

Web-Appendix of:

The Rich Domain of Uncertainty: Source Functions and Their Experimental Implementation

by

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This Web Appendix provides background information for Abdellaoui et al. (2011).

The dataset, codebooks, experimental software, and statistical codes, are at:

http://aurelienbaillon.com/research/papers/dataset/Dataset_Rich_Domain.zip

A.1. Obtaining Exact Quantitative Predictions

The following examples illustrate how measurements of uncertainty and ambiguity can be operationalized using source functions.

EXAMPLE A.1 [Home bias; within-person comparisons]. Consider options yielding \$40,000 or nil, as follows.

Foreign-option: (Favorable Foreign temperature: 40,000, otherwise: 0).

Paris-option: (Favorable Paris temperature: 40,000, otherwise: 0);

We assume that, both for Paris temperature and for foreign temperature, subject 2 (living in Paris) considers favorable and unfavorable temperatures to be equally likely, and that his utility function on the domain relevant for this example is well approximated by $u(x) = x^{0.88}$. Whereas under expected utility this information would completely determine the preference values of the options considered, under binary

RDU we need more information. All the required extra information is captured by the source functions, displayed in Figure 10a (main text p. 713) for subject 2. It leads to the following predictions.

Because the decision weight of outcome 40,000 is 0.20 for foreign temperature, the certainty equivalent for the foreign option is $u^{-1}(0.20 \times u(40,000)) = \$6,424$. We use the term *uncertainty premium* as an analog of risk premium, referring however to the context of uncertainty with unknown probabilities. Choi et al. (2007, Section IV.C) similarly used such premia to combine several components of risk and uncertainty attitudes. Assuming probability 0.50, the uncertainty premium for the foreign option is $\$20,000 - \$6,424 = \$13,576$. For risk with known probability $p = 0.50$, the decision weight is 0.40, giving a certainty equivalent of $\$14,121$ and a risk premium of $\$5,879$. Subject 2 exhibits ambiguity aversion for foreign temperature because he evaluates the choice-based probability 0.50 lower than the objective probability 0.50. We interpret the difference between the uncertainty premium and the risk premium, $\$13,576 - \$5,879 = \$7,697$, as an *ambiguity premium*.

Table A.1 gives similar calculations for Paris temperature, for which subject 2 exhibits considerably more favorable evaluations and is even ambiguity seeking, with a negative ambiguity premium. Subject 2 exhibits a strong home bias for temperature-related investments. This bias cannot be ascribed to beliefs or tastes because the beliefs and tastes are the same for the investments in Paris and foreign temperature. The home bias is explained by the different source functions displayed in Figure 10 (main text p. 713).

TABLE A.1. Calculations for Subject 2

	Paris temperature	foreign temperature
decision weight	0.49	0.20
expectation	20,000	20,000
certainty equivalent	17,783	6,424
uncertainty premium	2,217	13,576
risk premium	5,879	5,879
ambiguity premium	-3,662	7,697

□

EXAMPLE A.2 [More likelihood insensitivity, and more gambling and insurance; between-person comparisons]. Consider an option (Favorable Paris temperature: 40,000, otherwise: 0). Assume that there are eight exhaustive and mutually exclusive Paris-temperature events that are equally likely according to both subject 2 and subject 48. We assume, for clarity of exposition, that the utility function on the domain relevant for this example is well approximated by $u(x) = x^{0.88}$ for both subjects.

TABLE A.2. Calculations for Paris Temperature

	Subject 2, p=0.125	Subject 48, p=0.125	Subject 2, p=0.875	Subject 48, p=0.875
decision weight	0.35	0.08	0.52	0.67
expectation	5,000	5,000	35,000	35,000
certainty equivalent	12,133	2,268	19,026	25,376
uncertainty premium	-7,133	2,732	15,974	9,624
risk premium	-4,034	2,078	5,717	-39
ambiguity premium	-3,099	654	10,257	9,663

We consider two cases.

CASE 1. Assume that one of the eight events is favorable and seven are unfavorable, implying that the choice-based probability at 40,000 is 0.125. Figure 11 (main text p. 714) shows that the favorable event has weight 0.35 for subject 2, yielding certainty equivalent \$12,133. The columns in Table A.2 with $p=0.125$ give this number, and several other results that were calculated similarly as in Table A.1.

CASE 2. Assume that seven of the eight events are favorable and one is unfavorable, implying that the choice-based probability at 40,000 is 0.875. The two right columns in Table A.2 give results for this case.

Subject 2 has a higher certainty equivalent for $p=0.125$ than subject 48 does, but a lower one for $p=0.875$. Thus at the same time he exhibits more proneness to gambling (small probability at favorable outcome as in Case 1) and to insurance (small probability at unfavorable outcome as in Case 2) than subject 48 does. Both the risk and the ambiguity attitudes contribute to these differences between the two subjects, as the premiums show.

It is interesting to consider the changes in evaluations if the number of favorable events changes from one (Case 1) to seven (Case 2). Subject 2 exhibits little sensitivity to this big change in likelihood. His certainty equivalent of the investment changes only by approximately \$7,000 and does not even double, whereas the certainty equivalent of subject 48 changes drastically. We can conclude that subject 48 exhibits considerably more sensitivity to likelihood changes than subject 2 in the domain considered here.

Subjects 2 and 48 have the same beliefs (as argued by Smith 1969 and Winkler 1991), and the same tastes (as argued by Hogarth and Einhorn 1990). Their different behavior is generated by differences in their source functions, in other words, by differences in the non-Bayesian components of their behavior. \square

A.2. Experimental Details for both Studies

Subjects were sampled from two French engineering schools (Ecole des Travaux Publics and Ecole Nationale Supérieure d'Arts et Métiers). The samples were recruited by posters and internet-based registration. The subjects were acquainted with probability theory but not with decision theory.

Procedure. The experiment consisted of individual interviews using a computer, all done by the same interviewer. Subjects' choices were entered by the experimenter implying that subjects could focus on the questions. Subjects were told that there were no right or wrong answers.

The random incentive system. The random incentive system has become the almost exclusively used incentive system for individual choice in experimental economics (Holt and Laury 2002; Myagkov and Plott 1997). We used it in the first experiment.

For the second experiment, we asked subjects in a pilot study which form of the random incentive system would motivate them better, the traditional form paying one

randomly selected choice for each subject, in which case prizes will be moderate, or one were only one choice of one subject will be played for real but the prize is very large. The subjects expressed a clear preference for the single-large prize system that accordingly was implemented in our experiment.¹ Given that the high prize was usually €1,000, and that subjects would usually choose the more likely gain, the expected value of the subject selected exceeded $1,000/2 = €500$, and the expected gain (in addition to the €20) per subject in the real treatment exceeded $500/31 \approx €16$. This payment is in agreement with common payments for experimental subjects used in the traditional random incentive system and in other contexts, where in our case the flat payment of €20 is added to this amount. A form where not all subjects were paid was also used by Harrison, Lau, and Williams (2002). Two studies that examined differences between this form and the original form where each subject is paid, did not find a difference (Armantier 2006, p. 406; Harrison, Lau, and Rutström 2007, footnote 16). In our studies, as in most others, the data for the real-incentive treatment were of higher quality than the data for the hypothetical-choice treatment, confirming the effectiveness of the incentive system used.

Real incentives and chaining. It is well known that real incentives can be problematic in chained experiments (Harrison 1986). In the first experiment, we added the third step to our chained measurement of indifferences so as to ensure incentive compatibility. This is explained further in Appendix A.3.

Chaining was also used in our second experiment. Thus in our construction of the a_{ij} 's, where questions were influenced by the a_{ij} 's obtained before, one may be concerned about it being advantageous for subjects not to answer according to their true preferences in a question but instead to seek to improve the stimuli that will occur in future questions. We organized our chaining of the a_{ij} 's as follows so as to minimize the chaining problem. First, our subjects did not know about this chaining. In addition, we paid special attention during the interviews, all done individually, to signals that would suggest subjects' awareness of this chaining. No interview suggested any such awareness. The indifference values used in follow-up questions were midpoints of intervals and, hence, these values had not occurred before and

¹ In the decision actually played, the subject preferred a certainty equivalent of €400 to the chance mentioned, and this is what he received.

could not be recognized. Second, even if subjects would know that this chaining took place, then they would not know how this was done and they would not know in which direction to manipulate their choices. Even for someone who knows the actual organization of the $a_{i/j}$'s (including the readers), it is not clear in which direction to manipulate answers so as to improve future stimuli.

Van de Kuilen and Wakker (2011) interviewed subjects after a chained experiment and found that no subject had been aware of this chaining and its strategic implications. As regards the chained bisection method used to measure indifferences, we compared the questions used there with consistency-check questions that were not part of a chained procedure. We found no differences, which again suggests no strategically-driven biases. The parameters found for utility and source functions, and the discrepancies found between real and hypothetical choice, are all in agreement with common findings in the literature, and the subjective probabilities elicited are well calibrated. These findings further suggest that our data were not distorted by strategic considerations generated by chaining.

A.3. Experimental Details of the Ellsberg Experiment

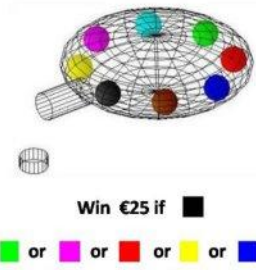
Subjects and decision context. 20 female and 47 male students participated. They were told that they could win up to €25 for their participation. Neither the subjects nor the experimenter knew the true composition of the unknown urn, and it was emphasized that a new unknown urn was generated for each subject. This procedure served to minimize inference about urns through communication with other subjects. We counterbalanced the order of presentation of the known and the unknown urn. The experiment took about 20 minutes per subject.

Prospects. We elicited the certainty equivalents of 32 prospects x_{EY} described in the following table.

TABLE A.3. List of Prospects

	S	x	y	E	P(E)
1	K	€25	€0	{R _K }	0.125
2	K	€25	€0	{R _K ,B _K }	0.25
3	K	€25	€0	{R _K ,B _K ,Y _K }	0.375
4	K	€25	€0	{R _K ,B _K ,Y _K ,A _K ,G _K ,P _K ,N _K ,C _K }	0.5
5	K	€25	€0	{R _K ,B _K ,Y _K ,A _K ,G _K }	0.625
6	K	€25	€0	{R _K ,B _K ,Y _K ,A _K ,G _K ,P _K }	0.75
7	K	€25	€0	{R _K ,B _K ,Y _K ,A _K ,G _K ,P _K ,N _K }	0.875
8	K	€15	€0	{R _K ,B _K ,Y _K ,A _K }	0.5
9	K	€25	€10	{R _K ,B _K ,Y _K ,A _K }	0.5
10	K	€10	€0	{R _K ,B _K ,Y _K ,A _K }	0.5
11	K	€15	€5	{R _K ,B _K ,Y _K ,A _K }	0.5
12	K	€20	€10	{R _K ,B _K ,Y _K ,A _K }	0.5
13	K	€25	€15	{R _K ,B _K ,Y _K ,A _K }	0.5
14	U	€25	€0		0.125
15	U	€25	€0	One randomly drawn color	0.125
16	U	€25	€0		0.125
17	U	€25	€0	{Y _U ,A _U }	0.25
18	U	€25	€0	{G _U ,P _U }	0.25
19	U	€25	€0	{N _U ,C _U }	0.25
20	U	€25	€0	{R _U ,B _U }	0.25
21	U	€25	€0	{R _U ,B _U ,Y _U }	0.375
22	U	€25	€0	{R _U ,B _U ,Y _U ,A _U }	0.5
23	U	€25	€0	{G _U ,P _U ,N _U ,C _U }	0.5
24	U	€25	€0	{R _U ,B _U ,Y _U ,A _U ,G _U }	0.625
25	U	€25	€0	{R _U ,B _U ,Y _U ,A _U ,G _U ,P _U }	0.75
26	U	€25	€0	{R _U ,B _U ,Y _U ,A _U ,G _U ,P _U ,N _U }	0.875
27	U	€15	€0	{R _U ,B _U ,Y _U ,A _U }	0.5
28	U	€25	€10	{R _U ,B _U ,Y _U ,A _U }	0.5
29	U	€10	€0	{R _U ,B _U ,Y _U ,A _U }	0.5
30	U	€15	€5	{R _U ,B _U ,Y _U ,A _U }	0.5
31	U	€20	€10	{R _U ,B _U ,Y _U ,A _U }	0.5
32	U	€25	€15	{R _U ,B _U ,Y _U ,A _U }	0.5

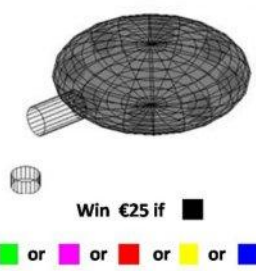
Which option do you choose?

Option 1 Play the lottery below	1	2	Option 2 Receive this amount for sure
 <p>Win €25 if ■</p> <p>Win €0 if ■ or ■ or ■ or ■ or ■ or ■ or ■</p>	<input type="radio"/>	<input type="radio"/>	0 €
	<input type="radio"/>	<input type="radio"/>	5 €
	<input type="radio"/>	<input type="radio"/>	10 €
	<input type="radio"/>	<input type="radio"/>	15 €
	<input type="radio"/>	<input type="radio"/>	20 €
	<input type="radio"/>	<input type="radio"/>	25 €

Continue
↔
Back

(a) A bet on “the ball is black” in urn K

Which option do you choose?

Option 1 Play the lottery below	1	2	Option 2 Receive this amount for sure
 <p>Win €25 if ■</p> <p>Win €0 if ■ or ■ or ■ or ■ or ■ or ■ or ■</p>	<input type="radio"/>	<input type="radio"/>	0 €
	<input type="radio"/>	<input type="radio"/>	5 €
	<input type="radio"/>	<input type="radio"/>	10 €
	<input type="radio"/>	<input type="radio"/>	15 €
	<input type="radio"/>	<input type="radio"/>	20 €
	<input type="radio"/>	<input type="radio"/>	25 €

Continue
↔
Back

(b) A bet on “the ball is black” in urn U

FIGURE A.1. First step of the elicitation process

Measuring indifference. Eliciting the certainty equivalent of a prospect consisted of three steps. The first step consisted of six choices between the prospect and a sure payment. Sure payments were equally spaced between the minimum and the maximum amount of the corresponding prospect, generating five intervals between these two amounts. Monotonicity was enforced: after each choice, every subsequent choice implied by monotonicity was automatically selected.

In the second step, a new set of eleven choices was presented, with sure payments now spanning the narrower range between the lowest sure payment preferred and the highest sure payment dispreferred in the first step, generating 10 subintervals between them.

In the third step, a large choice list was presented to the subject, with 51 choices between the prospect and a sure payment, generating 50 subintervals between the minimum and the maximum amount of the prospect. This choice list was obtained by refining each of the five intervals of the first step into 10 subintervals, and not just the interval refined in the second step. The large choice list was pre-filled based on the answers given in the preceding two stages while assuming monotonicity. It was presented to the subject for validation. The program allowed respondents to backtrack if they felt regret about a previous series of choices.

In the random incentive system, one of the answers from the third list was chosen at random. This way the system is incentive compatible and not subject to strategic behavior. With the three-step process, we obtain certainty equivalents with a precision of 1% of the distance between the highest and the lowest outcomes of the prospect. Our elicitation method was similar to the two-stage iterative choice list procedure of Andersen et al. (2006), where we added the third step.

Figure A.1 (a and b) (that in our experiments had colors making them considerably clearer) displays the screenshots of the first step in the elicitation process of the certainty equivalent associated with a bet on one color (in urn K and U respectively).

Uniformity. To determine $w_U(1/4)$, we can use each one of the four two-color events in Table A.3 (prospects 17-20), because these events all have probability $1/4$. Thus we get four measurements of $w_U(1/4)$; their differences were insignificant. We hence took the average.² In all calculations of source functions we similarly used averages over all relevant events.

² More precisely, we took the average certainty equivalent for these four events and used that to calculate $w_U(1/4)$.

A.4. Experimental Details of the Natural-Event Experiment

The method used to measure subjective probabilities was tested by Baillon (2008).

Procedure. 54 male and 8 female students participated. There were 5 minutes of instructions, 10 minutes of practice questions, and 70 minutes of experimental questions, interrupted for small breaks and cakes when deemed desirable. After finishing all questions pertaining to one source, we did not immediately start with the next source, but asked intermediate questions eliciting risk attitudes so as to prevent that subjects continued to think of one source when dealing with the next one.

As in Baillon (2008), for each subject and each source we first elicited boundary values $b_0 < b_1$ such that according to the subject there was “almost no chance” that the value to be observed would be outside the interval $(b_0, b_1]$. These bounds served only in graphical presentations for the subjects, and to help them get familiar with the stimuli, and their actual values play no role in our analysis. To obtain b_0 and b_1 , we made subjects choose between bets with probability 0.001 and bets on the events “ $< b_0$ ” and “ $> b_1$ ”, using \$1,000 as the prize to be won. Using the notation in the main text, we can write $E_1^1 = (-\infty, \infty)$,³ $a_0 = -\infty$, and $a_1 = \infty$. The values b_0 and b_1 are approximations of a_0 and a_1 .

The certainty equivalents of $1,000_{1/8}0$, $1,000_{1/4}0$, $1,000_{1/20}$, $1,000_{3/4}0$, and $1,000_{7/8}0$ were elicited after the CAC40 elicitations. The certainty equivalents of the lotteries $500_{1/20}$, $1,000_{1/2}500$, $500_{1/2}250$, $750_{1/2}500$, and $1,000_{1/2}750$ were elicited after the Paris-temperature elicitations. We explained to the subjects that the probabilities were generated by random numbers from a computer, with which our subjects were well acquainted. We followed the same procedure here as for unknown probabilities, so as to treat the source of known probability similarly as the sources of unknown probabilities.

Pilots were done with 18 subjects, to determine which sources and which incentive system to use in the real experiment. The pilots suggested that randomized and mixed orders of presentation, with choice questions pertaining to one source or aiming at one indifference question not asked in a row, were tiring and confusing for subjects. Hence we grouped related questions together in the real experiment.

Measuring indifferences. All indifferences were elicited through repeated choices and bisection until a satisfactory degree of precision had been reached. In each case, the second choice of the bisection was repeated later as a consistency check. No matching questions were used. Although bisection is more time consuming than matching, it has been found to provide more reliable results (Bostic, Herrnstein, and Luce 1990; Noussair, Robbin, and Ruffieux 2004). When measuring the midpoint of an interval $(a, b]$, we always started with $a/3 + 2b/3$ and then $2a/3 + b/3$ as the first two choice questions, and only then continued with usual bisection. Certainty equivalents were always measured using traditional bisection, starting with the expected value.

Dropping Subjects. For the certainty-equivalence measurements used to analyze risk attitudes, one subject was removed from the group with hypothetical choice. He always chose the sure option, suggesting that he did not seriously consider the choice options. To avoid introducing a bias towards risk seeking (the subject removed behaved as if most risk averse), we also removed the most risk seeking subject from this group. In the group of real incentives, we similarly removed one subject who always chose the safe option and one subject who always chose the risky option, for similar reasons. Thus 4 subjects were removed and 58 subjects remained, 29 in each treatment. The removal does not affect the results reported.

Measuring observed frequencies for CAC40 over the year 2006. The distribution is based on 254 days. The estimates concern increase rates from 5:30 PM one day until 1 PM the next day (the time period considered in our experiment), which can be estimated as $(\text{daily rates to the power } 19.5/24) - 1$.

Real incentives compared to hypothetical choice. In the second experiment, we used both a real-incentive treatment and a hypothetical-choice treatment so as to investigate the effects of real incentives when examining uncertainty and ambiguity attitudes. Throughout, we find more aversion, and less noise, for real incentives, in agreement with other studies (Hogarth and Einhorn 1990; Keren and Gerritsen 1999), and in agreement with findings in other domains (Camerer and Hogarth 1999). Our finding supports the principle that real incentives should be implemented whenever possible.

³ For simplicity, we do not express in notation that temperature is physically bounded below.

A.5. Alternative Statistical Analysis of the Ellsberg Experiment

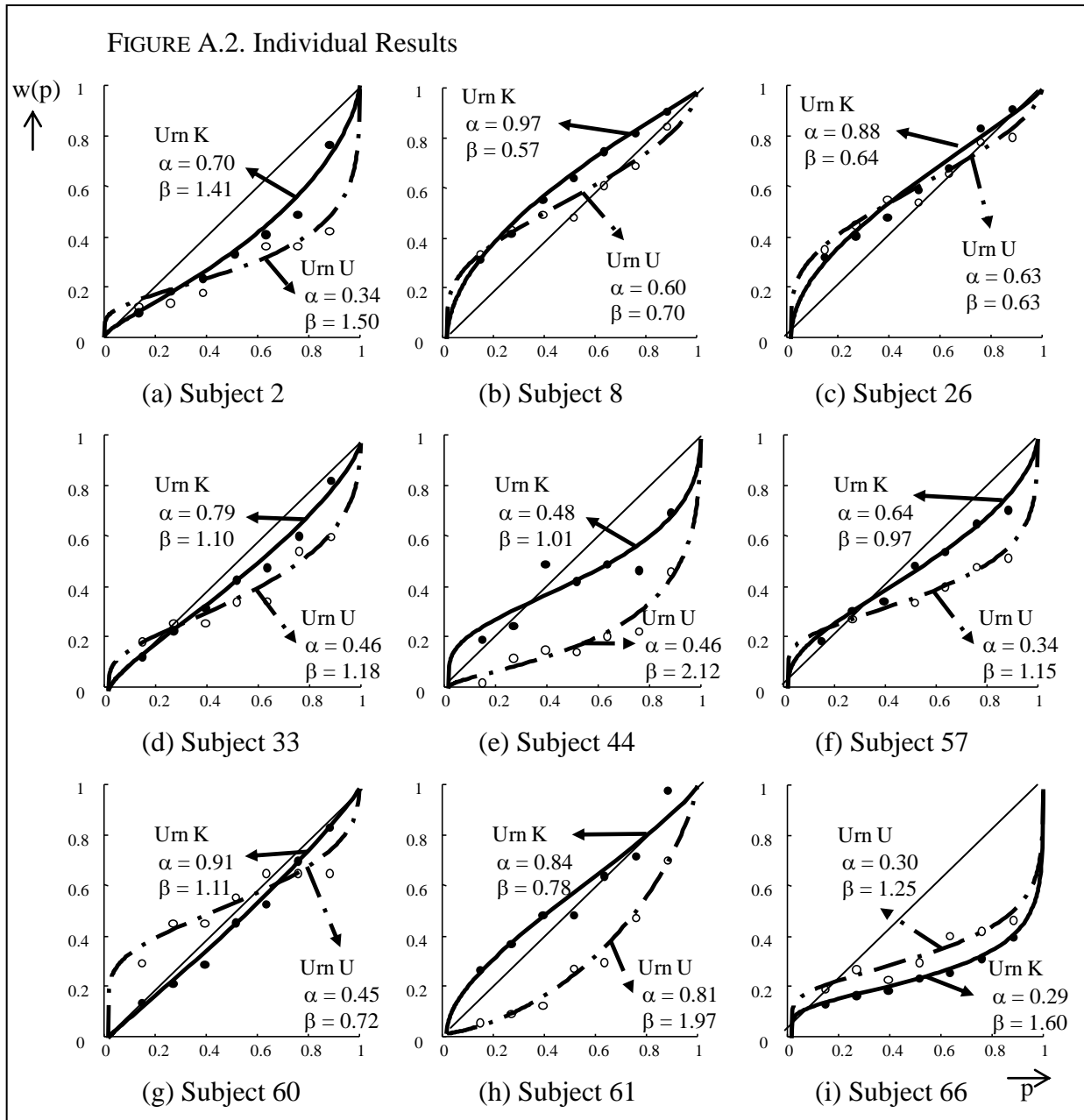
In the main text, we provided a simple nonparametric measurement of the source functions. Such measurements do not commit a priori to any properties. Thus we let the data speak. We added some parametric fittings, with the usual drawback of committing a priori to particular properties but the usual advantage of smoothing noise in the data. Our parametric fittings minimized squared distances. This appendix presents results from econometric techniques, based on probabilistic choice-error theories (Wilcox 2008). They give the same results as the analyses presented in the main text.

We illustrate the econometric approach using a representative agent analysis of our Ellsberg experiment (Study 1). We used choice lists to obtain indifference, giving 32×51 binary choices per subject. Therefore, maximum likelihood estimation on discrete choices can be used, with a Fechnerian error term and the standard error being corrected for potential correlation within individuals (Harrison and Rutström 2008, Appendix F). We assume power utility and Prelec's (1998) two-parameter source function (Eq. 10).

Our results are as follows. The power of the utility function does not depend on the source of uncertainty, and it does not differ from 1. For the source function, the "elevation" parameter β (0.85) does not differ across urns and is significantly lower than 1. The likelihood insensitivity parameter α (0.81 for known probability and 0.64 for unknown probability), finally, is also significantly lower than 1 and lower in the unknown urn than in the known urn. These results are all in agreement with the results reported in the main text.

A.6. Results at the Individual Level

Individual Behavior in the Ellsberg Experiment. There is much variation between individuals. The following figure displays the source functions of 9 subjects. The "diagonal" subjects 2, 44, and 66 were also reported in the main text. This appendix adds other subjects and details. The values corresponding to observations are represented by black (K) and white (U) circles, and the fitted source functions by a continuous line for K and a dash-dot line for U.



The curves of subjects 2, 33, and 57 display the common features, namely an inverse-S shaped source function in urn K and both more pessimism and less likelihood sensitivity in U than in K. Some subjects (8, 26 and 61) are globally optimistic under risk, exhibiting an almost concave source function in K. Their attitudes under ambiguity differ: Subject 26's likelihood insensitivity is larger for the unknown urn, whereas subject 61 becomes considerably more pessimistic for the unknown urn (concave source function). Both phenomena are present in subject 8's source function under ambiguity. Subject 44, whose risk attitude is mostly characterized by high likelihood insensitivity, is ambiguity averse, her source function for U being shifted

down. Subject 66, on the contrary, is ambiguity seeking; the source function for U, while displaying the same kind of curvature, is above that for K. Subject 60 also is mainly ambiguity seeking but becomes ambiguity averse for high probabilities: ambiguity generates lower likelihood sensitivity and more optimism.

Indexes. Figures 12 and 13 (main text p. 715) display the pessimism and insensitivity indexes observed in the real payment group of the natural-event experiment. The figures show the relationship between the indexes observed in the various sources with respect to the indexes elicited under risk. They highlight between-source and between-subject heterogeneity. The same results are provided for the Ellsberg experiment and the hypothetical payment group of the natural-event experiment in Figures A.3-A.5. For each graph, we mention the number of subjects above and below the diagonal and the correlations (ρ) together with their p-value.

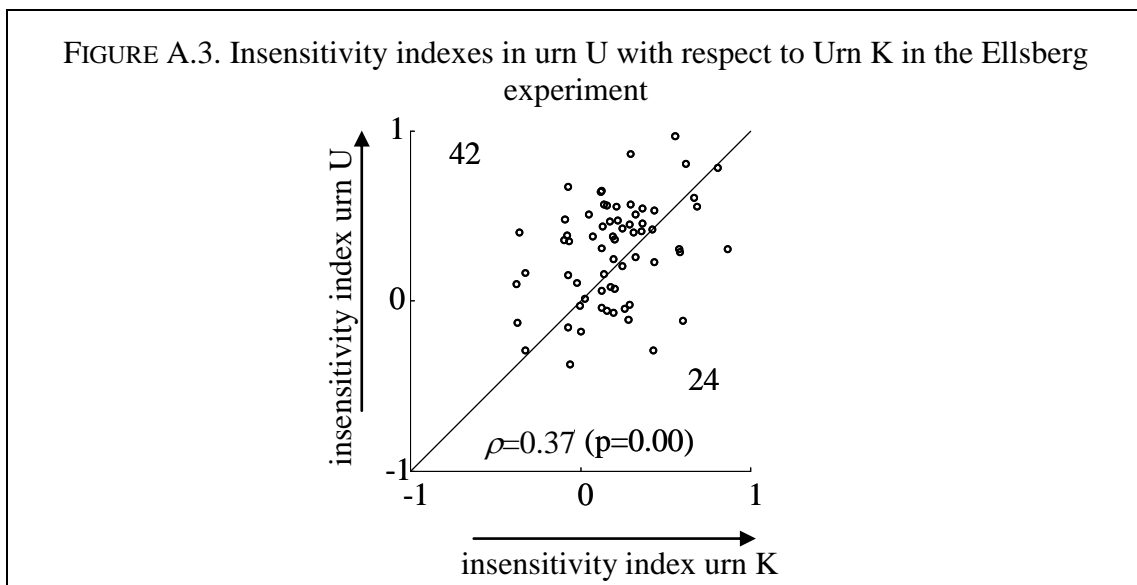


FIGURE A.4: Pessimism indexes in urn U with respect to Urn K in the Ellsberg experiment

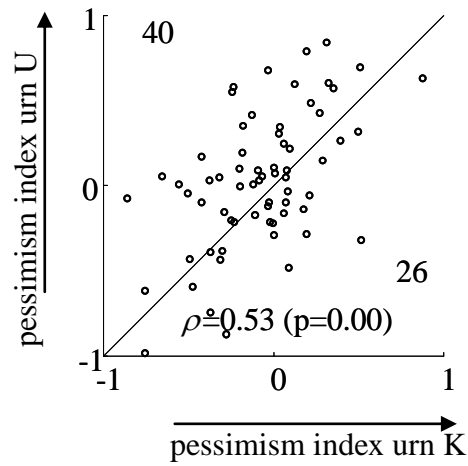


FIGURE A.5: Insensitivity indexes in the ambiguous sources with respect to risk in the natural-event experiment (hypothetical payment)

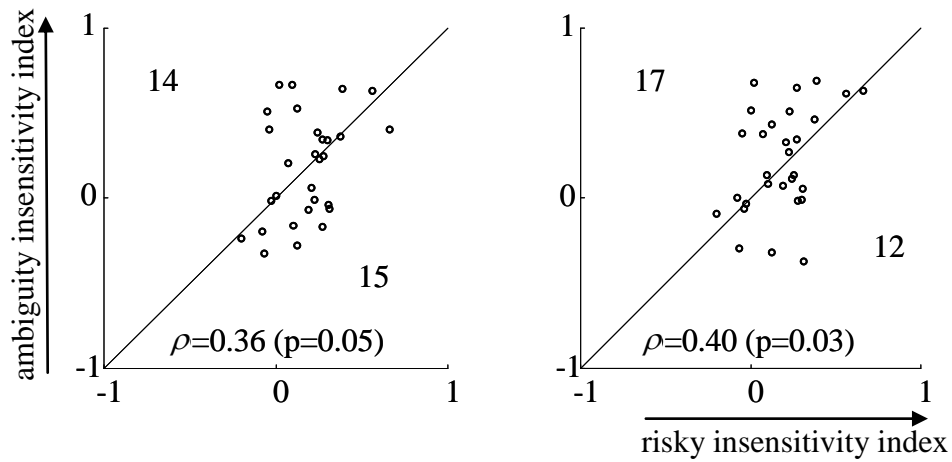
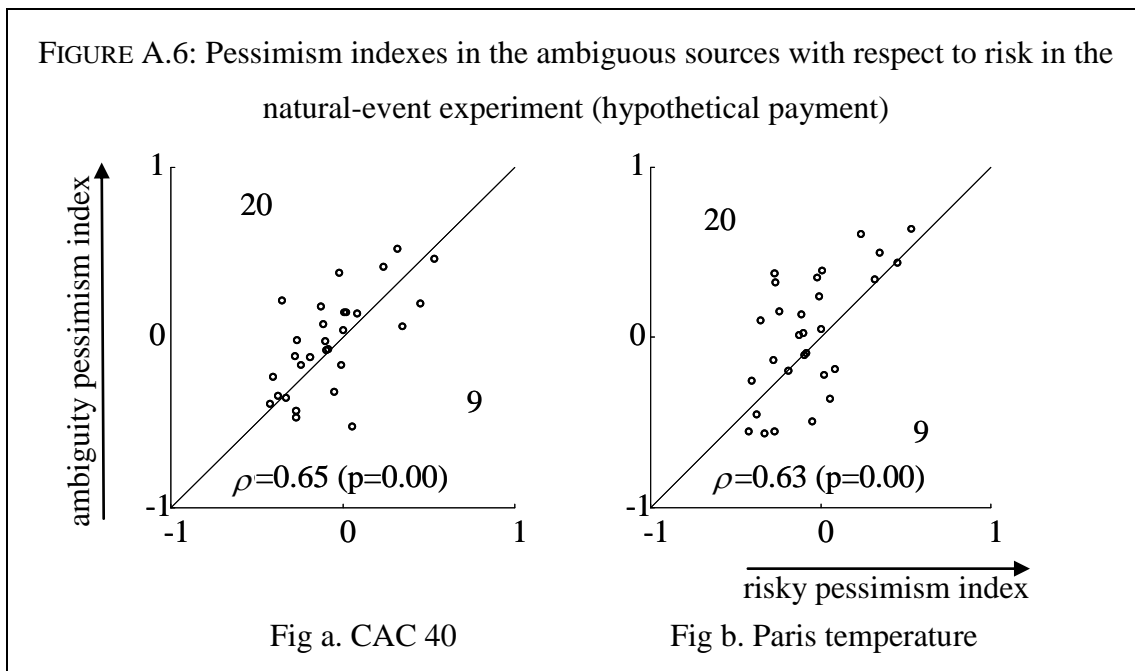


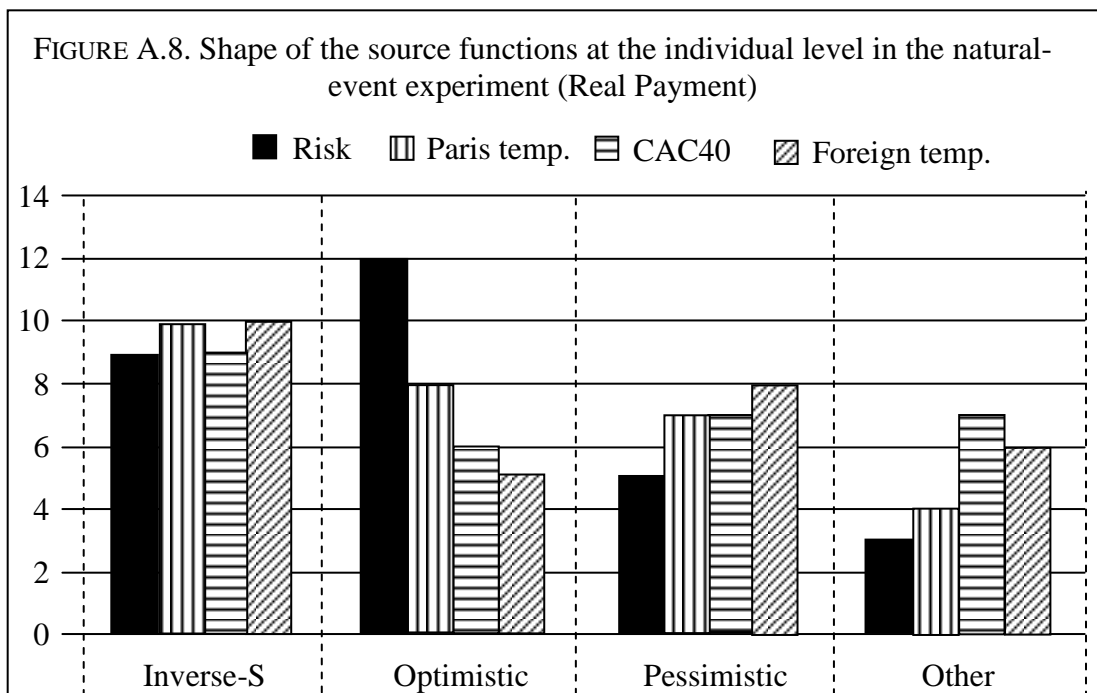
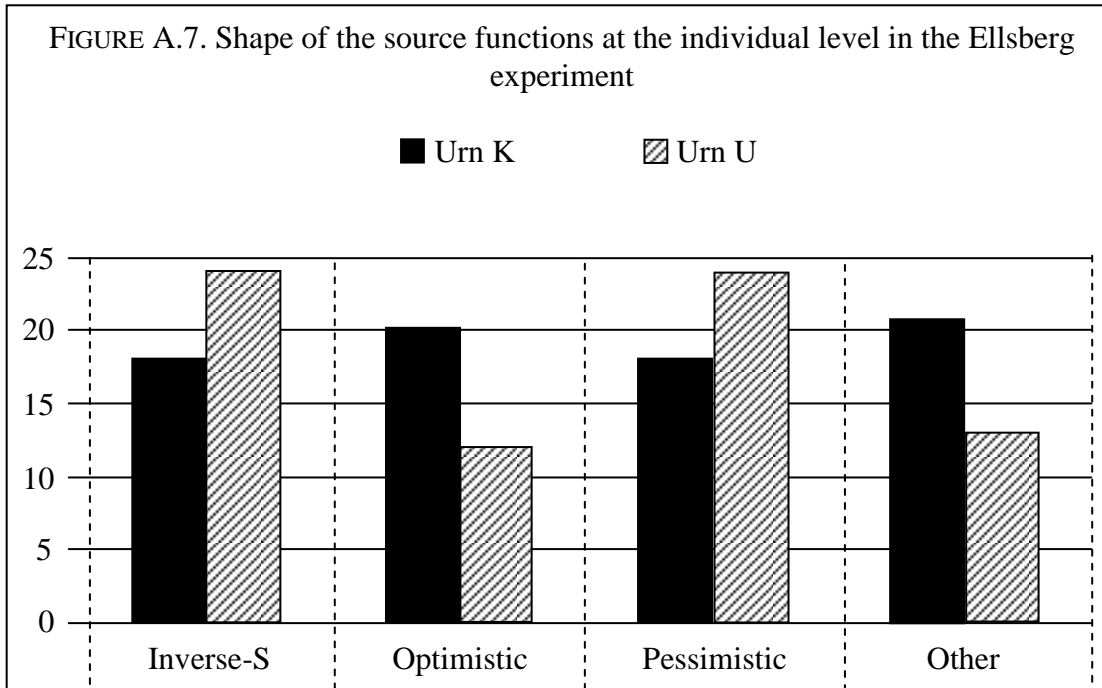
Fig a. CAC 40

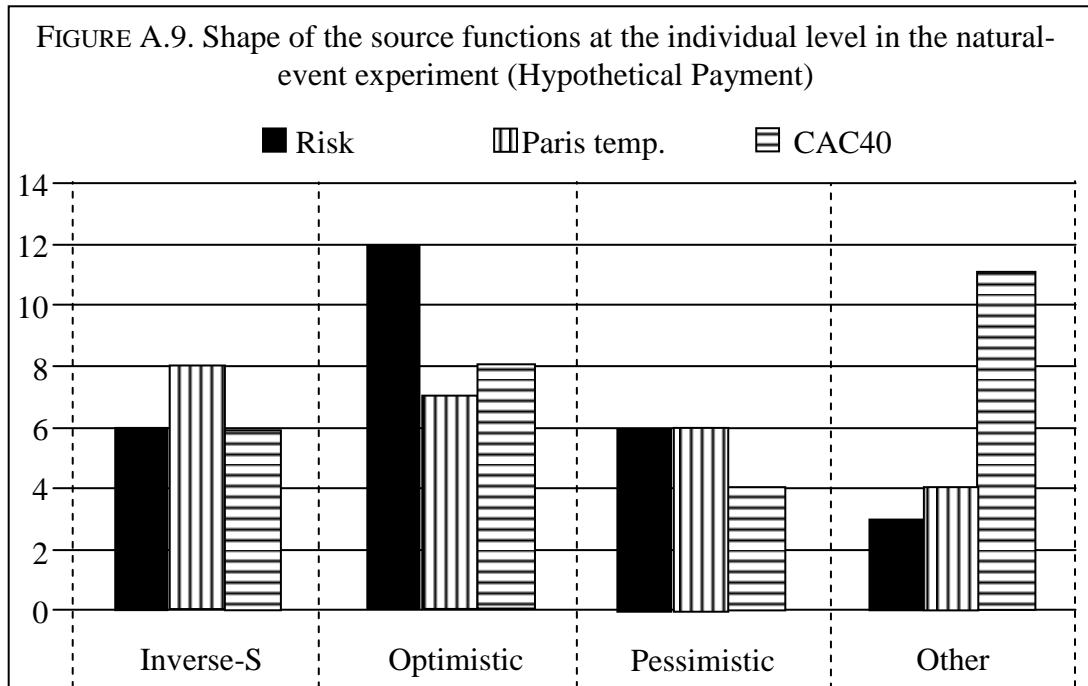
Fig. b. Paris temperature



Figures A.3-A.6 confirm the two findings described in the main text for Figures 12 and 13 there: we infer between-subject heterogeneity from the high and significant correlations. Between-source heterogeneity is confirmed by the high proportion of subjects above the diagonal in Figures A.3-A.6.

Shape of the source functions. The aggregate source functions represented in the main text are inverse-S shaped, as commonly found for risk in the literature. Figures A.7-A.9 show the number of subjects who exhibited particular shapes of nonparametric source functions: inverse-S shaped (taken as crossing the diagonal once, from above to below), optimistic (source functions always above the diagonal), pessimistic (source functions always below the diagonal), and other (source functions satisfying none of the aforementioned properties). We discuss three results. First, there are always many inverse-S source functions, whatever the source. Second, there are more optimistic source functions under risk than for the other sources. Third and correspondingly, there are more pessimistic source functions for the sources about which subjects had little knowledge (urn U or foreign temperature) than for risk.





Ambiguity attitude. In our experiments, the difference between the source functions in the uncertain sources and the source functions under risk captures the ambiguity attitude of the participants. At each probability level and for each source (except risk), we are thus able to determine if a subject was ambiguity averse or ambiguity seeking there. Figures A.10-A.12 display how many participants were of each kind. Whereas most participants are ambiguity averse whatever the probability level in the natural-event experiment, in the Ellsberg experiment clear ambiguity aversion arises only for high probabilities.

FIGURE A.10. Ambiguity attitude at each probability level in the Ellsberg experiment

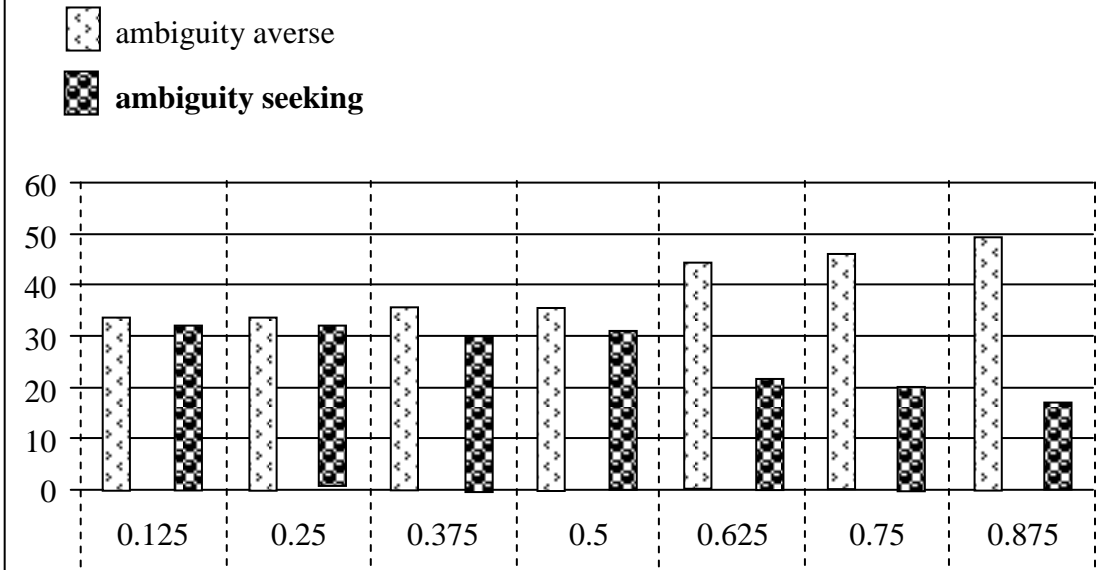
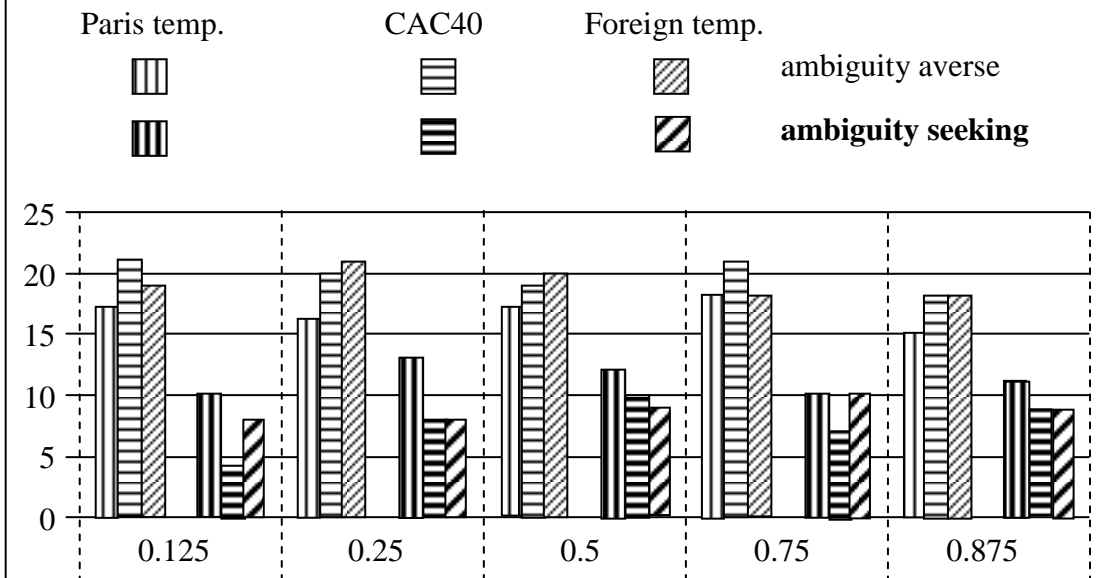
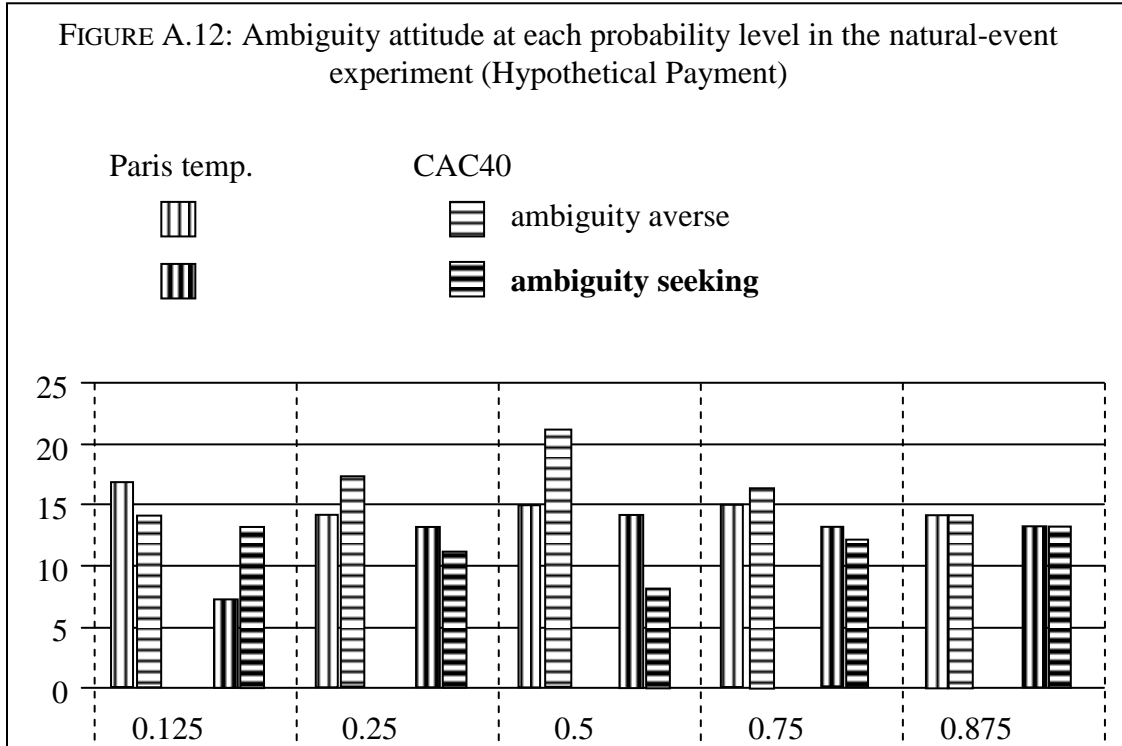


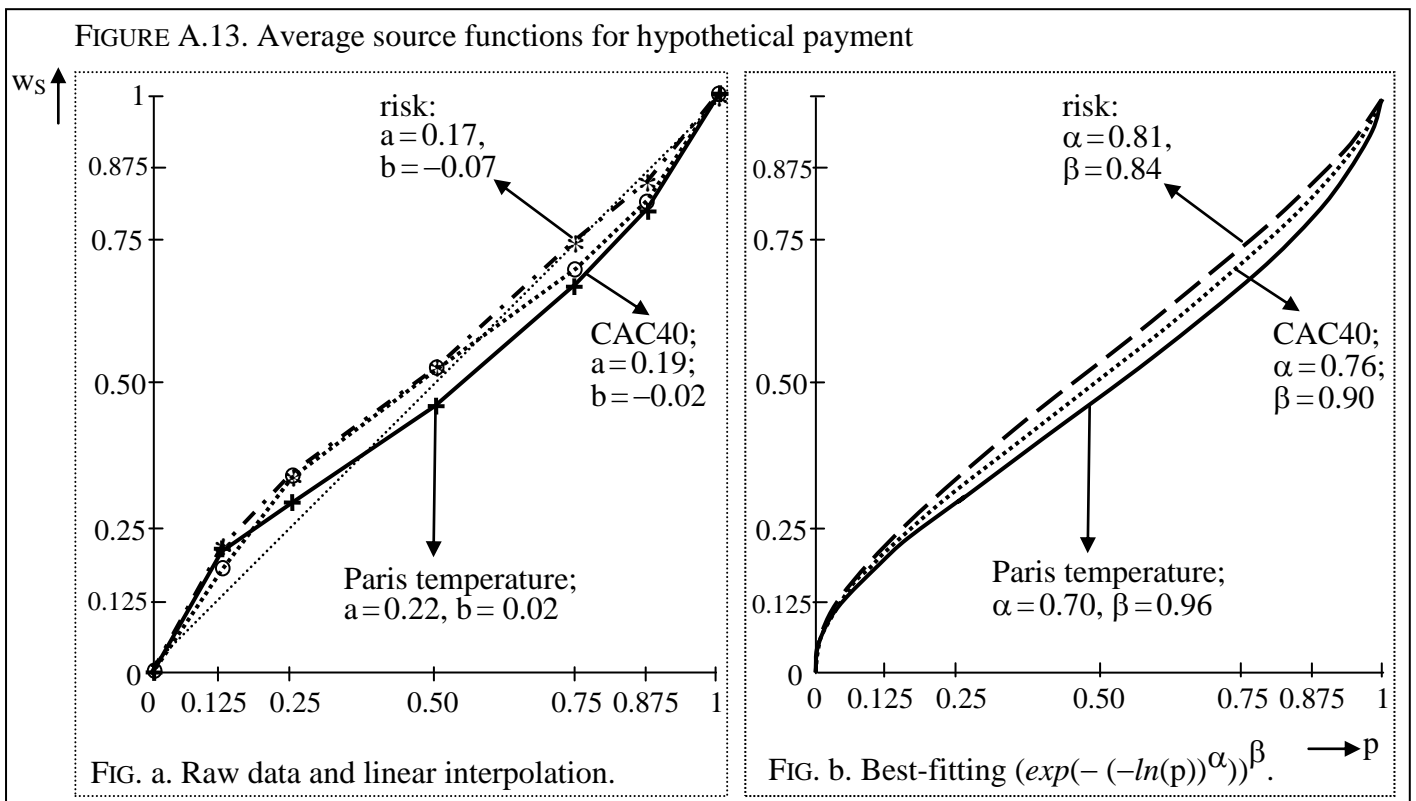
FIGURE A.11: Ambiguity attitude at each probability level in the natural-event experiment (Real Payment)





A.7. Aggregate Statistics

Figure A.13 is the analog for hypothetical payment of Figure 9 (main text p. 713).



The following tables include all the statistics used in the main text. Table A.4 provides additional statistics to Table 1 (main text p. 706). In all tables that follow, each row or column entitled “*t*-test...” provides p-values. All ANOVAs introduce the various sources as a factor. Throughout, HF p-values refer to ANOVAs corrected by the Huynh-Feldt ϵ . In Table A.7, several p-values are rounded to 0.05. However, they are followed by + or –, indicating whether the original values were slightly higher (+) or lower (-) than 0.05. We provide this extra information to clarify some claims in the main text.

TABLE A.4. Source Functions for K and U in the Ellsberg Experiment (66 Subjects)

P	Source	Std	Correlation between w_U and w_K (p-value)	Number of subjects with $w_s(p) < p$	Number of subjects with $w_U(p) < w_K(p)$
1/8	K	0.20	0.36 (0.00)	17	34
	U	0.22		26	
2/8	K	0.20	0.39 (0.00)	22	34
	U	0.23		30	
3/8	K	0.20	0.48 (0.00)	26	36
	U	0.23		31	
4/8	K	0.20	0.58 (0.00)	34	35
	U	0.21		40	
5/8	K	0.20	0.56 (0.00)	31	44
	U	0.22		39	
6/8	K	0.19	0.53 (0.00)	33	46
	U	0.23		41	
7/8	K	0.15	0.52 (0.00)	27	49
	U	0.22		45	

TABLE A.5.a. Source Functions in the Natural-Event Experiment (Real Payment; 29 Subjects)

P	Source	Median	Mean	Std	[25%, 75%]	<i>t</i> -tests $w_s(p)=p$	Number of subjects with $w_s(p)<p$
1/8	CAC40	0.19	0.23	0.21	[0.07, 0.31]	0.01	12
	Paris temp.	0.18	0.27	0.24	[0.08, 0.43]	0.00	10
	Foreign temp.	0.16	0.22	0.21	[0.07, 0.26]	0.03	11
	Risk	0.23	0.29	0.22	[0.14, 0.37]	0.00	7
2/8	CAC40	0.28	0.34	0.25	[0.14, 0.56]	0.06	13
	Paris temp.	0.35	0.37	0.26	[0.16, 0.52]	0.02	11
	Foreign temp.	0.20	0.29	0.24	[0.15, 0.40]	0.43	17
	Risk	0.34	0.39	0.23	[0.21, 0.52]	0.00	9
4/8	CAC40	0.42	0.48	0.28	[0.25, 0.76]	0.76	18
	Paris temp.	0.47	0.50	0.26	[0.33, 0.70]	0.95	16
	Foreign temp.	0.45	0.46	0.26	[0.26, 0.66]	0.38	16
	Risk	0.53	0.54	0.18	[0.40, 0.68]	0.22	12
6/8	CAC40	0.59	0.59	0.27	[0.33, 0.80]	0.00	20
	Paris temp.	0.66	0.64	0.25	[0.45, 0.85]	0.03	17
	Foreign temp.	0.64	0.63	0.24	[0.43, 0.83]	0.01	18
	Risk	0.75	0.72	0.18	[0.64, 0.86]	0.35	15
7/8	CAC40	0.77	0.71	0.25	[0.53, 0.95]	0.00	19
	Paris temp.	0.78	0.75	0.24	[0.70, 0.95]	0.01	18
	Foreign temp.	0.78	0.76	0.19	[0.67, 0.91]	0.00	19
	Risk	0.88	0.83	0.16	[0.75, 0.94]	0.10	14

TABLE A.5b. Source Functions in the Natural-Event Experiment (Real Payment; 29 Subjects) – Further Tests and Statistics

P	Source	ANOVA (including risk)		ANOVA (excluding risk)		Correlation with risk (p-value)	<i>t</i> -tests $w_s(p) = w_{risk}(p)$	Number of subjects with $w_s(p) < w_{risk}(p)$
		p-value	HF p-value	p-value	HF p-value			
1/8	CAC40	0.01	0.02	0.08	0.08	0.94 (0.00)	0.00	21
	Paris temp.					0.85 (0.00)	0.50	17
	Foreign temp.					0.73 (0.00)	0.02	19
2/8	CAC40	0.01	0.01	0.04	0.04	0.76 (0.00)	0.18	20
	Paris temp.					0.82 (0.00)	0.43	16
	Foreign temp.					0.73 (0.00)	0.00	21
4/8	CAC40	0.11	0.12	0.43	0.42	0.60 (0.00)	0.18	19
	Paris temp.					0.76 (0.00)	0.24	17
	Foreign temp.					0.78 (0.00)	0.01	20
6/8	CAC40	0.00	0.00	0.27	0.27	0.64 (0.00)	0.00	21
	Paris temp.					0.70 (0.00)	0.03	18
	Foreign temp.					0.74 (0.00)	0.00	18
7/8	CAC40	0.01	0.01	0.33	0.33	0.47 (0.01)	0.01	18
	Paris temp.					0.79 (0.00)	0.01	15
	Foreign temp.					0.67 (0.00)	0.02	18

TABLE A.6a. Source Functions in the Natural-Event Experiment (Hypothetical Payment; 29 Subjects)

P	Source	Median	Mean	Std	[25%,75%]	<i>t</i> -tests $w_s(p)=p$	Number of subjects with $w_s(p)<p$
1/8	CAC40	0.14	0.18	0.17	[0.06, 0.23]	0.10	14
	Paris temp.	0.16	0.21	0.19	[0.03, 0.34]	0.02	13
	Risk	0.22	0.22	0.13	[0.12, 0.31]	0.00	8
2/8	CAC40	0.31	0.34	0.19	[0.15, 0.46]	0.02	12
	Paris temp.	0.25	0.30	0.22	[0.11, 0.48]	0.27	15
	Risk	0.34	0.35	0.18	[0.23, 0.49]	0.01	9
4/8	CAC40	0.52	0.52	0.20	[0.37, 0.69]	0.57	10
	Paris temp.	0.47	0.46	0.26	[0.24, 0.70]	0.41	16
	Risk	0.53	0.52	0.15	[0.44, 0.65]	0.42	11
6/8	CAC40	0.78	0.70	0.20	[0.59, 0.85]	0.17	14
	Paris temp.	0.68	0.67	0.23	[0.52, 0.88]	0.08	16
	Risk	0.78	0.75	0.14	[0.71, 0.83]	0.95	12
7/8	CAC40	0.88	0.82	0.16	[0.74, 0.92]	0.06	14
	Paris temp.	0.87	0.80	0.18	[0.72, 0.93]	0.04	15
	Risk	0.89	0.85	0.13	[0.81, 0.93]	0.27	12

TABLE A.6b. Source Functions in the Natural-Event Experiment (Hypothetical Payment; 29 Subjects) – Further Tests and Statistics

P	Source	ANOVA (including risk)		<i>t</i> -tests $w_{CAC40}(p)=$ $w_{Paris}(p)$	Correlation with risk (p-value)	<i>t</i> -tests $w_s(p)=$ $w_{risk}(p)$	Number of subjects with $w_s(p)<$ $w_{risk}(p)$
		p- value	HF p-value				
1/8	CAC40	0.40	0.40	0.27	0.35 (0.06)	0.23	17
	Paris temp.				0.44 (0.02)		
2/8	CAC40	0.37	0.37	0.26	0.50 (0.01)	0.86	14
	Paris temp.				0.46(0.01)		
4/8	CAC40	0.21	0.21	0.21	0.52(0.00)	0.94	15
	Paris temp.				0.57(0.00)		
6/8	CAC40	0.08	0.08	0.49	0.65(0.00)	0.09	15
	Paris temp.				0.57(0.00)		
7/8	CAC40	0.09	0.10	0.32	0.68(0.00)	0.18	14
	Paris temp.				0.70(0.00)		

TABLE A.7. Insensitivity Indexes

Experiment	Ellsberg (66 subjects)		Natural-Event / Real Payment (29 subjects)				Natural-Event Hypothetical Payment (29 subjects)		
	K	U	CAC 40	Paris temp.	Foreign temp.	Risk	CAC 40	Paris temp.	Risk
Mean	0.19	0.31	0.41	0.39	0.29	0.30	0.19	0.22	0.17
Median	0.19	0.37	0.38	0.47	0.27	0.27	0.24	0.14	0.20
Std	0.27	0.31	0.32	0.34	0.33	0.29	0.31	0.31	0.19
[25%, 75%]	[0.02, 0.35]	[0.08, 0.52]	[0.18, 0.65]	[0.16, 0.65]	[0.06, 0.55]	[0.09, 0.51]	[-0.06, 0.41]	[-0.01, 0.48]	[0.01, 0.28]
<i>t</i> -test $a_s=0$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of subjects with $a_s>0$	50	52	25	24	23	27	18	21	22
<i>t</i> -test $a_s=a_{\text{risk}}$ (or a_K)		0.00	0.07	0.05+	0.87		0.73	0.35	
Number of subjects with $a_s>a_{\text{risk}}$ (or a_K)		42	14	19	17		14	17	
ANOVA	p- value		0.05–				0.62		
	HF p- value		0.05+				0.62		
ANOVA (without risk)	p- value		0.05+				0.52 (paired <i>t</i> -test)		
	HF p- value		0.06						
Correlation with risk (urn K) (p-value)		0.37 (0.00)	0.50 (0.01)	0.72 (0.00)	0.58 (0.00)		0.36 (0.05+)	0.40 (0.03)	
Correlation between a_s and b_s (p-value)	-0.29 (0.02)	0.00 (0.98)	0.20 (0.30)	-0.01 (0.97)	-0.08 (0.67)	-0.35 (0.06)	0.01 (0.97)	-0.09 (0.63)	-0.16 (0.40)
<i>t</i> -test between Hypothetical and Real Payment			0.01	0.05+		0.05–			

TABLE A.8. Pessimism Indexes

Experiment	Ellsberg		Natural-Event / Real Payment				Natural-Event Hypothetical Payment		
	K	U	CAC 40	Paris temp.	Foreign temp.	Risk	CAC 40	Paris temp.	Risk
Mean	-0.08	0.04	0.05	-0.01	0.06	-0.11	-0.02	0.02	-0.07
Median	-0.04	0.04	0.08	0.06	0.06	-0.03	-0.01	0.03	-0.10
Std	0.33	0.40	0.45	0.45	0.39	0.34	0.29	0.36	0.25
[25%, 75%]	[-0.30, 0.09]	[-0.20, 0.31]	[-0.29, 0.49]	[-0.30, 0.26]	[-0.14, 0.34]	[-0.34, 0.13]	[0.25, 0.16]	[-0.22, 0.35]	[-0.28, 0.02]
<i>t</i> -test $a_s=0$	0.06	0.40	0.51	0.87	0.40	0.11	0.70	0.72	0.13
Number of subjects with $a_s>0$	27	37	13	16	16	9	17	15	13
<i>t</i> -test $a_s=a_{\text{risk}}$ (or a_K)		0.01	0.00	0.04	0.00		0.23	0.07	
Number of subjects with $a_s>a_{\text{risk}}$ (or a_K)		40	23	18	20		20	20	
ANOVA	p-value		0.00				0.13		
	HF p-value		0.00				0.13		
ANOVA (without risk)	p-value		0.20				0.35		
	HF p-value		0.20						
Correlation with risk (p-value)		0.53 (0.00)	0.78 (0.00)	0.86 (0.00)	0.82 (0.00)		0.65 (0.00)	0.63 (0.00)	
<i>t</i> -test between Hypothetical and Real Payment			0.45	0.72		0.68			

A.8. Individual Parameters

TABLE A.9. Individual Parameters of the Utility Function and of the Prelec Weighting Function, and Individual Indexes – Ellsberg Experiment

	Power utility		Prelec weighting function				Indexes			
	ρ		α		β		a		b	
	K	U	K	U	K	U	K	U	K	U
1	0.75	0.95	0.70	0.34	1.41	1.50	0.21	0.56	0.26	0.44
2	0.68	0.44	1.05	0.63	0.55	0.42	0.16	0.48	-0.32	-0.43
3	1.67	1.70	1.84	0.97	1.43	0.61	-0.38	0.11	-0.01	-0.28
4	0.90	0.85	0.84	0.89	0.95	1.09	0.12	0.07	0.01	0.08
5	1.00	1.51	0.71	0.54	0.87	0.72	0.24	0.44	-0.04	-0.12
6	1.05	1.00	1.00	1.36	0.87	1.20	0.00	-0.17	-0.09	0.04
7	0.50	1.00	0.97	0.60	0.57	0.70	0.19	0.37	-0.30	-0.15
8	1.11	1.37	0.77	0.35	1.31	1.65	0.13	0.58	0.21	0.50
9	1.00	1.02	0.86	1.00	0.95	1.23	0.12	-0.03	0.00	0.11
10	2.10	1.23	0.53	0.48	1.31	1.07	0.35	0.42	0.28	0.16
11	1.35	7.46	0.71	1.05	0.70	2.01	0.26	-0.04	-0.18	0.36
12	1.14	1.16	0.77	0.69	0.69	0.91	0.19	0.26	-0.20	0.00
13	0.44	24.7	0.52	1.53	0.34	0.89	0.60	-0.11	-0.51	-0.04
14	0.99	1.00	0.81	0.84	0.68	1.19	0.20	0.08	-0.21	0.11
15	1.17	1.41	0.67	0.73	1.02	0.89	0.25	0.21	0.08	-0.02
16	0.15	0.86	1.32	1.41	0.23	1.30	0.42	-0.28	-0.66	0.06
17	1.08	0.98	0.62	0.79	0.88	0.65	0.32	0.26	-0.01	-0.22
18	0.76	0.18	0.44	0.49	0.44	0.16	0.62	0.82	-0.38	-0.74
19	1.47	2.04	0.57	0.01	1.91	1.90	0.35	1.01	0.51	0.70
20	1.05	0.60	0.94	1.50	0.39	0.25	0.31	0.41	-0.48	-0.59
21	2.71	4.25	0.70	0.43	0.62	1.88	0.28	0.46	-0.25	0.56
22	0.86	0.70	1.38	0.62	0.67	0.64	-0.08	0.40	-0.25	-0.20
23	1.24	0.55	0.70	0.78	1.05	0.38	0.22	0.48	0.08	-0.48
24	5.52	2.37	1.04	0.77	1.18	1.09	-0.08	0.16	0.07	0.10
25	0.74	1.08	0.88	0.63	0.64	0.63	0.18	0.39	-0.24	-0.21
26	0.90	1.63	0.49	0.68	0.96	1.01	0.43	0.24	0.07	0.06
27	0.94	1.00	1.10	1.15	0.93	1.21	-0.08	-0.15	-0.07	0.06
28	1.00	1.00	1.02	0.87	0.96	0.84	-0.03	0.11	-0.03	-0.09
29	0.79	0.15	0.76	0.53	0.58	0.08	0.29	0.87	-0.29	-0.87
30	3.89	0.94	1.62	0.74	1.01	1.07	-0.33	0.18	-0.10	0.10
31	3.22	2.51	3.03	0.53	9.63	2.20	-0.37	0.41	0.32	0.61
32	2.17	1.77	0.79	0.46	1.10	1.18	0.13	0.45	0.09	0.23
33	1.65	12.6	0.55	0.61	1.17	3.56	0.36	0.55	0.19	0.80
34	0.61	0.49	1.00	0.87	0.58	0.48	0.12	0.32	-0.31	-0.38
35	1.38	3.85	1.04	1.80	0.49	0.47	0.19	-0.06	-0.38	-0.38
36	0.67	2.09	1.11	1.98	0.37	0.44	0.28	-0.10	-0.50	-0.42
37	2.11	1.26	0.78	0.36	1.33	0.52	0.12	0.66	0.19	-0.28

38	0.85	1.96	0.93	1.04	0.69	1.48	0.15	-0.05	-0.19	0.20
39	1.04	0.94	1.08	1.06	0.82	1.03	-0.01	-0.02	-0.12	0.01
40	0.84	2.40	0.89	0.45	0.41	1.08	0.42	0.43	-0.43	0.18
41	3.30	6.13	1.12	0.58	2.00	4.22	-0.08	0.68	0.31	0.85
42	1.98	0.79	0.58	0.61	1.94	0.52	0.36	0.46	0.51	-0.31
43	1.30	2.58	0.48	0.46	1.01	2.12	0.43	0.54	0.12	0.60
44	1.51	2.10	1.31	0.46	0.68	2.04	-0.10	0.49	-0.24	0.59
45	1.07	0.86	1.17	0.64	1.04	0.64	-0.10	0.36	-0.03	-0.21
46	1.71	0.70	1.51	0.95	4.00	1.65	0.02	0.02	0.39	0.27
47	1.59	2.05	0.61	0.41	0.94	1.39	0.32	0.52	0.03	0.36
48	0.46	0.95	0.61	0.64	0.30	0.91	0.58	0.29	-0.56	0.01
49	4.91	2.25	0.96	0.37	8.13	2.10	0.68	0.56	0.87	0.64
50	5.22	2.65	1.67	1.61	0.95	0.84	-0.33	-0.29	-0.11	-0.17
51	0.92	1.29	0.89	0.33	0.90	2.23	0.11	0.65	-0.04	0.69
52	1.72	0.81	0.84	0.60	1.29	0.71	0.07	0.39	0.17	-0.13
53	0.87	0.98	0.53	0.61	0.44	0.94	0.57	0.31	-0.38	0.04
54	0.84	3.75	1.04	1.16	0.43	0.84	0.29	-0.01	-0.43	-0.09
55	0.87	0.75	0.64	0.34	0.97	1.15	0.29	0.57	0.05	0.25
56	3.19	2.15	1.84	1.14	2.19	1.03	-0.37	-0.12	0.21	-0.05
57	0.83	0.45	0.80	0.40	1.03	0.65	0.15	0.57	0.05	-0.15
58	0.09	0.98	0.70	0.65	0.08	0.81	0.86	0.31	-0.87	-0.07
59	0.26	0.02	1.39	0.51	0.15	0.01	0.55	0.98	-0.76	-0.98
60	2.01	1.59	0.77	0.81	0.99	1.57	0.17	0.09	0.03	0.31
61	1.15	1.01	0.91	0.45	1.11	0.72	0.04	0.52	0.07	-0.09
62	0.95	1.10	0.84	0.81	0.78	1.97	0.13	0.17	-0.13	0.42
63	0.16	0.21	0.56	0.35	0.15	0.25	0.81	0.79	-0.76	-0.61
64	0.73	2.18	1.53	1.76	0.55	1.53	-0.07	-0.37	-0.33	0.06
65	1.32	1.23	0.29	0.30	1.60	1.25	0.66	0.62	0.50	0.32
66	1.74	1.07	1.10	0.71	2.05	2.52	-0.08	0.36	0.35	0.58

TABLE A.10. Individual Parameters of the Utility Function and of the Prelec Weighting Function – Natural-Event Experiment

	Utility power	Prelec weighting function							
	ρ	α				β			
	Risk	CAC40	Paris temp.	Foreign temp.	Risk	CAC40	Paris temp.	Foreign temp.	Risk
Real Payment									
1	0.56	0.15	0.17	0.21	0.49	1.14	0.89	1.68	1.06
2	0.81	0.91	0.44	0.51	0.90	1.39	0.62	0.94	0.94
3	2.65	1.45	3.61	3.30	0.81	0.97	1.06	1.04	1.00
4	1.04	0.80	1.56	1.50	1.04	2.46	2.92	5.51	1.35
5	0.78	0.39	0.82	1.47	0.38	0.46	0.36	0.93	0.22
6	0.97	0.41	0.47	0.75	0.82	0.95	1.17	1.15	1.06
7	0.73	0.32	0.18	0.19	0.55	0.83	0.99	1.12	0.72
8	1.05	0.21	0.22	0.27	0.49	1.60	2.15	1.89	1.42
9	0.62	0.15	0.21	0.15	0.25	1.89	2.14	1.38	1.65
10	0.24	0.38	0.54	0.83	0.52	0.52	0.53	0.36	0.29
11	0.82	0.58	0.33	0.43	0.47	0.87	0.88	0.67	0.70
12	0.23	3.60	1.96	1.60	1.00	0.06	0.12	0.20	0.26
13	0.84	1.02	1.41	1.22	0.92	1.93	0.71	1.29	1.25
14	1.20	1.30	0.36	0.97	0.44	0.59	1.74	3.64	1.75
15	0.92	0.57	0.65	0.70	0.45	1.29	1.06	0.84	0.93
16	0.59	0.28	0.64	0.67	0.92	1.66	1.13	1.62	0.95
17	0.63	1.65	0.94	0.67	0.65	0.14	0.22	0.70	0.28
18	0.70	0.32	1.44	0.71	1.07	1.13	0.78	1.54	0.71
19	0.50	0.22	0.55	0.70	1.01	1.57	1.57	1.11	0.63
20	0.75	4.07	0.78	1.07	1.10	0.33	0.56	0.74	0.51
21	0.40	1.62	0.73	1.08	0.74	0.29	0.14	0.20	0.50
22	1.11	0.84	0.67	0.80	0.84	1.20	1.37	1.32	1.06
23	2.00	0.71	1.17	1.51	1.83	3.02	2.83	3.81	1.66
24	0.51	1.96	0.95	1.10	0.92	0.29	0.61	1.03	0.69
25	0.08	0.56	1.73	2.85	0.69	0.10	0.04	0.01	0.11
26	1.13	0.73	0.75	0.84	0.91	2.36	1.25	1.24	1.44
27	2.00	0.13	0.36	1.69	0.39	2.90	3.45	15.95	1.15
28	0.28	1.03	0.38	0.31	0.90	0.55	0.69	0.82	0.48
29	0.51	0.98	2.50	1.51	1.21	1.05	0.24	0.73	0.46
Hypothetical Payment									
1	0.56	0.94	0.81		1.07	0.50	0.30		0.50
2	1.03	1.41	0.87		0.77	0.73	1.54		0.92
3	1.63	0.63	0.85		0.68	1.21	2.19		1.94
4	0.89	0.44	1.41		0.86	0.33	0.45		1.06
5	1.32	1.02	2.97		0.94	1.63	3.64		0.48
6	0.55	0.57	0.98		0.75	0.79	0.80		0.80
7	0.71	0.65	1.14		1.45	0.38	0.30		0.59
8	3.29	1.37	2.14		1.18	1.21	13.9		2.17
9	0.43	0.27	0.25		0.94	1.37	1.30		1.00

10	1.68	1.59	0.62		0.86	0.78	0.73		0.56
11	0.42	0.52	0.30		0.31	0.84	0.83		0.68
12	1.24	0.64	1.00		0.70	1.26	1.05		0.75
13	1.01	0.92	0.47		1.00	1.27	0.61		1.03
14	1.71	1.80	2.28		1.01	0.73	3.13		0.62
15	0.92	1.12	1.24		0.75	0.97	3.02		0.58
16	0.22	0.35	0.30		0.82	0.57	0.54		0.43
17	1.02	0.28	0.39		0.35	1.55	2.23		1.75
18	0.96	0.36	0.49		0.86	1.02	1.59		0.96
19	0.79	1.21	0.99		1.14	0.89	0.71		0.66
20	0.70	1.63	1.04		1.12	0.47	0.41		0.46
21	0.83	3.16	2.15		1.10	5.49	0.68		1.21
22	0.66	1.00	2.09		0.93	0.53	0.21		0.89
23	0.70	0.87	1.02		0.93	0.45	0.30		0.41
24	0.64	0.56	0.31		0.63	1.72	1.99		1.31
25	1.77	1.67	1.38		1.06	12.5	3.03		2.11
26	1.01	3.87	3.31		0.75	0.08	71.15		0.58
27	0.97	1.05	1.12		1.20	0.88	0.83		0.82
28	0.59	0.86	0.57		0.80	1.15	1.11		0.77
29	0.96	1.48	1.13		1.35	1.36	1.22		1.18

TABLE A.11. Individual Indexes – Natural-Event Experiment

	Indexes							
	a				b			
	CAC40	Paris temp.	Foreign temp.	Risk	CAC40	Paris temp.	Foreign temp.	Risk
Real Payment								
1	0.80	0.78	0.75	0.42	0.30	0.12	0.55	0.13
2	0.02	0.55	0.41	0.09	0.19	-0.19	0.06	-0.01
3	-0.08	-0.40	-0.31	0.12	0.04	-0.04	0.01	0.02
4	0.25	-0.16	0.07	-0.04	0.48	0.29	0.46	0.15
5	0.65	0.47	-0.17	0.79	-0.35	-0.48	-0.09	-0.65
6	0.50	0.43	0.18	0.13	0.08	0.21	0.11	0.04
7	0.62	0.77	0.75	0.41	0.02	0.19	0.28	-0.12
8	0.76	0.78	0.70	0.42	0.52	0.69	0.60	0.33
9	0.84	0.77	0.81	0.70	0.65	0.70	0.44	0.52
10	0.63	0.50	0.46	0.68	-0.28	-0.30	-0.49	-0.56
11	0.35	0.61	0.54	0.50	-0.01	0.06	-0.14	-0.12
12	0.41	0.53	0.45	0.54	-0.65	-0.72	-0.62	-0.60
13	-0.03	-0.09	-0.14	0.01	0.27	-0.17	0.06	0.13
14	0.15	0.56	0.27	0.46	-0.19	0.52	0.57	0.49
15	0.33	0.26	0.27	0.46	0.23	0.09	-0.04	0.07
16	0.66	0.26	0.28	0.04	0.51	0.14	0.32	-0.03
17	0.57	0.60	0.35	0.62	-0.72	-0.65	-0.14	-0.59
18	0.60	-0.15	0.17	0.06	0.24	-0.16	0.31	-0.17
19	0.75	0.40	0.21	0.12	0.50	0.35	0.09	-0.25
20	-0.19	0.28	0.03	0.16	-0.30	-0.30	-0.16	-0.34
21	0.26	0.76	0.56	0.40	-0.51	-0.78	-0.68	-0.34
22	0.07	0.21	0.12	0.07	0.12	0.25	0.19	0.05
23	0.38	-0.01	-0.08	-0.38	0.64	0.41	0.40	0.09
24	0.20	0.17	-0.05	0.14	-0.43	-0.26	0.00	-0.20
25	0.88	0.85	0.90	0.82	-0.83	-0.89	-0.93	-0.83
26	0.32	0.14	0.07	0.02	0.50	0.18	0.16	0.22
27	0.92	0.75	0.43	0.53	0.86	0.86	0.65	0.22
28	0.20	0.58	0.63	0.27	-0.29	-0.12	0.01	-0.38
29	-0.02	0.15	-0.13	0.22	-0.02	-0.40	-0.17	-0.35
Hypothetical Payment								
1	0.26	0.52		0.22	-0.35	-0.56		-0.33
2	-0.06	0.08		0.18	-0.15	0.25		-0.01
3	0.24	0.14		0.25	0.20	0.45		0.45
4	0.68	0.14		0.09	-0.52	-0.35		0.05
5	-0.05	-0.37		0.31	0.22	0.11		-0.36
6	0.39	0.12		0.24	-0.06	-0.09		-0.09
7	0.52	0.39		-0.06	-0.47	-0.55		-0.28
8	-0.19	0.01		-0.09	0.08	0.51		0.34
9	0.67	0.69		0.02	0.39	0.36		-0.02
10	-0.16	0.36		0.27	-0.10	-0.13		-0.28
11	0.41	0.64		0.66	-0.01	0.03		-0.11

12	0.26	-0.01		0.27	0.19	0.02		-0.13
13	0.02	0.52		0.00	0.15	-0.21		0.01
14	-0.27	-0.31		0.12	-0.16	0.16		-0.25
15	-0.04	0.06		0.30	-0.01	0.33		-0.27
16	0.65	0.70		0.38	-0.23	-0.25		-0.41
17	0.64	0.62		0.56	0.47	0.64		0.53
18	0.54	0.44		0.12	0.15	0.40		0.00
19	-0.15	0.09		0.10	-0.11	-0.19		-0.19
20	-0.01	0.28		0.22	-0.34	-0.45		-0.38
21	-0.32	-0.29		-0.08	0.15	-0.18		0.08
22	0.22	0.38		0.07	-0.31	-0.49		-0.06
23	0.37	0.47		0.37	-0.38	-0.55		-0.43
24	0.36	0.66		0.26	0.42	0.62		0.23
25	0.41	-0.06		-0.04	0.53	0.35		0.31
26	0.35	-0.01		0.30	-0.42	0.38		-0.28
27	-0.01	-0.03		-0.03	-0.07	-0.10		-0.10
28	0.07	0.34		0.20	0.08	0.14		-0.12
29	-0.23	-0.08		-0.21	0.05	0.06		0.00

REFERENCES FOR WEB APPENDIX

- Abdellaoui, Mohammed, Aurélien Baillon, Lætitia Placido, and Peter P. Wakker (2011), “The Rich Domain of Uncertainty: Source Functions and Their Experimental Implementation,” *American Economic Review* 101, 695–723.
- Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström (2006), “Elicitation Using Multiple Price List Formats,” *Experimental Economics* 9, 383–405.
- Armantier, Olivier (2006), “Do Wealth Differences Affect Fairness Considerations,” *International Economic Review* 47, 391–429.
- Baillon, Aurélien (2008), “Eliciting Subjective Probabilities through Exchangeable Events: an Advantage and a Limitation,” *Decision Analysis* 5, 76–87.
- Bostic, Raphael, Richard J. Herrnstein, and R. Duncan Luce (1990), “The Effect on the Preference-Reversal Phenomenon of Using Choice Indifferences,” *Journal of Economic Behavior and Organization* 13, 193–212.
- Camerer, Colin F. and Robin M. Hogarth (1999), “The Effects of Financial Incentives in Experiments: A Review and Capital-Labor-Production Framework,” *Journal of Risk and Uncertainty* 19, 7–42.
- Choi, Syngjoo, Raymond Fisman, Douglas Gale, and Shachar Kariv (2007), “Consistency and Heterogeneity of Individual Behavior under Uncertainty,” *American Economic Review* 97, 1921–1938.
- Harrison, Glenn W. (1986), “An Experimental Test for Risk Aversion,” *Economic Letters* 21, 7–11.
- Harrison, Glenn W., Morten I. Lau, and E. Elisabet Rutström (2007), “Estimating Risk Attitudes in Denmark: A Field Experiment,” *Scandinavian Journal of Economics* 109, 341–368.
- Harrison, Glenn W., Morten I. Lau, and Melonie B. Williams (2002), “Estimating Individual Discount Rates in Denmark: A Field Experiment,” *American Economic Review* 92, 1606–1617.
- Harrison, Glenn W. and E. Elisabet Rutström (2008), “Risk Aversion in the Laboratory.” In Jim C. Cox and Glenn W. Harrison (eds.), *Risk Aversion in Experiments*, Research in Experimental Economics Vol. 12, Bingley, UK.

- Hogarth, Robin M. and Hillel J. Einhorn (1990), "Venture Theory: A Model of Decision Weights," *Management Science* 36, 780–803.
- Holt, Charles A. and Susan K. Laury (2002), "Risk Aversion and Incentive Effects," *American Economic Review* 92, 1644–1655.
- Keren, Gideon B. and Léonie E.M. Gerritsen (1999), "On the Robustness and Possible Accounts of Ambiguity Aversion," *Acta Psychologica* 103, 149–172.
- Myagkov, Mikhail G. and Charles R. Plott (1997), "Exchange Economies and Loss Exposure: Experiments Exploring Prospect Theory and Competitive Equilibria in Market Environments," *American Economic Review* 87, 801–828.
- Noussair, Charles, Stephane Robbin, and Bernard Ruffieux (2004), "Revealing Consumers' Willingness-to-Pay: A Comparison of the BDM Mechanism and the Vickrey Auction," *Journal of Economic Psychology* 25, 725–741.
- Prelec, Drazen (1998), "The Probability Weighting Function," *Econometrica* 66, 497–527.
- Smith, Vernon L. (1969), "Measuring Nonmonetary Utilities in Uncertain Choices: The Ellsberg Urn," *Quarterly Journal of Economics* 83, 324–329.
- van de Kuilen, Gijs and Peter P. Wakker (2011), "The Midweight Method to Measure Attitudes towards Risk and Ambiguity," *Management Science* 57, 582–598.
- Wilcox, Nathaniel T. (2008), "Stochastic Models for Binary Discrete Choice under Risk: A Critical Primer and Econometric Comparison." In James C. Cox & Glenn W. Harrison, (Eds), *Risk Aversion in Experiments*; Research in Experimental Economics 12, 197–292, Emerald, Bingley, UK.
- Winkler, Robert L. (1991), "Ambiguity, Probability, and Decision Analysis," *Journal of Risk and Uncertainty* 4, 285–297.