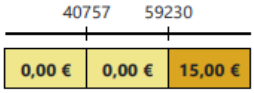
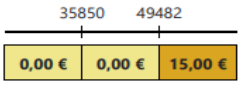
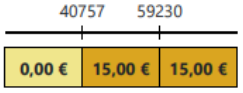
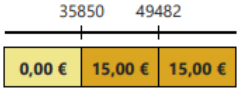
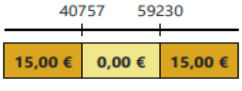
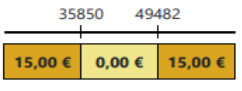
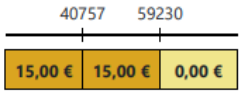
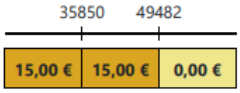
After the instruction part was over, the experiment started.

[48] 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, 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.

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 is given in the following Tables A1a-A1d.

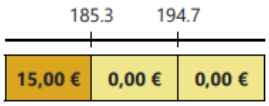
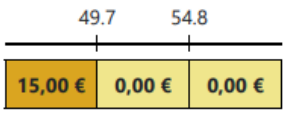
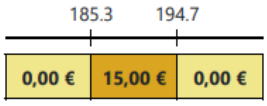
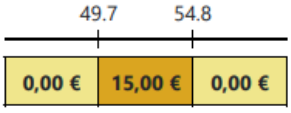
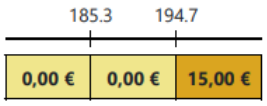
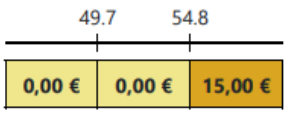
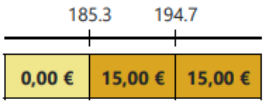
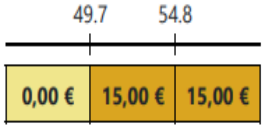
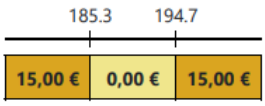
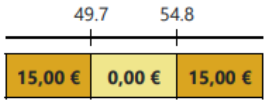
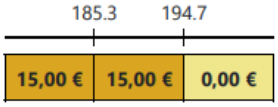
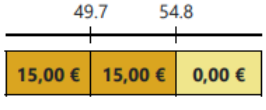
Figure A1 – The Bingo Blower in action

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		the number of COVID-19 new positive cases in France is less than 35850	
	E_2	the number of COVID-19 new positive cases in Italy lies between 40757 and 59230 included		the number of COVID-19 new positive cases in France lies between 35850 and 49482 included	
	E_3	the number of COVID-19 new positive cases in Italy is greater than 59230		the number of COVID-19 new positive cases in France is greater than 49482	
Complementary events	E_{23}	the number of COVID-19 new positive cases in Italy is greater than or equal to 40757		the number of COVID-19 new positive cases in France is greater than or equal to 35850	
	E_{13}	the number of COVID-19 new positive cases in Italy is less than 40757 or greater than 59230		the number of COVID-19 new positive cases in France is less than 35850 or greater than 49482	
	E_{12}	the number of COVID-19 new positive cases in Italy is less than or equal to 59230		the number of COVID-19 new positive cases in France is less than or equal to 49482	

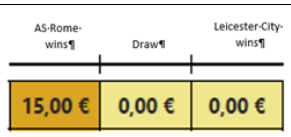
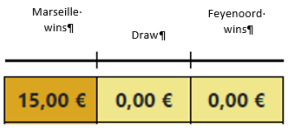
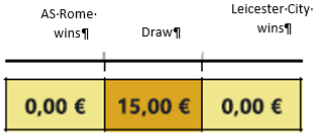
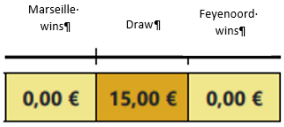
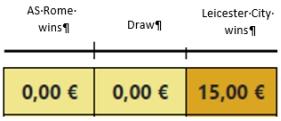
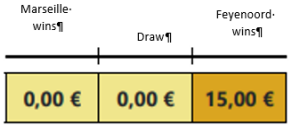
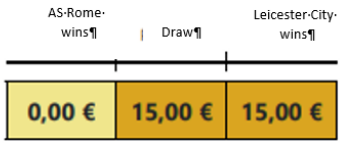
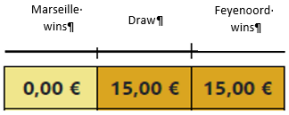
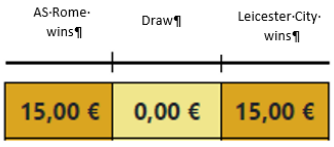
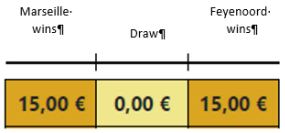
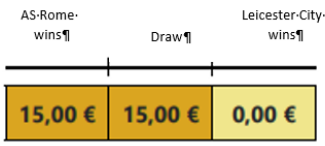
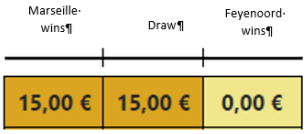
Note: Events occurring on 5th May 2022.

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		the value of the Spread OAT France-BUND 10 years is less than 49.7	
	E_2	the value of the Spread BTP Italy-BUND 10 years lies between 185.3 and 194.7 included		the value of the Spread OAT France-BUND 10 years lies between 49.7 and 54.8 included	
	E_3	the value of the Spread BTP Italy-BUND 10 years is greater than 194.7		the value of the Spread OAT France-BUND 10 years is greater than 54.8	
Complementary events	E_{23}	the value of the Spread BTP Italy-BUND 10 years is greater than or equal to 185.3		the value of the Spread OAT France-BUND 10 years is greater than or equal to 49.7	
	E_{13}	the value of the Spread BTP Italy-BUND 10 years is less than 185.3 or greater than 194.7		the value of the Spread OAT France-BUND 10 years is less than 49.7 or greater than 54.8	
	E_{12}	the value of the Spread BTP Italy-BUND 10 years is less or equal to 194.7		the value of the Spread OAT France-BUND 10 years is less or equal to 54.8	

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		Marseille wins at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	
	E_2	AS Rome draws at home against Leicester City in regular time in the UEFA Conference League second-leg semi-final		Marseille draws at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	
	E_3	Leicester City wins away against AS Rome in regular time in the UEFA Conference League second-leg semi-final		Feyenoord wins away against Marseille in regular time in the UEFA Conference League second-leg semi-final	
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,		Marseille does not win at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	
	E_{13}	AS Rome does not draw at home against Leicester City in regular time in the UEFA Conference League second-leg semi-final		Marseille does not draw at home against Feyenoord in regular time in the UEFA Conference League second-leg semi-final	
	E_{12}	Leicester City does not win away against AS Rome in regular time in the UEFA Conference League second-leg semi-final		Feyenoord does not win away against Marseille in regular time in the UEFA Conference League second-leg semi-final	

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	
	E_2	you extract a Blue ball	
	E_3	you extract a Yellow ball	
Complementary events	E_{23}	you extract a Blue or Yellow ball	
	E_{13}	you extract a Red or Yellow ball	
	E_{12}	you extract a Red or Blue ball	

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-19 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 a questionnaire regarding demographic characteristics, namely their age (in years), gender (male, female or non-binary gender), and region of residence in Italy (i.e., North, Centre, 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 one 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 of the COVID-19 pandemic in Italy and France, the interest rate spread in Italy and France, and 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 regarding Italy and France. In each case, self-assessments were measured on a 7-point Likert scale (from 1: no knowledge/no involvement; to 7: highest/knowledge/involvement). The experimental design presumed that, within each treatment, subjects were more informed and 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 hypothesis.

Based on this information, we run OLS regressions by treatment for the b-index of ambiguity aversion and the a-index of ambiguity-generated insensitivity, treating each index computed for France, Italy and Ellsberg as a different observation s=1, 2, 3 for each subject i=1,…N (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 = {b-index, a-index}, we estimated the following baseline model:

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

where Italy Scenario and France Scenario are two dummy variables, and Ellsberg is the reference category (if not specified differently below). Therefore, estimated λ_1 or λ_2 measured potential differences in ambiguity reaction when evaluating Italy or France scenarios relative to Ellsberg's.

Then, we added two binary measures of self-assessed knowledge and emotional involvement:

$$\text{Ambiguity index}_{is} = \alpha + \lambda_1 \text{ Scenario Italy} + \lambda_2 \text{ Scenario France} + \beta \text{ Binary Differential Knowledge}_i + \gamma \text{ Binary Differential Emotional Involvement}_i + \text{error}_{is}$$

Binary Differential Knowledge and *Binary Differential Emotional Involvement* were constructed using the Likert-scale responses. *Binary Differential Knowledge* for each subject was derived as follows. We computed Differential Knowledge, which is defined as the difference between the self-reported level of information for Italy and the corresponding subjective valuation for France, divided by the latter. Then, we constructed a binary variable, taking the value of unity if a subject's differential knowledge was above the within-treatment median, and zero otherwise. Binary Differential Knowledge measures whether a subject felt to have relatively superior information about the decision context in Italy than in France. Similarly, *Binary Differential Emotional Involvement* for each subject was computed as the difference between the self-reported degree of emotional involvement for each decision context in Italy and France, divided by the latter, assigning the value of unity to observations above the within-treatment median, and zero otherwise. As pointed out in the main text, differential knowledge and differential emotional involvement amplify any self-assessed difference upwards, the lower the reference level in the France scenario. Namely, the same numerical difference between levels of involvement, for example, translates into a higher index of differential emotional involvement when the reference level is lower. The regressions using differential knowledge and differential emotional involvement, when they are not reported in the following tables, are available on request from the authors.

Finally, we added a set of individual variables to estimate the following model:

Ambiguity $index_{is}$ = $\alpha+\lambda_1$ Scenario Italy+ λ_2 Scenario France+ β Binary Differential $Knowledge_i+\gamma$ Binary Differential Emotional $Involvement_i+\delta$ $Easiness_i+\varepsilon$ $Age_i+\zeta$ $Experience_i+\mu$ $Age_i+\eta$ $Gender_i+\theta$ Region of $residence_i+\kappa$ $Session_i$ $+error_{is}$ (B.1)

The covariates are: i) *Easiness*, a binary variable equal to zero if the subject found the experiment easy, and equal to unity if they found it difficult; ii) *Experience*, a categorical variable equal to zero if the subject declared no experience with past experiments (i.e. the reference category), equal to one if they had intermediate experience having participated to one to five past experiments, and equal to two if they had high experience (i.e., participation to more than 5 past experiments); iii) demographic variables: *Age* (in years); *Gender*, a categorical variable equal to zero if male (i.e., the reference category), equal to one if female; and equal to two if non-binary gender (corresponding to two subjects, one in the COVID-19 and one in the Economics treatments); *Region of residence,* a categorical variable equal to one if the subject resided in Southern Italy and the Islands (i.e., the reference category); equal to two if they resided in Central Italy, and equal to three if they resided in Northern Italy; iv) *Session*, a binary variable equal to zero if the subject was in the first session on 4th May 2022 and equal to one if they participated to the second session on 5th May 2022. The additive error term *error* 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 models.

COVID-19 treatment

Table B1 presents the OLS estimates for the **COVID-19 treatment**. Standard errors, appearing in brackets, are clustered by subjects. Columns 1 and 2 show the model for the a-index with the scenario dummies, where Ellsberg is the reference category in Column 1 and France is the reference category in Column 2. Column 3 adds the binary measures of differential knowledge and differential emotional involvement to the model of Column 1. Column 4 presents the full model. In Columns 5 and 6, differential knowledge and differential involvement replace the corresponding binary variables using the model of Column 4. In this case, the Breusch-Pagan test showed that the residuals of the regression on the a-index were serially correlated with those of the regression for the b-index (p=0.072). Therefore, the columns present a Seemingly Unrelated Regression.

Column 4 shows that subjects were, on average, ambiguity-generated insensitive (the estimated intercept equals 0.774, p-value=0.00). They were more ambiguity-generated insensitive when evaluating France scenario prospects than Ellsberg's (p-value=0.02), when their differential knowledge was above rather than equal to or below the median (p-value= 0.025), when they found the experiment difficult rather than easy, when they were younger, and if males relative to non-binary gender (p-values= 0.00), other things being equal.

The SUR estimates of Columns 5 and 6, replacing the binary measures with the qualitative measures for differential knowledge and differential involvement, confirm the results of Column 4 for the a-index. Moreover, they show that ambiguity-generated insensitivity was lower when differential emotional involvement was higher (p-value=0.063) and if subjects were resident in the North relative to the South or Islands (p-value=0.088). A tentative explanation for the negative correlation between the a-index and differential emotional involvement is as follows. Emotional involvement likely had a negative valence when referred to the COVID-19 decision context (although we did not measure valence). Higher differential involvement means stronger negative emotions associated with the familiar scenario than the unfamiliar one. The psychological literature maintains that negative emotions may elicit more rational behaviour, but no

clear-cut evidence exists (Loewenstein and Lerner, 2003). We observe the same effect on the a-index, possibly related to a more careful evaluation of the familiar scenario.

Regarding the b-index, Column 6 shows that ambiguity aversion was negatively correlated with differential knowledge (p-value=0.024), which implies a higher willingness to bet associated with relatively superior knowledge of the familiar scenario. Ambiguity aversion was lower for highly experienced vs. inexperienced participants in past experiments (p-value=0.074) and for residents of Central Italy vis-à-vis South Italy and Islands (p-value=0.01), other things being equal.

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

	(1) a-index OLS estimates	(2) a-index OLS estimates	(3) a-index OLS estimates	(4) a-index OLS estimates	(5) a-index SUR estimates	(6) b-index SUR estimates
France Scenario	0.269**		0.269**	0.269 **	0.269***	-0.011
	(0.106)		(0.106)	(0.111)	(0.103)	(0.037)
Italy Scenario	0.095	-0.174*	0.095	0.095	0.094	-0.036
	(0.123)	(0.101)	(0.124)	(0.129)	(0.120)	(0.050)
Ellsberg scenario		-0.269**				
		(0.106)				
Binary differential knowledge			0.230**	0.191**		
			(0.104)	(0.082)		
Binary differential emotional involvement			-0.077	-0.063		
			(0.143)	(0.094)		
Differential Knowledge					0.106***	-0.081**
					(0.031)	(0.036)
Differential Emotional Involvement					-0.044*	-0.005
					(0.024)	(0.023)
Easiness				0.489***	0.433***	-0.058
				(0.099)	(0.099)	(0.104)
Experience						
Intermediate				-0.044	-0.052	0.026
				(0.108)	(0.097)	(0.098)
High				-0.133	-0.121	-0.249*
				(0.120)	(0.104)	(0.140)
Age				-0.019***	-0.02***	0.008
				(0.003)	(0.003)	(0.005)
Gender						
Female				-0.103	-0.072	-0.032
				(0.088)	(0.085)	(0.064)
Non-binary				-0.726***	-0.609***	0.171
				(0.111)	(0.118)	(0.133)
Region Of Residence						
Centre Italy				0.091	0.100	-0.194***
				(0.082)	(0.082)	(0.069)
Northern Italy				-0.213	-0.206*	-0.110
				(0.143)	(0.121)	(0.099)
Session Dummy	NO	NO	NO	YES	YES	YES
Intercept	0.369***	0.638***	0.274***	0.774***	0.781***	0.189
	(0.086)	(0.076)	(0.091)	(0.155)	(0.154)	(0.170)
Breusch–Pagan χ^2	0.013 (p-value=0.91)	0.013 (p-value= 0.91)	0.306 (p-value= 0.58)	2.4 (p-value=0.12)	3.233 (p-value=0.0721)	
Number Of Obs	126	126	126	126	126	126
Number Of participants	42	42	42	42	42	42

Note 1: *** p<0.01, ** p<0.05, * p<0.1. Standard errors adjusted for clusters in participants appear in brackets.
Note 2: a-index of ambiguity insensitivity, b-index of ambiguity aversion; pooled data.
Note 3: Columns 1 to 4 present OLS estimates of the a-index. Column 1 presents the baseline model, where Ellsberg is the reference category. Column 2 uses France as the reference category. Columns 3 and 4 add the binary measures of differential knowledge and differential emotional involvement and individual controls to the model of Column 1. Columns 5 and 6 present the SUR model of the a-index and the b-index using differential knowledge and differential involvement based on the Likert-scales responses and the full set of controls.
Note 4: Differential knowledge is the difference between the self-reported degree of knowledge in Italy and France, divided by the latter. Differential emotional involvement is the difference between the self-reported degree of emotional involvement in Italy and France, divided by the latter. Self-reports are measured on a 7-point Likert scale regarding the number of positive COVID-19 cases in each country. Binary Differential Knowledge takes the value of unity if Differential knowledge is above the sample median, and zero otherwise. Binary Differential Emotional Involvement takes the value of unity if Differential Emotional involvement is above the sample median, and zero otherwise.
Note 5: Reference categories: Ellsberg for scenario (but for Column 2), No experience for experience, male for gender, South and Islands for residence.

Economics treatment

Table B2 Economics treatment. Ambiguity aversion (b-index) and ambiguity-generated insensitivity (a-index)

	(1) b-index SUR estimates	(2) b-index SUR estimates	(3) b-index SUR estimates	(4) a-index SUR estimates	(5) a-index SUR estimates	(6) a-index SUR estimates
France Scenario	-0.064	-0.064	-0.064	0.211**	0.211**	0.211**
	(0.042)	(0.042)	(0.042)	(0.088)	(0.088)	(0.088)
Italy Scenario	-0.065**	-0.065**	-0.065**	0.193**	0.193**	0.193**
	(0.027)	(0.027)	(0.027)	(0.092)	(0.092)	(0.092)
Binary Differential Knowledge		-0.041	-0.032		-0.206	-0.176
		(0.054)	(0.048)		(0.137)	(0.122)
Binary Differential Emotional Involvement		0.037	0.023		0.04	0.032
		(0.064)	(0.056)		(0.139)	(0.14)
Easiness			-0.076			-0.098
			(0.067)			(0.161)
Experience						
Intermediate			0.067			-0.143
			(0.069)			(0.206)
High			0.278***			-0.291
			(0.105)			(0.222)
Age			-0.021			-0.003
			(0.018)			(0.032)
Gender						
Female			-0.101			0.286*
			(0.071)			(0.162)
Non-binary			-0.129**			-0.009
			(0.064)			(0.123)
Region Of Residence						
Centre Italy			0.046			0.132
			(0.062)			(0.141)
Northern Italy			0.101			-0.160
			(0.116)			(0.139)
Session Dummy	NO	NO	YES	NO	NO	YES
Intercept	0.102***	0.097*	0.614	0.222***	0.272***	0.264
	(0.039)	(0.054)	(0.389)	(0.074)	(0.1)	(0.828)
Breusch-Pagan χ^2	6.271 (p= 0.012)	5.778 (p=0.016)	8.85 (p= 0.003)	6.271 (p= 0.012)	5.778 (p=0.016)	8.85 (p= 0.003)
Number Of Observations	135	135	135	135	135	135
Number Of Participants	45	45	45	45	45	45

Note 1: *** p<0.01, ** p<0.05, * p<0.1. Standard errors adjusted for clusters in participants appear in brackets.
Note 2: b-index of ambiguity aversion; a-index of ambiguity insensitivity, pooled data.
Note 3: Columns 1 and 4, 2 and 5, and 3 and 6 present the SUR estimates of the b-index and a-index, respectively, considering first the baseline models, then adding the binary measures of differential knowledge and differential emotional involvement, finally adding the full set of controls.
Note 4: Differential knowledge is the difference between the self-reported degree of knowledge in Italy and France, divided by the latter; Differential emotional involvement is the difference between the self-reported degree of emotional involvement in Italy and France, divided by the latter. Self-reports are measured on a 7-point Likert scale regarding the interest rate spread for 10-year government bonds. Binary Differential Knowledge takes the value of unity if Differential knowledge is above the sample median, and zero otherwise. Binary Differential Emotional Involvement takes the value of unity if Differential Emotional involvement is above the sample median, and zero otherwise.
Note 4: Reference categories: Ellsberg for scenario, No experience for experience, Male for gender, South and Islands for region of residence.

Table B2 reports the results of the SUR estimates for the b-index and the a-index in the **Economics treatment**. Standard errors, clustered at the individual level, appear in brackets. Columns 1 and 4 show the results when regressing the b-index and a-index, respectively, on the France and Italy dummies, using Ellsberg's as a reference category. The b-index was negatively correlated with the Italy dummy (p=0.015), implying less ambiguity aversion when evaluating prospects for Italy than Ellsberg's (Column 1). The a-index was positively correlated with the France (p=0.016) and Italy (p=0.036) scenarios, implying more ambiguity-generated insensitivity when evaluating natural uncertainty than Ellsberg's (Column 4). These findings were unaffected by adding the binary measures of differential knowledge and differential emotional involvement regarding sovereign interest rate spreads. These binary variables were equal to one when the difference in the self-reported degree of knowledge in Italy and France divided by the latter was above the median, and zero otherwise, and similarly for emotional involvement. Their estimated coefficients were not statistically different from zero (Columns

2 and 5). Adding the full set of controls (Columns 3 and 6) did not change the main results. Moreover, ambiguity aversion resulted significantly higher for high experience relative to inexperienced participants ($p<0.01$) and marginally lower for non-binary gender relative to males ($p<0.1$; Column 3). Ambiguity-generated insensitivity was marginally higher for females than males ($p<0.1$; Column 6). The other variables were not statistically different from zero in either regression. We also ran SUR replacing the binary measures with differential knowledge and differential emotional involvement. None was statistically significant. These results are available from the authors on request.

Football treatment

Table B3 presents separate OLS estimates for the b-index (Columns 1-3) and for the a-index (Columns 4-7) in the **Football treatment** because the Breusch-Pagan test did not detect any correlation between the residuals of the two regressions. Column 1 regresses the b-index on an Ellsberg dummy variable, taking the value of one for Ellsberg observations and zero otherwise (i.e., France and Italy observations). Subjects were, on average, more ambiguity averse when evaluating Ellsberg than football uncertainty ($p=0.097$). The result remained robust when adding the binary measures of differential knowledge and differential emotional involvement (equal to unity when the difference between the self-assessed degree of knowledge or involvement of Italy and France football, divided by the latter, was higher than the median, and zero otherwise, see Column 2) and the full set of controls (Column 3). However, the Ellsberg dummy became marginally statistically not significant in this latter case ($p=0.109$). Column (3) shows that subjects who found the experiment difficult rather than easy ($p<0.01$), females relative to males ($p=0.025$), and residents in the South and Islands were more ambiguity averse, other things being equal.

Subjects exhibited less ambiguity-generated insensitivity when evaluating France than Italy scenarios ($p=0.085$, Column 4). Adding binary differential knowledge and binary differential emotional involvement first (Column 5), then the full set of controls (Column 6), did not alter the results. Subjects who found the experiment difficult and residents in Northern Italy showed less insensitivity than subjects who found the experiment difficult and residents in the South and Islands ($p<0.01$, Column 6), respectively, other things being equal.

Column (7) excludes from the analysis the observations of the Ellsberg prospects. Ambiguity-generated insensitivity was positively correlated with the dummy for differential knowledge ($p=0.041$). Subjects who found the experiment difficult ($p=0.001$) and older ones ($p=0.097$) exhibited less ambiguity-generated insensitivity.

Table B3 Football treatment. OLS estimates of ambiguity aversion (b-index) and ambiguity-generated insensitivity (a-index)

	(1) b-index OLS	(2) b-index OLS	(3) b-index OLS	(4) a-index OLS	(5) a-index OLS	(6) a-index OLS	(7) a-index OLS excluding Ellsberg's prospects
France Scenario	NA	NA	NA	-0.117*	-0.117*	-0.117*	-0.117*
				(0.067)	(0.067)	(0.069)	(0.07)
Ellsberg Scenario	0.049*	0.049*	0.049				
	(0.029)	(0.029)	(0.030)	-0.132	-0.132	-0.132	
				(0.114)	(0.114)	(0.118)	
Binary Differential Knowledge		-0.011	-0.046		0.073	0.157	0.38**
		(0.043)	(0.044)		(0.103)	(0.13)	(0.153)
Binary Differential Emotional Involvement		-0.021	0.028		0.058	-0.033	-0.077
		(0.044)	(0.045)		(0.093)	(0.097)	(0.107)
Easiness			0.183***			-0.553***	-0.504***
			(0.057)			(0.135)	(0.128)
Experience							
Intermediate			0.039			-0.012	-0.159
			(0.058)			(0.1)	(0.125)
High			-0.06			0.278	0.094
			(0.081)			(0.183)	(0.183)
Age			0.009			0.036	-0.053*
			(0.01)			(0.023)	(0.026)
Gender							
Female			0.072**			0.056	0.076
			(0.035)			(0.097)	(0.113)
Region Of Residence							
Centre Italy			-0.087**			-0.006	0.044
			(0.034)			(0.102)	(0.116)
Northern Italy			-0.121**			-0.395***	-0.308**
			(0.06)			(0.117)	(0.128)
Session Dummy	NO	NO	YES	NO	NO	YES	YES
Intercept	0.048*	0.063*	-0.160	0.438***	0.381***	1.2**	1.634***
	(0.027)	(0.039)	(0.229)	(0.067)	(0.084)	(0.48)	(0.571)
Number Of Observations	138	138	138	138	138	138	92
Number Of Participants	46	46	46	46	46	46	46

Note 1: *** p<0.01, ** p<0.05, * p<0.1. Standard errors adjusted for clusters in participants appear in brackets.
Note 2: b-index of ambiguity aversion; a-index of ambiguity insensitivity, pooled data.
Note 3: 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. In Columns (4) to (6) scenario is specified as a categorical variable, with Italy as a reference. Column (7) excludes the observations of the Ellsberg prospects and differential emotional involvement.
Note 4: Differential knowledge is the difference between the self-reported degree of knowledge in Italy and France, divided by the latter; Differential emotional involvement is the difference between the self-reported degree of emotional involvement in Italy and France, divided by the latter. Self-reports are measured on a 7-point Likert scale regarding football. Binary Differential Knowledge takes the value of unity if Differential knowledge is above the sample median, and zero otherwise. Binary Differential Emotional Involvement takes the value of unity if Differential Emotional involvement is above the sample median, and zero otherwise.
Note 5: Reference categories. No experience for experience and South and Island for region of residence.

Between-subjects analysis

Section 5 of the main text compares our results across treatments. The first result was that median differential knowledge and differential emotional involvement were each greater in the COVID-19 vs. Economics treatments and the Football vs. Economics treatments. These results are confirmed when testing knowledge and emotional involvement separately for Italy, as shown in Table B4 below. However, for France, there is a different pattern. First, there is evidence of stronger information for COVID-19 than Football. Second, there is evidence that emotional involvement regarding COVID-19 is stronger than in Economics and Football and that emotional involvement in Economics is stronger than in Football (but at less than 10% significance level).

Table B4. Kruskal-Wallis and Dunn test for knowledge and involvement in Italy and France

	KRUSKAL-WALLIS TEST	Dunn test COVID-19 vs. ECONOMICS	Dunn test COVID-19 vs. FOOTBALL	Dunn test ECONOMICS vs. FOOTBALL
Knowledge in Italy	H=28.149*** p-value=0.00	z=5.2391*** adj p-value=0.00	z=-2.009 adj p-value=0.13	z= -3.315*** adj p-value=0.00
Knowledge in France	H=6.028* p-value=0.049	z=-1.8235 adj p-value=0.21	z=2.3535* adj p-value=0.06	z= 0.5287 adj p-value=1
Involvement in Italy	H=31.518*** p-value=0.00	z=5.53376*** adj p-value=0.00	z= 3.6674 adj p-value=0.00	z= -1.9336*** adj p-value=0.16
Involvement in France	H=19.494*** p-value=0.00	z= 2.2407* adj p-value=0.08	z=4.4147*** adj p-value=0.00	z= 2.2001* adj p-value=0.08

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.

In Section 5, we found evidence of differences in ambiguity-generated insensitivity between treatments for the France scenarios (see Table 13). To investigate this issue further, we ran OLS estimates of the a-index. Table B5 shows the results. We first regressed the a-index for the France scenarios (N=133) on a categorical variable for treatment, where the reference category was COVID-19 (Column 1). Then, we added binary measures of differential knowledge and differential emotional involvement (Column 2) equal to one if the observation was above the relevant treatment median and zero otherwise. Finally, we add the full set of individual controls (Column 3). We also replicated the final analysis first by dropping binary differential emotional involvement (Column 4), and then binary differential knowledge (Column 5). The estimates confirmed that the Football and Economics treatments were associated with lower ambiguity-generated insensitivity than COVID-19 and that the a-index was positively correlated with the binary measure of differential knowledge (although this was marginally significant, i.e. p=0.106, in Columns 3 and 4). In all specifications, ambiguity-generated insensitivity is negatively correlated with age.

Table B5. OLS estimates of a-index for France scenarios

	(1)	(2)	(3)	(4)	(5)
Economics treatment	-0.204*	-0.168	-0.212*	-0.212*	-0.249**
	(0.116)	(0.122)	(0.125)	(0.119)	(0.123)
Football treatment	-0.317***	-0.288***	-0.296***	-0.295***	-0.322**
	(0.099)	(0.103)	(0.104)	(0.096)	(0.103)
Binary Differential Knowledge		0.163*	0.154	0.154	
		(0.093)	(0.098)	(0.095)	
Binary Differential Emotional Involvement		-0.036	0.001		0.046
		(0.098)	(0.102)		(0.01)
Easiness			0.066	0.065	0.085
			(0.15)	(0.148)	(0.148)
Experience			-0.125	-0.125	-0.128
Intermediate			(0.118)	(0.117)	(0.12)
High			-0.104	-0.104	-0.093
			(0.143)	(0.142)	(0.147)
Age			-0.015**	-0.015**	-0.014**
			(0.006)	(0.006)	(0.007)
Gender			0.143	0.143	0.145
Female			(0.09)	(0.088)	(0.091)
Non-binary			0.144	0.144	0.239**
			(0.134)	(0.133)	(0.119)
Region of residence			0.072	0.072	0.069
Centre Italy			(0.097)	(0.098)	(0.098)
Northern Italy			-0.237	-0.237	-0.243*
			(0.15)	(0.147)	(0.145)
Session dummy	NO	NO	YES	YES	YES
Intercept	0.638***	0.567***	0.894***	0.894***	0.926***
	(0.075)	(0.088)	(0.207)	(0.209)	(0.206)
Number of obse and participants	133	133	133	133	133

Note 1: *** p<0.01, ** p<0.05, * p<0.1. Standard errors adjusted for clusters in participants appear in brackets.
Note 2: a-index of ambiguity insensitivity, pooled data between treatments, given the France scenario.
Note 3: Columns (1) controls for treatment dummies, using COVID-19 as a reference category. Column 2 adds Binary Differential Knowledge and Binary Differential Emotional Involvement. Column (3) adds individual controls. Columns (4) and (5) replicate Column (3) dropping alternatively Binary Differential Emotional Involvement and Binary Differential Knowledge.
Note 4: Differential knowledge is the difference between self-reported knowledge in Italy and France divided by the latter; Differential emotional involvement is the difference between self-reported emotional involvement in Italy and France divided by the latter. Self-reports are measured on a 7 point Likert scale regarding COVID-19, Economics and Football. Binary Differential Knowledge takes the value of unity if Differential Knowledge is above the sample median, and zero otherwise. Binary Differential Emotional Involvement takes the value of unity if Differential Emotional Involvement is above the sample median, and zero otherwise.
Note 5: Reference categories. COVID-19 for treatment, No experience for experience, Male for gender, and South and Island for Region of residence.