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Abstract: This paper presents the results of two experiments testing reaction to risk and uncertainty of a sample of 66 Italian university students. Risky prospects were based on games of chance, while uncertain lotteries were based on the forthcoming results of either the May 2001 Italian general political election or the June 2004 election for the European Parliament. We computed decision weights for risk and uncertainty; we also collected data as regards the subjects' degree of belief, expressed by probability judgements, for the same uncertain events. Our results show that the subjects' behaviour is consistent with expected utility theory as regards risk, but not under uncertainty. In particular, our subjects show a strong superadditivity in the decision weights and the possibility effect (lower subadditivity) is stronger than the certainty effect (upper subadditivity). There is also evidence that emotions, actual competence and confidence positively affect the possibility effect, whereas they do not have any influence on the certainty effect, reinforcing the lack of symmetry between the two effects.

Keywords: Uncertainty, Subadditivity, Emotions, Competence, Confidence.

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1. Introduction

The aim of this paper is that of presenting two experiments based on real election outcomes for testing whether there is any role played by both emotions and competence in assessing probabilities under uncertainty. In particular, the paper wants to test the different role that self-assessed competence (i.e. "confidence") and actual competence may actually play in inducing preference for uncertainty and how they both interact with self-reported emotions. Moreover, in the experiments reported in this paper, psychological questions on subjects' emotional involvement are introduced in order to test whether upper subadditivity (i.e. the "certainty effect") or lower subadditivity (i.e. the "possibility effect", see Tversky and Fox, 1995) are influenced by emotions in addition to competence, which is the second original contribution of this work.[1]

Recent and less recent developments of the theoretical literature on decision making under risk and uncertainty have elaborated new models that are better than Expected Utility (EU) and Subjective Expected Utility (SEU), at least from a mere descriptive point of view, for evaluating decisions taken under these conditions: experiments have in fact shown that violations of EU are a pervasive phenomenon. Most of these theoretical developments allow for both non linearity in probabilities (see e.g. Kahneman and Tversky, 1979) and the use of decisions weights under risk. Under uncertainty, the majority of the models generally allows for subadditivity in probabilities (such that the sum of probabilities for complementary events is less than one: see Tversky and Kahneman, 1992, Tversky and Wakker, 1995, and Schmeidler, 1989). However, several experiments have shown that the individual probability judgements under uncertainty might exhibit superadditivity as well as subadditivity in probabilities (see for example Heath and Tversky, 1991, Di Mauro, 2002, Di Mauro and Maffioletti, 2001, 2002, 2004; Keppe and Weber, 1995, Kilka and Weber, 2001, and Maffioletti and Santoni, 2005): in other words, subjects might exhibit love as

[1] One accepted result in the theoretical and experimental literature on lower and upper subadditivity, thus on the shape of the weighting function, is that the certainty effect has the same weight as the possibility effect, see for example Tversky and Fox (1995) and Abdellaoui et al. (2005). This paper shows that these effects can be influenced by psychological variables in different ways, implying that they might not be equally important.

well as aversion to uncertainty. Instead of using the Ellsberg's urn for simulating real uncertainty, a few of the above mentioned experiments have used real events such as political elections, football matches or variation in the stock exchange indexes. In such experiments, there is evidence that uncertainty partially depends on the level of self-assessed competence of the experimental subjects on the relevant topic: when subjects feel they are competent on the topic they are betting on, they often prefer to bet on a judgmental probability than on an equivalent risky probability, namely they show preference for uncertainty in such a case (see e.g. Heath and Tversky, 1991, and Keppe and Weber, 1995). However, events such as political elections or football games are very often a source of highly emotional involvement. In particular, emotions might have an influence on the shape of the weighting function or, more likely, on the shape of the utility function. Emotions might interact with competence in determining probabilities as well as utility assessments.

Only recently economists have started evaluating the role emotions might have in economics (see Elster, 1998, for a survey). The study of emotions in economic choices has taken at least three directions. First, the measurement of the existence and the direction of causality of a relationship between self-reported happiness, or life satisfaction, and measures of economic performance (see Frey and Stutzer, 2002, for a survey).[2] Secondly, the investigation of the role of emotions[3] in explaining "non rational behaviour" in economic choices (see Camerer and Loewenstein, 2004, for a survey):[4] the certainty and the possibility effect, reactions to risk and uncertainty, the presence of

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[2] Happiness seems to be positively related to the mental or physical health of a person, but not necessarily to the length of her life, or to her absolute or relative income level. A few experiments have been run on this topic: for example, Charness and Grosskopf (2001) find that, while there is no strong correlation between happiness and concern for relative payoffs, there is a correlation between the willingness to lower another person's payoff below one's own ("competitive preferences", using their words) and unhappiness.

[3] Happiness cannot be defined as a proper emotion from a psychological point of view, but it is likely to be something more complex. Proper emotions are: social emotions like anger, hatred, guilt, shame, pride, pridefullness, admiration and liking; counterfactual emotions like regret, disappointment, elation; emotions that are generated by what can happen, like fear and hope, or by what it has already happened, like joy and grief. Emotions can be driven by the others, like envy or jealously. Elster (1998) mentions also what he defines as border cases, such as surprise, love, disgust, enjoyment, worry, boredom and frustration.

[4] Emotions have played traditionally a role in a few of the alternative models to EU, but such a role has been auxiliary until now. For example, according to Regret Theory (see Loomes and Sugden, 1982) and Disappointment Theory (see Bell, 1982) people choose according to emotions like regret, rejoicing or disappointment, while aversion to uncertainty has been considered to be driven by fear, and proneness to uncertainty by hope (see Viscusi and Chesson, 1999, for

regret or disappointment in decision making, the endowment effect, fairness and trust in game theory and labour economics can all be considered good examples of this research agenda.[5] Lastly, the measurement of the brain activities by considering the area of the brain that is activated when taking economic decisions involving emotions (i.e. "activation"). For example, Bechara et al. (1997) suggest that emotions may reside in the ventromedial prefrontal cortex and that this part of the brain is activated when subjects are taking decisions under uncertainty (as in the Ellsberg Paradox). Similarly, Camille et al. (2004) and Coricelli et al. (2005) show the involvement of the orbitofrontal cortex of subjects taking decision under risk in which they experience regret. Other studies try to measure emotions with simpler (and less costly) devices than the use of functional magnetic resonance imaging: in experiments on the ultimatum and the power-to-take games, Bosman et al. (2001) and Bosman and van Winden (2002) show that emotions drive, for example, the rejection of an unfair offer by using the skin conductancy method, while Lerner et al. (2004) show that the endowment effect can be influenced by incidental emotions provoked by the experimenters (i.e. emotions induced by a prior irrelevant situation, such as the vision of a film clip). In particular, Rottenstreich and Hsee (2001) show that weighting functions under risk might be different when affect rich or affect poor outcomes are involved (e.g. a $100 voucher for paying a bill is different from a $100 voucher to be used for a meal for two in a nice romantic restaurant).

This paper is more related to the second stream of the economic literature. By integrating the experimental methodological approaches of economic and psychological decision theories, this paper investigates the role of emotions in both the assessment of probabilities, and the valuation of outcomes, and the decision-making under uncertainty. This paper uses choices between gambles with real money at stake, as a typical methodology of experimental economics, while introducing

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experimental evidence). More recently, Caplin and Leahy (2001) have developed a theory in which agents experience anticipate feelings prior to the resolution of uncertainty: they might feel anxiety or pleasure and their feelings will determine their reaction to uncertainty and consequently their actions or the timing of their action (for example, they might decide to postpone their actions).

[5] "Most economic theory minimises the influence of human emotions and assumes that what people believe and choose follows rationality principles", see Camerer (2003: 1673).

psychological variables through self-assessment, as in most psychology works. Moreover, the context of our experiments is one of political elections, which was chosen for both its emotional content and its similarity with the context of Heath and Tversky's (1991) seminal work.[6]

The plan of the paper is a follows. Section 2 presents the experiments and elaborates the data for decision weights and judged probabilities. Section 3 tests for the presence of emotional involvement, competence and confidence effects. Section 4 considers tests for bounded subadditivity under uncertainty and how this may be affected by emotions, competence and confidence. Section 5 concludes.

2. The experiments

These experiments were designed to test whether and to what extent individual attitudes to ambiguity depend on self-reported emotions and or actual or self-assessed competence. If emotions interact with competence in determining subjects' certainty equivalents, an experimenter might mistakenly identify an effect of competence where there is actually emotional involvement, thus wrongly identifying non linearity of the weighting function where there is actually non linearity of the utility function. The experimental design partially follows Tversky and Fox (1995), Fox, Rogers and Tversky (1996) and Maffioletti and Santoni (2005) as regards subjects' utility functions and probability estimates. However, our experiment introduces psychological questions on subjects' emotional involvement for testing whether upper or lower subadditivity is influenced by emotions in addition to competence (see sections 3, 4 below). Subjects were in fact asked questions related to the kind of emotions they felt in case of a particular resolution of the uncertain event.

We run two experiments. In the first experiment, 35 students (23 males and 12 females, median age 25 years old) were recruited in the Faculty of Political Science at the University of Milan. In the second experiment, the participants were 31 students (17 males and 14 females,

[6] The study of emotion in politics is an active area of research in political science (see Marcus, 2000, for a survey), but this paper does not consider such a literature. Moreover, this paper does not manipulate emotions, as for example in

median age 23 years old) in the Faculty of Political Science at the University of Eastern Piedmont in Alessandria. Both universities are located in the Italian North-West. All the participants were volunteers who chose to participate in a study on decision making. Subjects were asked to evaluate a questionnaire that was composed of about forty questions.[7] The questions were given in random order to the subjects and they were randomised individually.

The questionnaire was composed of two parts. In the first part, subjects were initially asked to match risky prospects, described in terms of rolling a dice, with two positive outcomes. Then, they were asked to price risky prospects, described in terms of a random draw of a single ball from an urn containing ten balls, with one single positive outcome. The first set of questions allowed us to assess subjects' utility functions, while the second set of questions was designed for assessing their probability functions under risk. In the second part of the questionnaire, the subjects were asked to price uncertain prospects: in the Milan experiment, these referred to the proportion of votes the Casa delle Libertà (House of Liberties) coalition[8] was forecasted to obtain in the forthcoming Italian general political election of May 2001, while in the Alessandria experiment they were asked a corresponding forecast for the Forza Italia party as regards the European parliamentary elections of June 2004.

Three questions were aimed at measuring the subjects' emotional states with respect to an election outcome: in both experiments, the subjects had to rank on a scale between zero and ten both their "negative emotional involvement", and their "positive emotional involvement", and their "degree of satisfaction" with respect to an electoral victory of either the Casa delle Libertà in the Milan experiment or Forza Italia in the Alessandria experiment, zero being the point of lower emotional involvement (i.e. of neutral feeling). These alternative ways of measuring emotions in terms of their psychological "valence" (namely, the degree of subjective feelings of pleasure or pain

Lerner et al. (2004), but it simply tries to measure the role played by the self-assessed emotional involvement attached to the states of the world used in our lotteries.

7 The questionnaires are available from the authors upon request.

associated with them) are consistent with a view of emotions as physic costs or benefits that enter into the subject's utility functions as separate arguments alongside with money (see Elster, 1998: 51-64 for a critical assessment of such an approach).[9]

One additional question was designed to measure the "degree of information and competence" in politics. In the Milan experiment, subjects were asked to report, on a scale between zero and ten, their self-assessed degree of competence. However, in the Alessandria experiment they had to answer to ten questions regarding Italian and European politics (see section 2.2.4 below), from which we computed, on a scale between zero and ten, their actual degree of competence in politics. Several authors (see for example Kilka and Weber, 2001) have argued that competence induces to overestimate the probability of a monetary gain in experiments with ambiguous prospects. This hypothesis will be tested in section 2.3 below.[10] Moreover, we wanted also to check whether self-assessed competence (namely, confidence) makes any difference as compared to actual or effective competence in evaluating ambiguous prospects.

In the Milan experiment, participants received a 2,000 Italian lire (about 1 euro) instant lottery ticket for participating in one 1-hour session. At the end of the experiment, four subjects were chosen at random; a week later, they played two of the lotteries for real according to their answers and the Italian general election outcome, each lottery giving the possibility of winning up to 120,000 Italian lire (about 60 euros; the average monthly Italian salary is 1,000 euros). The average payment for these subjects was 110,000 Italian lire (about 55 euros). In the Alessandria

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8 The coalition was composed of the following centre-right parties: Forza Italia, Alleanza Nazionale, Biancofiore CCD-CDU, and Lega Lombarda.

9 See Kahneman et al. (2004: 430-431) for similar methods of eliciting subjects' feelings that however involve a retrospective report on an emotional state.

10 These psychological questions were all based on subjects' self assessment. While competence can be measured by direct testing rather than self assessment, this is very difficult for emotions and requires sophisticated technical equipment (e.g. electromyographs for measuring facial muscles, brian magnetic resonance imaging, skin conductancy methods). It could be argued that subjects might not be very good in forecasting their own emotions or that their anticipated feelings may differ from their actual feelings due to the workings of an "aspiration treadmill" (namely, the pain associated to an election outcome is relative to expectations, and expectations are likely to adjust over time, as long as people eventually go on with their lives, see Kahneman et al., 2004). Such arguments are however irrelevant in our case. In order to test the effect of emotions in assessing probabilities under uncertainty, we are interested in individuals' anticipated emotions: it is irrelevant for us what subjects feel once uncertainty is resolved.

experiment, the incentive mechanism was the same, but since we moved from the Italian lira to the euro, the premium was 60 euros for each lottery. Again, at the end of the experiment, four subjects were chosen at random; a week later, they played two of the lotteries for real according to their answers and the European parliamentary election outcome. Students in Alessandria were luckier than their Milan colleagues, since they received an average payment of 104 euros.

2.1. Risky prospects under a linear value function

The first part of the questionnaire was designed to measure subjects' value functions and their attitudes towards risky choices in games of chance. A set of *matching questions* asked the subjects to compare complete and incomplete prospects: by throwing a fair six-sided dice, in the Milan experiment the subjects could win 120,000 liras (60 euros in the Alessandria experiment) if number 1 was landed, 60,000 Italian liras (30 euros in Alessandria) if number 2 came out, and nothing otherwise. This complete prospect had to be compared with an incomplete prospect B, paying X Italian lire if number 1 was landed, 30,000 Italian liras if number 2 was landed instead, and nothing otherwise; in the Alessandria experiment the incomplete prospect was paying X euros if number 1 was landed, 12 euros if number 2 was landed instead, and nothing otherwise. The subjects were asked to state the sum of money X making them indifferent between playing the lottery A and B for real. Similarly, the subjects had to compare a complete lottery C, paying 110,000 lire (55 euros in the Alessandria experiment) if number 1 came out, 70,000 lire (35 euros) if number 2 was landed, and nothing otherwise; with an incomplete lottery D, paying X liras (euros) with number 1 and 40,000 liras (20 euros) with number 2 being landed, and paying nothing otherwise.

The data show that the median value of X for both prospects (A v. B and C v. D) was equal to the one making the lotteries indifferent in expected value (X=150,000 Italian liras for A v. B and X=140,000 liras for C v. D in the Milan experiment; X =78 euros for A v. B and X=70 euros for C

v. D in the Alessandria experiment).[11] We interpret these results as evidence of a linear value function for monetary gains. Therefore, we shall assume linearity in the analysis that follows.

Under the assumption of a linear value function, the set of pricing questions designed allows us to calculate each subject's decision weights at different probability levels. The procedure is as follows (see Fox et al. 1996, and Maffioletti and Santoni 2005 for further details): subjects were asked to state their minimum selling price for nine risky prospects, each offering to pay either 120,000 Italian liras or 60 euros with a given probability of winning equal to p=0.1, 0.2, 0.3... up to p=0.9, and paying nothing with probability 1-p. Under the assumption of a linear value function, for example v(liras)=liras with v(0 liras)=0, decision weights at each probability level, W(p), are obtained by dividing the stated minimum selling price at each probability value, (S, p), by either 120,000 Italian liras or 60 euros: W(p)=(S,p)/(120,000) or W(p)=(S,p)/(60). The median values of these decision weights are reported in Tables 1.1. and 1.2. below.

[Tables 1.1 and 1.2 in here]

Tables 1.1. and 1.2. show that the median decision weights are equal to the corresponding probabilities in the Alessandria experiment and very close to the corresponding probability levels in the Milan experiment. The same data for the Milan experiment are also represented in Figure 1 below (the data for the Alessandria experiment correspond to the 45 degree line in Figure 1). This behaviour is consistent with the results reported by Fox et al. (1996) for experiments with option traders (see also Maffioletti and Santoni, 2005, for an experiment with trade union leaders) who find evidence of a linear weighting function under risk.

[Figure 1 in here]

2.2. Ambiguous prospects under a linear value function

This part of the experiment consisted of prospects based on the proportion of votes either Forza Italia was forecasted to obtain in the June 2004 European parliamentary elections (Alessandria) or

[11] About 45% of the subjects (16 out of 35 in the Milan experiment; 14 out of 31 in the Alessandria experiment)

the Casa della Libertà coalition was forecasted to obtain in the May 2001 Italian general political elections (Milan). The subjects were asked to report, first, their minimum selling price for lotteries based on the election outcome and, secondly, their judgement of probability for the same lotteries. Our working assumption of linearity of the subjects' value function allows us to derive the decision weight at the corresponding probability level by dividing the minimum selling price (namely, the certainty equivalent) by the lottery prize. However, reported judged probabilities give us a direct psychological measure of the decision weight at that particular probability level that does not depend on any specific assumption about the shape of the value function. Each ambiguous lottery paid either 60 Euros (for the 2004 European elections) or 120,000 Italian liras (for the 2001 Italian general election) if the relevant party would have obtained a given proportion of votes in the relevant ballot, and nothing otherwise.[12] Nine targets, differing according to the election considered and presented in random order to the subjects, were selected.[13] They are reported in Figure 2 below (the 2004 European election targets are shown in round brackets).

[Figure 2 in here]

These targets allow us to divide up the event space in different ways. Then, we can check for the presence of lower and upper subadditivity as well as for the influence of space partitioning in assessing probabilities under uncertainty. Let us consider $\Omega = \{E_1 \cup E_i \cup \ldots . E_n)$, where E_i are all disjoint events, $W(\Omega)=1$, $W(\varnothing)=0$ and $\sum W(E_i)$ can be different from 1 (as long as weighting functions differ from probabilities): different ways of partitioning the space Ω allow us to verify whether $D=1- \sum W(E_i)$ depends on the chosen partition (as being supposed by Support Theory). The particular targets were selected on the basis of the latest available opinion polls published in the

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reported the expected value for at least one lottery.

12 The irrevocable exchange rate is 1 Euro for 1936.27 Italian liras.

13 As regards the 2001 Italian general election, the proportion referred to the majoritarian ballot vote for the Lower House (Camera dei Deputati). In 2001, the Italian electoral system was mixed: two-thirds of the seats were allocated according to the first-past-the-post majority rule, while one-third of the seats was allocated according to the proportional rule, with a different ballot for each rule. However, there is a proportional electoral system for the European Parliament,

Italian national press either in April 2001 or in May 2004. A typical pricing question for the 2001 Italian general elections was as follows:[14]

> On Sunday the 13th of May 2001, the general political elections will be held.
> You possess a ticket of the following lottery:
> You win 120,000 Italian liras if the Casa delle Libertà polls between 43% (included) and 53% (excluded) of the votes in the majoritarian ballot vote for the Camera dei deputati, otherwise you win nothing.
> What is the minimum selling price at which you are willing to sell your lottery ticket?
> Price=

The typical pricing question for the 2004 European parliamentary elections was similarly phrased:

> On Saturday the 12th and Sunday the 13th of June 2004, the European parliamentary elections will be held.
> You possess a ticket of the following lottery:
> You win 60 Euros if Forza Italia polls between 25% (included) and 29% (excluded) of the votes, otherwise you win nothing.
> What is the minimum selling price at which you are willing to sell your lottery ticket?
> Price=

Judgement probability questions were presented after the pricing questions. They were based on the same target events and their order of presentation was again randomized. Typical questions were as follows:

> On Sunday the 13th of May 2001, the general political elections will be held.
> The Casa delle Libertà polls between 43% (included) and 53% (excluded) of the votes in the majoritarian ballot vote for the Camera dei deputati.
> Judged probability=

> On Saturday the 12th and Sunday the 13th of June 2004, the European parliamentary elections will be held.
> Forza Italia polls between 25% (included) and 29% (excluded) of the votes.
> Judged probability=

2.2.1. Decision weights and data poolability

Under the assumption of a linear value function, we can derive a typical decision weight as W(p)=(Minimum selling price)/(120,000) for the 2001 Italian election lotteries and

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thus the nine targets for the 2004 election were different (see Figure 2 below). Representatives in both the Camera and the European Parliament are elected by voters at least eighteen years old.

W(p)=(Minimum selling price)/(60) for the 2004 European election lotteries, respectively. Thus, for each individual subject, we can calculate, first, the decision weight corresponding to each individual lottery; secondly, the sum of the decision weights for those lotteries covering the full space of possible events (namely, the proportion of votes 0-100%). For example, the four lotteries A, B, C and D cover the full space of events 0-100%: by adding up the decision weights for these four lotteries for each subject, we can check it out whether they sum up to unity, which can be considered as evidence of a neutral attitude towards ambiguity, more than unity or less than unity: in the former case, the subject would overestimate the probability of a monetary gain, which can be taken as evidence of ambiguity proneness; in the latter case, the subject would underestimate it, which can be considered as evidence of ambiguity aversion. In both experiments, the lotteries that can be summed up to cover the full space of events are: ABCD; ABH; AED; CDI; FD; AG; HI. The sum of the decision weights for each individual subject is reported in Table 2 below: for example, TWABCD indicates the sum of the decision weights for the four lotteries ABCD. The second column of Table 2 identifies the election type: 1 for the 2004 European elections, and 2 for the 2001 Italian elections. The last column of Table 2 represents the median value of the six different sums of decision weights for each subject. The last row shows the median value across subjects for each different sum of lotteries under the assumption of data poolability.

We indeed tested for data poolability by computing both a t-test for independent samples, under the null hypothesis of equal means, and the Wilcoxon-Mann-Whithey test for independent samples, under the null hypothesis of equal medians, for each sum of decision weights referred to the two different groups (elections). Both tests cannot reject the null hypothesis at conventional significance levels, but for the TWHI Wilcoxon-Mann-Whitney test:[15] however, given that the t-test

14 The full set of questions, in Italian, is available from the authors upon request.

[15] The p-values for the two tests were as follows (note: the t-test is reported in italics, the Wilcoxon-Mann-Whithey test is reported in round brackets): TWABCD=*0.334* (0.207); TWABH= *0.18* (0.112); TWAED=*0.199* (0.277); TWCDI=*0.289* (0.26); TWAG=*0.465* (0.228); TWFD=*0.096* (0.109); TWHI=*0.16* (0.027).

strongly rejects the null hypothesis for TWHI, and since N=66, we take these results as overall evidence of data poolability, which we assume henceforth.[16]

[Table 2 in here]

By inspection of Table 2 above, we can note that no more than seven individual subjects (namely 10.6% of the total for the decision weights TWFD) show a neutral attitude towards ambiguity (namely, a unitary sum of the decision weights). For the six sums of lotteries, the proportion of ambiguity prone subjects varies between 95.4% (see TWABCD) and 72.7% (see TWFD) of the total. The median decision weight for each sum of lotteries (see the last row of Table 2) is greater than unity, which can be considered as evidence of ambiguity proneness: in particular, the median value of the median sum of the decision weights is 1.5. However, note that the median decision weight is decreasing in the number of lotteries (namely, the number of intervals) needed to cover the full space of events: for example, the median sum of the decision weights is equal to 1.92 with four lotteries (ABCD), to 1.52 with three lotteries (see AED) and to 1.17 with two lotteries (AG, FD and HI). This framing or "space partitioning" effect is also apparent by looking at the individual values: about 69% of the subjects show a decreasing superadditivity of the sum of the decision weights in the number of lotteries. This type of framing effect has been already documented in the literature (see e.g. Tversky and Koehler, 1994, and Fox and Rottenstreich, 2003).

We formally test whether reaction to ambiguity depends on the number of lotteries by using the Wilcoxon signed ranks test for pairs of dependent samples. These results are shown in Table 3.1 below. For example, we test whether reaction to ambiguity is significantly different when considering the sum of decision weights from four lotteries, ABCD say, rather than from three lotteries, AED say; when considering three, ABH say, rather than two lotteries, FD say, and so on. For all possible combinations, we can always reject the null hypothesis of no difference in ambiguity reaction (p-value=0). We take this result as evidence of a framing or space partitioning effect. We also used the Wilcoxon test to compare pairs of dependent samples, for given number of lotteries, ABH v. AED or AG v. AD say, to check it out whether reaction to ambiguity depends on the length, rather than on the number, of the intervals in which the space is divided: we cannot reject the null hypothesis that the length of the intervals does not influence ambiguity reaction, see Table 3.2 below. Hence, we can conclude that the Wilcoxon tests show that ambiguity reaction depends on the number of lotteries but not on the length of the interval in which the space is divided.

[Tables 3.1, 3.2, 3.3 in here]

We can take a further step and test whether an increase in the number of intervals leads to an increase in the additivity of probabilities (implying here a monotonical increase in ambiguity proneness) by computing a Page test for ordered alternatives (see e.g. Hollander and Wolfe, 1999: 284-294), based on different combinations of three related samples, under the null hypothesis that the median decision weights across subjects are the same against the alternative hypothesis that they are ordered in magnitude: an increase in the additivity of probabilities according to the number of times in which the space Ω is partitioned (namely, the bigger is the number, the higher is the additivity) can be considered as a direct test of Fox and Rottenstreich's (2003) extension of Support Theory to decision making under uncertainty. As shown in Table 3.3 above, for all the combinations the Page test strongly rejects the null hypothesis, thus providing evidence that an increase in the number of intervals elicits more ambiguity proneness.[17]

2.2.2. Judged probabilities and data poolability

After completing the pricing questions, the subjects were asked to state their degrees of belief as expressed by their judgement of probability for all the target events. Because the targets were

[16] We have generally chosen to use non parametric statistics when evaluating the results for the two separate experiments, being the number of subjects around 35. However, when testing poolability we have used both tests, since the power of the parametric one is higher and they both give, but for one case, the same results.

exactly the same as for the pricing questions (see Figure 2 above for a description),[18] the full space of events is covered by the following lotteries: ABCD, ABH, AED, CDI, AG, DF, HI. By denoting with P(A) the judged probability of the uncertain event A, we can calculate the sum of the judged probabilities for the lotteries covering the full space of events, P(A)+P(B)+P(G) or P(A)+P(F) say: if the sum of the judged probabilities is equal to unity, we can take this result as evidence of a neutral attitude to ambiguity; if it is less (respectively, more) than unity, we can consider it as evidence of ambiguity aversion (respectively, proneness). Table 4 below reports the individual data for the pooled dataset: actually, both the t-test for independent samples, under the null hypothesis of equal means, and the Wilcoxon-Mann-Whithey test for independent samples, under the null hypothesis of equal medians, for each sum of decision weights for the two different groups cannot reject the null hypothesis of data poolability at conventional significance levels.[19]

[Table 4 in here]

The median sum of the judged probabilities shows some evidence of ambiguity proneness (see the last row of Table 4). However, this is less pronounced than in the case of the decision weights: in particular, the median value of the median sums of the judged probabilities is 1.3. The fact that the additivity of the weighting function is more pronounced than the additivity of the judged probabilities tells us not only that choice under uncertainty can be alternatively measured with decision weights or judged probabilities (see Fox and Rottenstreich, 2003), but that such additivity can be influenced by emotional factors or it can capture modifications of the utility function rather than a distortion in the probabilities. In order to understand which explanation is the more plausible, we shall look at the relationship between emotions and subadditivity in the decision weights and in the judgemental probabilities (see section 4 below).

[17] As long as ties are observed in the data for several individuals in one or more lotteries and average ranks are used to deal with these ties, the large-sample approximation (which applies here given that N=66), overestimates the null variance of the Page statistics, thus the procedure is conservative, see Hollander and Wolfe (1999: 292) for a discussion.
[18] The lexicographic labelling of the targets was slightly different for the Italian general election experiment, see the questionnaires: for the sake of clarity, we report the standard labelling here.

Before making a detailed comparison with Table 3 (see the next paragraph), we can test for the presence of framing and interval length effects, by computing the relevant Wilcoxon tests. As reported in Table 5.1 below (see also Table 4), there is evidence that "superadditivity" of the sum of the judged probabilities depends on space partitioning: we can strongly reject the null hypothesis that ambiguity reaction is independent of framing (p-values=0). At the same time, we cannot reject the null hypothesis that ambiguity reaction is independent of the length of the intervals, but for one test at the 2% significance level, see Table 5.2 below. Similarly, we can compute a Page test for ordered alternatives to check whether an increase in the number of intervals leads to a monotonical increase in ambiguity proneness. Table 5.3 below shows that the Page test strongly rejects the null hypothesis, which we interpret as evidence that increasing the number of intervals elicits more ambiguity proneness in this case as well.

[Tables 5.1, 5.2, 5.3 in here]

2.2.3. Comparing decision weights and judged probabilities

The analysis made above suggests us that our student subjects are ambiguity prone, although this is more pronounced when ambiguity is measured by looking at the sum of the decision weights rather than of the judged probabilities (consistently with Tversky and Fox, 1995, two-stage procedure, see also section 3 below). Moreover, the previous analysis shows that there are framing effects: ambiguity reaction depends on the number of intervals used to cover the full event space, but not on the interval length.

Next, we can Wilcoxon test the null hypothesis that reaction to ambiguity is independent of the method used for measuring it, namely decision weights v. judged probabilities, by pairing related samples and by taking as given both the number of lotteries and the interval length: for example TWABCD v. TPABCD; TWABH v. TPABH; TWAED v. TPAED and so on. Table 6

[19] The p-values for the two tests were as follows (note: the t-test is reported in italics, the Wilcoxon-Mann-Whithey test is reported in round brackets): TPABCD=*0.73* (0.657); TPABH= *0.63* (0.495); TPAED=*0.69* (0.704); TPCDI=*0.386* (0.198); TPAG=*0.635* (0.686); TPFD=*0.628* (0.686); TPHI=*0.368* (0.393).

below shows that, a part for the TWCDI v. TPCDI case, we can reject the null hypothesis at the 5% significance level or less.

[Table 6 in here]

These tests suggest us that using decision weights, rather than judged probabilities, for measuring ambiguity reaction can introduce biases for at least two reasons. First, the value function may actually be non linear, as we have assumed instead: actually, judged probabilities measure ambiguity reaction independently of the shape of the value function. Secondly, the value function may depend not only on the monetary prize, but also on emotions and or competence/confidence. As we have already argued, if there is emotional involvement in the election outcome, and this is not appropriately taken into account, the sum of the decision weights may be biased (upwards or downwards, depending on whether we have, respectively, a positive or negative involvement) and thus our inference as regards subjects' ambiguity reaction; similarly, if a subject considers herself an expert in politics: Kilka and Weber (2001) argue that the feeling of competence induces subjects to behave more optimistically than otherwise they would do, which would imply here that both decision weights and judged probabilities can be upward biased (see Heath and Tversky, 1991). The next section will try to quantify the role, if any, of emotion, competence/confidence in ambiguity reaction.

3. Emotions, competence and confidence in political choice under uncertainty

The study of emotion's role in politics is an active area of research in political science and social psychology. Most of the literature has tried to identify how both positive emotions (like hope) and negative emotions (like fear) can influence political choices such as voting behaviour, voters' evaluation of party leaders, political parties and politics, and important political decisions made by political leaders (see Marcus, 2000, for a survey).[20] This paper does not aim at contributing to this

[20] There is a related literature looking at how politics impacts emotions by considering, for example, how politicians can use campaigns to manipulate emotions, thus causing changes in political behaviour, see e.g. Brader, (2005).

literature, but rather it aims at assessing the role of emotions, competence and confidence (i.e. self-reported competence) when subjects are evaluating lotteries involving an uncertain event like the outcome of a political election. In particular, following the social psychology literature (see also Kahneman and Krueger, 2006: 9-14), this paper measures self-reported emotions by asking subjects to judge intensity of their emotions as regards an election outcome: subjects were asked to report two separate answers, one defined by the positive dimension and the other by the negative dimension on a scale from 0 (no emotional involvement) to 10 (highest emotional involvement). The typical questions for the 2001 and 2004 elections, respectively, were as follows:[21]

> Consider the case in which the Polo coalition wins the 2001 Italian general political elections. On a scale between 1 and 10 state your level of positive (*negative*) emotional involvement (1 showing the lowest positive (*negative*) emotional involvement, 10 the highest positive (*negative*) emotional involvement):
>
> 0----1----2----3----4----5----6----7----8-----9-----10
>
> Consider the case in which Forza Italia polls the relative majority of votes in the 2004 European Parliamentary elections. On a scale between 1 and 10 state your level of negative (*positive*) emotional involvement (1 showing the lowest negative (*positive*) emotional involvement, 10 the highest negative (*positive*) emotional involvement):
>
> 0----1----2----3----4----5----6----7----8-----9-----10

Table 7 below reports some descriptive statistics. First, note that negative emotions are more intense than positive emotions in both elections, hence in the pooled dataset,[22] although the difference is less pronounced for the 2001 than for the 2004 elections:[23] this difference may partly reflect the different political and electoral context (in 2001, the Polo coalition actually won the elections and did very well in Milan, whereas by 2004 Berlusconi's Forza Italia was less popular and actually performed badly in the North-West of Italy), although one would expect less emotional involvement

[21] In both experiments, the questionnaire also asked subjects to report their "degree of satisfaction", on a scale between 0 (no feelings) and 10 (highest degree of satisfaction), for each prospective election outcome.

[22] A t-test strongly rejects the null hypothesis that the mean positive emotions and the mean negative emotions are the same for both experiments (p-value: 0 for the Alessandria experiment, 0.003 for the Milan experiment) and for the pooled data (p-value: 0.011).

[23] This finding is consistent with the results of a survey, based on a sample of 1,048 Italians interviewed in March 2004, on the emotions evoked by politics on a 0-10 scale, the mean value for negative (positive) emotions is 6 (3), see Cavazza and Corbetta (2005).

(both positive and negative) in the European than in the Italian political elections. The last row of Table 7 contains descriptive statistics for the *net affect*, defined as the difference between positive emotions and negative emotions for each subject: psychologists commonly use this variable as a measure of subjective mood (see Kahneman and Krueger, 2006).

[Table 7 in here]

As long as we cannot reject the null hypothesis of either equal means (i.e. the t-test for independent samples) or equal medians (i.e. the Wilcoxon-Mann-Whithey test for independent samples) for the two experiments,[24] we report on the pooled dataset henceforth. Figure 3 below shows each subject's self-reported emotion, measured in the positive-negative emotions space (note that each point may represent more than one subject): points above (below) the 45 degree line show subjects with *positive* (*negative*) net affect.

[Figure 3 in here]

As long as positive and negative emotions are negatively correlated (-0.65) in our data,[25] we alternatively use each of these measures as a proxy for the degree of emotional involvement in our analysis below, along with the *net affect* measure. Our a priori is that positive (negative) emotions or positive values of net affect, should induce subjects to behave more optimistically (pessimistically), thus biasing upwards (downwards) decision weights and judged probabilities.

Following the seminal work by Heath and Tversky (1991), this paper also tries to evaluate the role that competence may play in choice under uncertainty. In the two experiments, we measured competence in alternative ways: in the Milan experiment for the 2001 general political election, the subjects assessed, on a ten-point scale, their level of competence in politics:[26] self-assessed competence is denoted as "confidence". In the Alessandria experiment for the 2004

[24] The p-values for the two tests were as follows (note: the t-test is reported in italics, the Wilcoxon-Mann-Whithey test is reported in round brackets): negative emotions=*0.7* (0.34); positive emotions= *0.2* (0.17); satisfaction=*0.11* (0.12).

[25] Similarly, satisfaction is highly correlated with both positive (0.9472) and negative emotions (-0.69089).

[26] "Do you rate yourself as being an expert in politics? On a scale between 1 and 10, report on the level of knowledge and competence that you feel having as regards politics (0 not at all an expert, 10 very expert)."

European parliamentary elections, the subjects answered to ten questions on Italian and European politics,[27] and we measured their level of competence on a ten-point scale (one point was given for each correct answer). According to Kilka and Weber (2001), one should expect that people who consider themselves experts behave more optimistically than they would do otherwise.

Table 8 below reports descriptive statistics for confidence and competence, as well as the results of tests strongly rejecting the null hypothesis of data poolability. It turns out that self-assessed confidence in the Milan experiment was significantly lower than competence in the Alessandria experiment, both at mean and median values. Although this comparison seems problematic, this result suggests us that confidence and competence should be distinguished when evaluating subjects' reaction to uncertainty.

[Table 8 in here]

3.1. Testing for emotional involvement, competence and confidence

The analysis of section 2 above has shown that our subjects exhibit superadditivity of both decision weights and judged probabilities, although the latter is less pronounced. This section wants to test whether this is affected by emotions, competence and confidence, other things given. First, we consider the role, if any, of emotions, competence and confidence in explaining the difference between decision weights and judged probabilities for each subject *i* in our data. As long as there are seven sum of decision weights/judged probabilities (i.e. ABCD, ABH, AED, CDI, AG, FD, HI), one can treat each space partitioning as if it were a different time period *t* and estimate the following model:[28]

$(\text{Decision Weight-Judged Probability})_{it}=$

---

[27] The questions were as follows: Who is UDC's party secretary? What's the name and party of the Italian minister for arts and culture? Who is the Spanish prime minister? Who is the European Union competition commissioner? To which European parliamentary group do the Democratic of the Left party belong to? Which is the Italian party belonging to the European Party of liberals, democrats and reformers? Who is the President of the Italian Senate? What is the electoral system for the European parliamentary election? What's the name and party of the minister for the Italians in the world? Who is the Italian minister for EU policy?

[28] All estimates are run by using the STATA 9.0 package. Estimated coefficient are rounded at the third decimal point.

$\alpha+\beta \text{Emotions}_i+\gamma \text{Competence}_i+\delta \text{Confidence}_i+\eta \text{Age}_i+\theta \text{Sex}_i+ \lambda \text{Dummy13}+\tau \text{ Time Dummy}_t+ v_{it}$.

where the dependent variable is the difference between the Decision Weight and the Judged Probability computed for each individual *i* in correspondence of the same space partitioning *t*; Emotions denote for each individual *i* either self-assessed positive emotions, or negative emotions or net affect (positive less negative emotions), on a scale between 0 (indifference) and 10 (highest level); Competence is measured for Group 1's subjects (Alessandria, i=1…31) on a ten-question politics questionnaire and takes the value of zero for Group 2's (Milan, i=32…66); Confidence is self-assessed expertise in politics for Group 2's subjects and is equal to zero for Group 1's: both Competence and Competence are measured on a scale between 0 (indifference) and 10 (highest level); Age is the subject's age; Sex is a dummy variable equal to 0 for females (N=26) and 1 for males (N=40); Dummy13 is a dummy variable, taking the value of 1 for subject 13, and zero otherwise: this variable is introduced to take care of an outlier in our data; "time" dummies are introduced for controlling within-subjects fixed space partitioning effects; v_{it} is an additive normally distributed random term.

Table 9 (columns 1-3) presents the OLS estimates for the pooled model with fixed "time" effects. It turns out that positive (negative) emotions or net affect, competence and confidence enter with the expected positive (negative) sign, and are statistically significant at the 1% level or less. Both age (significant at the 1% level) and the sex dummy (significant at the 5% level) enter with a negative sign, implying that being older and male lowers on average the difference in superadditivity between decision weights and judged probabilities. Next, we try to control for individual unobserved heterogeneity by running a random effects estimation, as reported in Table 9 (columns 4-6): the estimated coefficients corresponds to those of the OLS pooled model, as expected, but random effects increase the efficiency of our estimates by decomposing the unobservables into an individual specific component and a white-noise component. As a result, the statistical significance of the estimated coefficients is lowered: confidence and competence become significant at the 5% level or less, positive or negative emotions become insignificant, while net affect is significant at the 8.5% level only; age remains significant at the 10% level or less, while the sex dummy is now insignificant.

[Table 9 in here]

Because our endogenous variable is the difference between decision weights and judged probabilities, this result does not necessarily imply that emotions do not matter in choice under uncertainty, but rather that they are not fully able to explain such a difference in our data. We shall return to this point below. Moreover, from Table 9 there is also evidence that both self-assessed competence (i.e. confidence) and actual competence provoke an upward bias in the sum of the decision weights relative to judged probabilities, as predicted by the Kilka and Weber (2001) hypothesis.

Finally, Tables 10 and 11 below present the results of both pooled OLS regressions and random effects estimates, when the dependent variable is either the sum of decision weights or the sum of judged probabilities. First, note that positive emotions and net affect enter with the predicted positive sign and are statistically significant at the 5% significance level or less in the pooled OLS regression for both the decision weights and judged probabilities, but these variables are statistically significant for decision weights only in the random effects estimate. Moreover, negative emotions enter with the expected negative sign, but they are statistically significant for decision weights and in the OLS regression only. We interpret these results as evidence of an effect of emotions on the value function that biases upwards the sum of the decision weights rather than a "wishful thinking" effect, which should show up in the sum of the judged probabilities as well. However, as long as this effect was rather weak when considering the difference between decision weights and judged probabilities (see Table 9, column 6 above), this interpretation should be taken cautiously. Second, note that confidence and competence are statistically significant at conventional levels in the OLS regressions only, but they enter with opposite sign (positive for decision weights and negative for judged probabilities), which may explain the weak positive effect previously found (see Table 9, columns 4-6, above). Moreover, this result suggests us that the Kilka and Weber (2001) hypothesis is not fully confirmed in our data: we would expect that confidence and competence in politics should affect the subjects' behaviour irrespectively of how we measure their reaction to ambiguity.

[Tables 10 and 11 in here]

4. Testing for bounded subadditivity (SA)

Tversky and Fox (1995: 271-272) introduce the concept of bounded subadditivity (SA) for uncertainty. Let S be the certain event, such that the corresponding decision weight is unity W(S)=1; let A and B be two disjoint uncertain events defined on S. Provided that W(AUB)<1, and W(B)>0, a weighting function W (.) under uncertainty is said to satisfy SA, if it satisfies the following two conditions:

a. **Lower Subadditivity**: W(A) ≥ W(AUB)-W(B), or **DW**=W(A)+W(B)-W(AUB) ≥ **0**;
b. **Upper Subadditivity**: W(S)-W(S-A) ≥ W(AUB)-W(B), or **DWprime**=1-W(S-A)-W(AUB)+W(B**)** ≥ **0**.

Lower subadditivity captures the "possibility effect", that is the fact that adding an event A to the null event has more impact than subtracting it from some non-null event B. Upper subadditivity captures the "certainty effect", that is the fact that subtracting an event A from certainty has more impact than subtracting it from some uncertain event AUB. Note that, under expected utility, D=Dprime=0. Similar concepts can be defined for judged probabilities (see Tversky and Fox, 1995: 279): let P(A) be the degree of belief as regards event A, then bounded subadditivity satisfies the following two conditions:

a. **Lower Subadditivity**: DP=P(A)+P(B)-P(AUB) ≥ 0;
b. **Upper Subadditivity**: DP=1-P(S-A) -P(AUB)+ P(B) ≥ 0.

Hence, Figure 4 below reports seven tests for lower subadditivity and three tests for upper subaddivity.

[Figure 4 in here]

Following Tversky and Fox (1995), we compute the median values of D: *d;* and of Dprime: *dprime*, for each subject across the various tests of lower and upper SA. We also compute *s=1-d-dprime*, which can be interpreted as a global sensitivity measure. Again, SA is satisfied if $d \geq 0$, $dprime \geq 0$ and $s \leq 1$, whereas expected utility implies that d=dprime=0 and s=1. Tables 12.1 and 12.2 below report the values of *d*, *dprime*, and *s* for each individual subject for decision weights and judged probabilities, respectively. Table 13 below reports median values of these indexes across respondents for the pooled dataset. [29] Looking at the individual values of Tables 12, it turns out that SA is satisfied by no less than 88% of subjects by considering median values across tests. Table 13 shows that the value of s for judged probabilities is greater than the corresponding index for decision weights, that is judged probabilities exhibit less SA than decision weights: following Tversky and Fox (1995: 279), we can interpret this result as "evidence of a two-stage decision-making process, in which the subject first assess the probability P of an uncertain event A, and then transforms this value by the risky weighting function W", such that W(A) may be proxied by W(P(A)). However, contrary to Tversky and Fox (1995), we find evidence that, as regards decision weights, lower SA has *more* impact than upper SA (see Table 13 below): in other words, the possibility effect is more pronounced than the certainty effect in this case. This result is consistent with our findings of section 2 above (that the sum of decision weights for complementary events is greater than unity) and is in contrast with Tversky and Fox's (1995) evidence in favour of "subcertainty" (a sum of decision weights that is less than one). This result might be explained with a model of decision making under ambiguity such as the one developed by Einhorn and Hogarth (1995).

[Tables 12.1 and 12.2 in here]

[Table 13 in here]

4.1. Emotion, competence, confidence and bounded subadditivity

[29] By using the data of Tables 12, we tested for data poolability (both t-test for equal means, and Wilcoxon-Mann-

We next test whether lower subadditivity or upper subadditivity are affected by emotions, competence and confidence, by regressing these variables on our measures of either lower or upper subadditivity, after controlling for age, sex and introducing a dummy variable for subject 13. Table 14.1 and 14.2 below present the OLS estimates for decision weights and judged probabilities, respectively.

[Table 14.1 and 14.2 in here]

These tables show that, as regards decision weights, see Table 14.1, both positive emotions (at the 5% level), net affect (at the 10% level), competence and confidence (both at the 1% level) affect the degree of lower subadditivity *dw*, namely the possibility effect, positively; however, they influence neither the degree of upper subadditivity, namely the certainty effect, *dwprime*, nor global sensitivity *sw*. Moreover, there is no effect on the corresponding variables for judged probabilities, see Table 14.2. These results give a possible key for interpreting our analysis of section 4 above: emotion, competence and confidence seem to explain why the possibility effect is stronger than the certainty effect for decision weights. Moreover, given that we do not find any corresponding effect for judged probabilities, these results may be consistent with the idea that emotion, competence and confidence affect the utility function.

5. Conclusions

In this paper we have considered how reaction to real uncertainty may be influenced by emotion, self-assessed competence (i.e. confidence) or actual competence of the decision makers by presenting two related experiments based on real political election outcomes. Next, the experiment has checked for subjects' attitudes under uncertainty. The Italian political general election of May 2001 (the Milan experiment) and the European parliamentary elections of June 2004 (the Alessandria experiment) were used as natural experiments of an uncertain event. In addition to the design followed by Fox, Rogers and Tversky (1996), subjects were asked to report their emotional

Whitney test for equal medians) for lower and upper subadditivity. These tests cannot reject the null hypothesis.

involvement (both positive and negative) on the possible occurrence of an election outcome and their degree of competence in politics. Competence in politics was self-assessed in the Milan experiment, whereas it was objectively measured in the Alessandria experiment.

Our results on the pooled dataset show that the subjects' behaviour is consistent with expected utility theory as regards risk. However, the subjects strongly react to uncertainty. In particular, our paper confirms that, if we partition the space of events in more than two intervals, the sums of the decision weights are consistently greater than unity: this superadditivity effect is an increasing function of the number of intervals in which the event space is divided upon, whereas it does not depend on the interval length. A similar, but less strong, result is found when considering judgemental probabilities. We take these results as overall evidence in favour of partition effects and Support Theory (see Tversky and Koehler, 1994, and Fox and Rottenstreich, 2003).

The two first original results of our paper are the following: with real uncertainty involving lotteries based on political elections, the majority of subjects shows superadditivity in decision weights and individual subjects exhibit both lower subadditivity (the possibility effect) and upper subadditivity (the certainty effect), but these effects are not symmetric contrary to what predicted by Tversky and Fox (1995): in particular, the possibility effect is more pronounced than the certainty effect, the decision weights for complementary events sum to more than one, which is the opposite of Tversky and Fox's results in support of subcertainty (according to which the sum of the decision weights is less than one). However, similarly to their paper, here the two effects are stronger for decision weights than for probability judgements.

The second original contribution of this paper is to test the influence of emotions, competence and confidence on additivity of decision weights and judgemental probabilities, on the difference between these two variables as well as on lower and upper subadditivity. In order to do so we regressed the sum of the decision weights or the sum of the judged probabilities, or the difference between the two variables for each individual on measures of self-assessed emotional involvement, confidence and competence. The finding was that a higher degree of positive emotion or net affect (the difference between positive and negative emotions) positively influence the sum of the decision weights, but have no effect on the sum of the judged probabilities, whereas competence only positively affect the difference between these two variables. However, emotions and competence were found to affect significantly lower subadditivity, with no effect on upper subadditivity instead, which reinforces the former result that the certainty effect and the possibility effect are not symmetric. Because this paper does not find any evidence that the sum of the judged probabilities are affected by emotions or competence, the first result is taken as evidence of the value function depending on emotions along with monetary rewards, rather than as evidence of "wishful thinking". We are aware however that the same result is equally allowed by theories of decision making under ambiguity such as the one by Einhorn and Hogarth (1995). Hence, we will encourage additional research on this point.

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Tables

Table 1.1. Risky prospects: Decision weights under a linear value function in the Alessandria experiment.

	RA	RB	RC	RD	RE	RF	RG	RH	RI
MEDIAN VALUE	6	12	18	24	30	36	42	48	54
DECISION WEIGHT	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
PROBABILITY LEVEL	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ADJUSTMENT NEEDED FOR W(p)=p	//	//	//	//	//	//	//	//	//

Note: Median values in euros.

Table 1.2. Risky prospects: Decision weights under a linear value function in the Milan experiment.

	RA	RB	RC	RD	RE	RF	RG	RH	RI
MEDIAN VALUE	15,000	20,000	30,000	50,0000	60,000	70,000	84,000	96,000	110,000
DECISION WEIGHT	0.125	0.16	0.25	0.416	0.5	0.58	0.708	0.8	0.916
PROBABILITY LEVEL	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ADJUSTMENT NEEDED FOR W(p)=p	-0.025	+0.04	+0.05	-0.016	//	+0.02	-0.008	//	-0.016

Note: Median values in Italian liras.

Table 2. Sum of the decision weights

Subject	GROUP	TWABCD	TWABH	TWAED	TWCDI	TWAG	TWFD	TWHI	MEDIAN
1	1	2.70	2.25	1.80	2.20	1.30	1.17	1.75	**1.8**
2	1	2.17	1.67	1.67	2.17	1.17	1.17	1.67	**1.67**
3	1	2.50	1.50	1.80	1.90	1.10	1.00	0.90	**1.5**
4	1	2.10	1.68	1.82	1.85	1.27	1.77	1.43	**1.77**
5	1	1.92	1.75	1.25	1.50	1.42	1.08	1.33	**1.42**
6	1	1.30	1.00	1.50	1.30	1.03	0.90	1.00	**1.03**
7	1	2.33	1.67	1.92	2.33	1.25	1.42	1.67	**1.67**
8	1	2.08	1.67	1.67	1.67	1.25	1.42	1.25	**1.67**
9	1	2.17	1.17	1.42	1.42	0.67	1.00	0.42	**1.17**
10	1	2.25	2.00	1.75	1.58	1.42	1.25	1.33	**1.58**
11	1	2.00	1.67	1.67	1.50	1.17	1.17	1.17	**1.5**
12	1	1.83	1.33	1.58	1.67	1.17	1.00	1.17	**1.33**
13	1	6.08	3.67	4.08	4.00	2.58	3.33	1.58	**3.67**
14	1	1.33	1.50	1.00	1.33	0.83	1.17	1.50	**1.33**
15	1	1.92	1.42	1.67	1.58	1.08	1.33	1.08	**1.42**
16	1	1.75	1.50	1.40	1.58	1.08	1.17	1.33	**1.4**
17	1	1.88	1.33	1.47	1.63	1.23	1.13	1.08	**1.33**
18	1	2.78	2.62	3.62	2.58	1.57	2.22	2.42	**2.58**
19	1	1.75	2.05	1.48	1.00	1.33	0.67	1.30	**1.33**
20	1	2.25	1.92	1.75	1.67	1.25	1.50	1.33	**1.67**
21	1	1.75	1.50	1.58	1.33	1.08	1.25	1.08	**1.33**
22	1	2.25	2.08	1.83	1.50	1.33	1.33	1.33	**1.5**
23	1	1.80	1.42	1.50	1.55	1.08	1.17	1.17	**1.42**
24	1	1.37	1.03	1.03	1.02	0.87	0.68	0.68	**1.02**
25	1	1.93	1.58	1.60	1.85	1.17	1.72	1.50	**1.6**
26	1	0.67	0.75	0.75	0.50	0.92	0.67	0.58	**0.67**
27	1	2.00	1.68	1.72	1.75	1.27	1.67	1.43	**1.68**
28	1	3.33	2.50	2.50	2.50	1.67	1.83	1.67	**2.5**
29	1	1.50	1.58	1.42	1.75	1.08	1.50	1.83	**1.5**
30	1	2.25	1.83	1.75	1.58	1.33	1.25	1.17	**1.58**
31	1	1.42	1.08	1.08	1.50	0.75	1.08	1.17	**1.08**
32	2	1.54	1.04	1.04	1.42	0.63	1.04	0.92	**1.04**
33	2	0.83	0.67	0.67	0.58	0.58	0.50	0.42	**0.58**
34	2	1.63	1.13	1.54	1.54	1.04	1.33	1.04	**1.33**
35	2	2.92	2.00	2.08	2.00	1.67	1.50	1.08	**2**
36	2	1.79	1.71	1.33	1.33	0.92	1.00	1.25	**1.33**
37	2	1.33	1.33	1.00	1.25	0.92	0.75	1.25	**1.25**
38	2	2.33	1.75	1.75	1.75	1.25	1.17	1.17	**1.75**
39	2	2.00	1.25	1.75	1.67	1.17	1.42	0.92	**1.42**
40	2	2.00	1.83	1.83	1.58	1.67	1.33	1.42	**1.67**
41	2	1.71	1.75	1.83	1.13	1.08	1.00	1.17	**1.17**
42	2	1.75	1.75	1.29	1.50	0.92	1.08	1.50	**1.5**
43	2	2.58	2.00	2.00	2.00	1.67	1.17	1.42	**2**
44	2	1.75	1.50	1.42	1.33	1.33	1.25	1.08	**1.33**
45	2	1.67	1.42	1.42	1.25	0.75	1.08	1.00	**1.25**
46	2	2.17	1.33	1.42	1.75	1.08	1.00	0.92	**1.33**
47	2	1.83	1.00	0.83	1.58	0.58	0.83	0.75	**0.83**
48	2	4.17	3.75	2.92	3.58	2.50	2.50	3.17	**3.17**
49	2	3.00	2.33	2.50	2.42	1.83	1.50	1.75	**2.33**
50	2	2.17	1.83	1.50	1.33	1.17	0.92	1.00	**1.33**
51	2	1.92	1.25	1.50	1.92	1.08	1.33	1.25	**1.33**
52	2	1.99	1.50	1.50	1.66	0.99	1.33	1.17	**1.5**
53	2	1.21	1.08	1.21	0.54	0.58	0.54	0.42	**0.58**
54	2	1.92	1.42	1.83	1.25	1.33	1.00	0.75	**1.33**
55	2	1.72	1.05	1.68	1.71	1.01	1.67	1.04	**1.67**
56	2	1.83	1.58	1.50	1.75	1.17	1.25	1.50	**1.5**
57	2	1.25	1.00	1.17	1.50	0.83	1.08	1.25	**1.17**
58	2	1.58	1.33	1.42	1.50	1.08	1.08	1.25	**1.33**
59	2	2.00	1.33	1.75	1.92	1.50	0.58	1.25	**1.5**
60	2	1.25	0.92	0.67	1.00	1.17	0.83	0.67	**0.92**
61	2	1.25	1.04	1.33	1.02	1.21	1.04	0.82	**1.04**
62	2	2.83	2.00	2.08	2.42	1.38	1.33	1.58	**2**
63	2	2.42	2.08	2.17	1.50	1.33	1.25	1.17	**1.5**
64	2	2.25	1.67	1.42	1.75	1.08	1.42	1.17	**1.42**
65	2	1.75	1.33	1.33	1.58	1.00	1.08	1.17	**1.33**
66	2	1.00	0.67	0.83	0.88	0.75	0.75	0.54	**0.75**
MEDIAN		**1.92**	**1.5**	**1.52**	**1.58**	**1.17**	**1.17**	**1.17**	**1.42**

Note: If the sum is above (below) unity, this is taken as evidence of ambiguity proneness (aversion); if the sum is equal to unity, this is taken as evidence of ambiguity neutrality. Group 1 denotes the Alessandria experiment, while Group 2 the Milan experiment.

Table 3.1. Decision weights: Wilcoxon tests for framing effects

	ABCD v. ABH	ABCD v. AED	ABCD v. CDI	ABCD v. AG	ABCD v. FD	ABCD v. HI	ABH v. BG	ABH v. FD	ABH v. HI	AED v. AG	AED v. FD	AED v. HI	CDI v. AG	CDI v. FD	CDI v. HI
Z	-6.704	-6.426	-6.456	-7.038	-6.956	-6.938	-6.65	-6.6	-5.97	-6.43	-6.91	-6.7	-6.43	-6.91	-6.7
p-v	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Note: Null hypothesis, no difference in ambiguity reaction.

Table 3.2. Decision weights: Wilcoxon tests for interval length effect

	ABH v.AED	ABH v.CDI	AED v.CDI	AG v.FD	AG v.HI	FD v. HI
Z	-0.695	-1.294	-1.110	-1.345	-0.984	-0.316
p-value	0.487	0.196	0.267	0.179	0.325	0.752

Note: Null hypothesis, no difference in ambiguity reaction.

Table 3.3. Decision weights: Page tests for framing effects

	ABCD v.ABH v. AG	ABCD v. ABH v. FD	ABCD v. ABH v. HI	ABCD v. AED v.AG	ABCD v. AED v. FD	ABCD v. AED v. HI	ABCD v.CDI v. AG	ABCD v. CDI v. FD	ABCD v. CDI v. HI
Z	10.35	10	10	10.48	10.44	9.48	10.14	10.61	10
p-value	0	0	0	0	0	0	0	0	0

Note: Null hypothesis, no difference in ambiguity reaction.

Table 4. Sum of the judged probabilities

Subject	GROUP	TPABCD	TPABH	TPAED	TPCDI	TPAG	TPFD	TPHI	Median
1	1	1.48	1.25	1.15	1.25	1	1	1	**1.15**
2	1	0.7	1.2	0.7	0.6	0.6	0.5	1	**0.7**
3	1	2.5	1.5	1.8	2	1.1	1	0.9	**1.5**
4	1	1.54	1.32	1.19	1.2	1.04	1.2	0.73	**1.19**
5	1	2.65	2.05	2	2.4	1.3	1.5	1.75	**2**
6	1	1.3	1	1.5	1.6	1	0.9	1	**1**
7	1	1.9	1.3	1.6	1.8	1.1	1.6	1.2	**1.6**
8	1	1.15	0.95	0.95	1.5	1	0.85	1.3	**1**
9	1	1.35	1.05	0.88	0.73	0.85	0.55	0.6	**0.85**
10	1	1.5	1.35	1.3	1.65	1	1	1.1	**1.3**
11	1	2.4	1.7	1.7	2.1	1	1.4	1.4	**1.7**
12	1	2.35	1.65	1.5	1.5	1	1	0.9	**1.5**
13	1	1.05	1.15	1	1	0.4	1.1	0.85	**1**
14	1	2	1.5	1.4	1.5	1.1	1.1	1	**1.4**
15	1	1.9	1.6	1.4	1.4	1	1	0.9	**1.4**
16	1	1.75	1.5	1.3	1.6	1	1	1.3	**1.3**
17	1	1.95	1.55	1.25	1.7	1.05	1	1.3	**1.3**
18	1	2.1	1.65	1.3	1.65	1	1	1.2	**1.3**
19	1	0.82	0.9	0.92	1.32	1	0.82	1	**0.82**
20	1	3.05	2.45	2.45	2.2	1.9	1.2	1.4	**2.2**
21	1	1.85	1.8	1.45	1.45	1.2	1	1.1	**1.45**
22	1	2	1.3	1.6	1.8	0.9	1	0.7	**1.3**
23	1	1.7	1.5	1.45	1.5	1.15	1	1.15	**1.45**
24	1	1.5	1.1	1.2	1.3	0.9	1	0.9	**1.1**
25	1	2.07	1.47	1.38	1.25	0.86	0.9	0.9	**1.25**
26	1	1.5	1.2	1.3	1.3	1	1.15	1	**1.2**
27	1	1.49	1.32	1.19	1.25	1.04	1.2	0.78	**1.19**
28	1	1.71	1.7	1.31	1.61	1.3	1	1.1	**1.31**
29	1	1.75	1.4	2.1	1.9	1.1	1.5	1	**1.5**
30	1	2.4	1.8	1.75	1.9	1.15	1.4	1.3	**1.75**
31	1	1.6	1.3	1.4	1.4	1.4	0.75	0.8	**1.4**
32	2	1.05	1.00	1.15	1.05	1.00	1.00	1.00	**1**
33	2	1.70	1.20	1.20	1.45	1.00	0.90	0.95	**1.2**
34	2	1.41	1.11	1.31	2.30	1.01	1.30	2.00	**1.31**
35	2	1.48	1.25	1.12	1.08	0.82	0.68	1.00	**1.08**
36	2	1.60	1.30	1.40	1.35	0.90	0.90	1.05	**1.3**
37	2	1.90	1.80	1.10	1.70	1.00	0.90	1.60	**1.6**
38	2	2.60	2.00	2.00	1.90	1.40	1.30	1.30	**1.9**
39	2	1.80	1.05	1.55	1.75	0.90	1.30	1.00	**1.3**
40	2	1.90	1.70	1.25	1.75	0.90	0.95	1.55	**1.55**
41	2	2.31	2.10	1.91	1.51	1.80	1.01	1.30	**1.8**
42	2	1.80	1.50	1.20	1.20	1.00	1.10	0.90	**1.2**
43	2	1.90	1.50	1.30	1.20	1.10	0.90	0.80	**1.2**
44	2	2.95	2.15	2.15	2.45	1.25	1.55	1.65	**2.15**
45	2	1.45	1.20	1.35	1.20	1.10	0.90	0.95	**1.2**
46	2	2.10	1.70	1.70	1.50	1.50	0.80	1.10	**1.5**
47	2	1.05	1.15	0.85	1.00	1.05	1.00	1.10	**1.05**
48	2	2.30	1.95	1.55	1.65	1.20	0.80	1.30	**1.55**
49	2	1.70	1.30	1.60	1.40	1.10	1.10	1.00	**1.3**
50	2	2.10	1.50	1.50	1.70	1.10	1.10	1.10	**1.5**
51	2	2.10	1.70	1.65	1.70	1.35	1.25	1.30	**1.65**
52	2	1.50	1.38	1.10	1.30	1.10	0.80	1.18	**1.18**
53	2	1.35	1.10	1.00	1.20	0.80	0.70	0.95	**1**
54	2	1.80	1.10	1.10	1.10	1.00	1.00	0.40	**1.1**
55	2	1.16	0.86	1.51	1.20	1.01	1.00	0.90	**1.01**
56	2	1.50	1.30	1.20	1.30	1.00	1.10	1.10	**1.2**
57	2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**1**
58	2	0.95	0.75	0.80	1.05	0.55	0.70	0.85	**0.8**
59	2	1.90	1.70	1.50	1.20	1.05	1.05	1.00	**1.2**
60	2	1.20	1.25	1.20	1.05	1.00	1.00	1.10	**1.1**
61	2	2.45	2.00	1.85	1.82	1.40	1.10	1.37	**1.82**
62	2	2.20	1.50	1.55	1.90	1.05	1.20	1.20	**1.5**
63	2	1.45	1.05	1.20	1.40	0.90	1.10	1.00	**1.1**
64	2	1.60	1.20	1.20	1.50	1.05	1.10	1.10	**1.2**
65	2	2.05	1.45	1.80	1.60	1.30	1.40	1.00	**1.45**
66	2	1.30	1.00	1.00	1.20	0.90	0.90	0.90	**1**
Median		**1.73**	**1.33**	**1.31**	**1.47**	**1**	**1**	**1**	**1.31**

Note: If the sum is above (below) unity. this is taken as evidence of ambiguity proneness (aversion); if the sum is equal to unity. this is taken as evidence of ambiguity neutrality. Group 1 denotes the Alessandria experiment, while Group 2 the Milan experiment.

Table 5.1. Judged probabilities: Wilcoxon tests for framing effects

	ABCD v. ABH	**ABCD v. AED**	**ABCD v. CDI**	**ABCD v. AG**	**ABCD v. FD**	**ABCD v. HI**	**ABH v. AG**	**ABH v. FD**	**ABH v. HI**	**AED v. AG**	**AED v. FD**	**AED v. HI**	**CDI v. AG**	**CDI v. FD**	**CDI v. HI**
Z	-6.558	-6.413	-5.471	-6.923	-6.944	-6.687	-6.75	-6.32	-6.15	-6.73	-6.77	-5.48	-6.6	-6.8	-6.7
p-value	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Note: Null hypothesis, no difference in ambiguity reaction

Table 5.2. Judged probabilities: Wilcoxon tests for interval length effects

	ABH v. AED	**ABH v. CDI**	**AED v. CDI**	**AG v. FD**	**AG v. HI**	**FD v. HI**
Z	-1.392	-1.590	-3.106	-0.48	-0.470	-1.384
p-value	0.164	0.112	0.002*	0.628	0.638	0.166

Note: Null hypothesis, no difference in ambiguity reaction *Significant at 5% or less.

Table 5.3. Judged probabilities: Page tests for framing effects

	ABCD v.ABH v. AG	**ABCD v. ABH v. FD**	**ABCD v. ABH v. HI**	**ABCD v. AED v.AG**	**ABCD v. AED v. FD**	**ABCD v. AED v. HI**	**ABCD v.CDI v. AG**	**ABCD v. CDI v. FD**	**ABCD v. CDI v. HI**
Z	10.14	9.35	9.83	10.05	10.22	9.26	9.96	9.92	9.44
p-value	0	0	0	0	0	0	0	0	0

Note: Null hypothesis, no difference in ambiguity reaction.

Table 6. Wilcoxon test: decision weights v. judged probabilities

	TWABCD v. TPABCD	**TWABH v. TPABH**	**TWAED v. TPAED**	**TWCDI v. TPCDI**	**TWAG v. TPAG**	**TWFD v. TPFD**	**TWHI v. TPHI**
Z	-2.184	-2.044	-2.717	-1.463	-1.997(a)	-2.960(a)	-2.170(a)
p-value	0.029*	0.041*	0.007*	0.143	0.046*	0.003*	0.03*

Note. Null hypothesis: no difference in ambiguity reaction. * significant at the 5% level or less.

Table 7. Self-reported emotions

		N	Mean	Median	Standard Deviation
Negative Emotions	**Group 1**	30	6.13	7	3.47
	Group 2	35	5.4	5	3.47
	Pooled data	65	5.73	6	3.51
Positive Emotions	**Group 1**	31	3.23	3	3.07
	Group 2	35	4.17	4	3.30
	Pooled data	66	3.73	3.5	3.25
Satisfaction	**Group 1**	31	3.17	2	3.11
	Group 2	35	4.4	5	3.44
	Pooled data	65	3.83	3	3.37
Net affect (positive less negative emotions)	**Group 1**	30	-2.87	0	5.51
	Group 2	35	-1.228	0.5	6.4
	Pooled data	65	-2	0	6.1

Note: Group 1 denotes the Alessandria experiment for the 2004 European parliamentary election, Group 2 the Milan experiment for the 2001Italian general political election. Self-assessed emotions are reported on a scale between 0 (no involvement) and 10 (maximum involvement).

Table 8. Confidence and competence

	N	Mean	Median	Standard Deviation
Competence (Alessandria)	31	4	5	1.97
Confidence (Milan)	35	5.98	6	1.8
t-test for independent samples **t**=-4.2 p-value=0		**Wilcoxon-Mann-Whitney test for independent samples**: t=-4; p-value=0		

Note: Null hypothesis of equal means (t-test) or medians (Wilcoxon-Mann-Whitney test). Competence is based on a ten-question politics questionnaire (one point for each correct answer); Confidence is self-assessed expertise in politics, which is reported on a scale between 0 (no expertise) and 10 (very expert)

Table 9. Estimating the difference between decision weights and judged probabilities: pooled OLS and random effects estimates

	(1) Difference Decision Weight Judged Probs Pooled OLS	(2) Difference Decision Weight Judged Probs Pooled OLS	(3) Difference Decision Weight Judged Probs Pooled OLS	(4) Difference Decision Weight Judged Probs Random Effects	(5) Difference Decision Weight Judged Probs Random Effects	(6) Difference Decision Weight Judged Probs Random Effects
Positive emotion	0.021 (2.65)**	----------	-------------	0.021 (1.43)	--------------	----------
Negative emotion	---------	-0.02 (-2.76)**	---------------	-----------	-0.02 (-1.42)	----------
Net affect	----------	-----------	0.013 (3.14)**	-------------	------------	0.013 (1.72)
Confidence	0.042 (3.79)**	0.048 (4.21)**	0.046 (4.04)**	0.042 (1.86)	0.048 (2.08)*	0.046 (2.01)*
Competence	0.064 (4.32)**	0.065 (4.51)**	0.065 (4.34)**	0.064 (2.08)*	0.065 (2.09)*	0.065 (2.08)*
Age	-0.021 (-3.81)**	-0.025 (-4.56)**	-0.022 (-4.16)**	-0.021 (-1.77)	-0.025 (-2.09)*	-0.022 (-1.89)
Sex	-0.113 (-2.14)*	-0.115 (-2.11)*	-0.108 (-2.01)*	-0.113 (-1.11)	-0.115 (-1.11)	-0.108 (-1.06)
Dummy13	2.39 (5.32)**	2.412 (5.36)**	2.398 (5.33)**	2.39 (1.61)	2.412 (1.62)	2.398 (1.61)
Time1	0.125 (1.21)	0.12 (1.16)	0.12 (1.16)	0.125 (1.67)	0.12 (1.59)	0.12 (1.59)
Time2	0.043 (0.52)	0.04 (0.48)	0.04 (0.48)	0.043 (0.78)	0.04 (0.72)	0.04 (0.72)
Time3	0.098 (1.12)	0.101 (1.14)	0.101 (1.15)	0.098 (1.69)	0.101 (1.71)	0.101 (1.71)
Time4	0.02 (0.22)	0.017 (0.19)	0.017 (0.19)	0.02 (0.32)	0.017 (0.27)	0.017 (0.27)
Time5	-0.014 (-0.18)	-0.007 (-0.09)	-0.007 (-0.09)	-0.014 (-0.25)	-0.007 (-0.12)	-0.007 (-0.12)
Time6	0.059 (0.73)	0.069 (0.84)	0.069 (0.84)	0.059 (1.03)	0.069 (1.2)	0.069 (1.2)
Constant	0.352 (2.32)*	0.611 (4.20)**	0.464 (3.32)**	0.352 (1.15)	0.611 (2.08)*	0.464 (1.6)
Observ	462	455	455	462	455	455
F test	F(12, 449) = 6.08 [0]**	F(12, 442) = 6.43 [0]**	F(12, 442) = 6.21 [0]**	-------------	-----------	-----------
R-squared	0.32	0.32	0.32	0.32	0.32	0.32
Wald Chi^2(13)	--------------	---------------	---------------	= 25.33 [0.02]*	=26.03 [0.016]*	=25.33 [0.02]*

Columns (1)-(3): Robust t statistics in round brackets. Columns (4)-(6): Robust z statistics in round brackets. Robust p-values in square brackets. * significant at 5%; ** significant at 1%.
Note: Time dummies refer to space partitioning (ABCD, ABH, AED, CDI, AG, FD)

Table 10 Estimating decision weights: pooled OLS and random effects

	(1) Decision Weights Pooled OLS	(2) Decision Weights Pooled OLS	(3) Decision Weights Pooled OLS	(4) Decision Weights Random Effects	(5) Decision Weights Random Effects	(6) Decision Weights Random Effects
Positive Emotion	0.033 (4.59)**	------------	------------	0.033 (2.32)*	------------	
Negative Emotion	-----------	-0.015 (-2.16)*	-------------	----------	-0.015 (-1.1)	
Net affect	-----------	------------	0.014 (3.79)**	-----------	-------------	0.014 (1.96)*
Confidence	0.021 (2.26)*	0.025 (2.45)*	0.026 (2.62)**	0.021 (1.16)	0.025 (1.26)	0.026 (1.33)
Competence	0.044 (3.68)**	0.044 (3.24)**	0.044 (3.55)**	0.044 (1.71)	0.044 (1.48)	0.044 (1.64)
Age	-0.017 (-2.99)**	-0.024 (-4.12)**	-0.02 (-3.68)**	-0.017 (-1.36)	-0.024 (-1.87)	-0.02 (-1.65)
Sex	-0.121 (-2.51)*	-0.118 (-2.25)*	-0.121 (-2.41)*	-0.121 (-1.29)	-0.118 (-1.17)	-0.121 (-1.24)
Dummy13	1.99 (4.95)**	2.045 (5.08)**	2.014 (5.00)**	1.99 (1.28)	2.045 (1.28)	2.014 (1.28)
Time1	0.795 (8.81)**	0.792 (8.59)**	0.792 (8.67)**	0.795 (12.88)**	0.792 (12.73)**	0.792 (12.74)**
Time2	0.375 (4.78)**	0.373 (4.63)**	0.373 (4.68)**	0.375 (7.75)**	0.373 (7.65)**	0.373 (7.65)**
Time3	0.399 (5.16)**	0.404 (5.06)**	0.404 (5.11)**	0.399 (8.18)**	0.404 (8.17)**	0.404 (8.17)**
Time4	0.423 (5.42)**	0.423 (5.32)**	0.423 (5.36)**	0.423 (8.71)**	0.423 (8.66)**	0.423 (8.65)**
Time5	-0.035 (-0.51)	-0.028 (-0.41)	-0.028 (-0.41)	-0.035 (-0.76)	-0.028 (-0.62)	-0.028 (-0.61)
Time6	0.015 (0.21)	0.024 (0.32)	0.024 (0.33)	0.015 (0.32)	0.024 (0.52)	0.024 (0.52)
Constant	1.398 (9.75)**	1.767 (11.93)**	1.622 (11.86)**	1.398 (4.62)**	1.767 (5.80)**	1.622 (5.57)**
Observations	462	455	455	462	455	455
R-squared	0.46	0.44	0.45	0.46	0.44	0.45
F test	F(12, 449) = 19.45 [0]**	F(12, 442) = 17.84 [0]**	F(12, 442) = 18.22 [0]**	--------------	------------	------------
Wald Chi^2(13)	-----------	------------	-------------	= 1486.87 [0]**	= 1370.64 [0]**	= 1418.73 [0]**
Number of sub |				66	65	65
Columns (1)-(3): Robust t statistics in round brackets. Columns (4)-(6): Robust z statistics in round Brackets. Robust p-values in square brackets. * significant at 5%; ** significant at 1%.						

Note: Time dummies refer to space partitioning (ABCD, ABH, AED, CDI, AG, FD)

Table 11 Estimating judged probabilities: pooled OLS and random effects

	(1) Judged Probabilities OLS	(2) Judged Probabilities OLS	(3) Judged Probabilities OLS	(4) Judged Probabilities Random Effects	(5) Judged Probabilities Random Effects	(6) Judged Probabilities Random Effects
Positive Emotions	0.012 (2.51)*	------------	--------------	0.012 (1.15)	-------------	-------------
Negative Emotions	--------	0.005 (1)	----------------	-------------	0.005 (0.49)	--------------
Net affect	---------	-------------	0.002 (0.67)	--------------	--------------	0.002 (0.33)
Confidence	-0.021 (-2.72)**	-0.023 (-3.00)**	-0.02 (-2.66)**	-0.021 (-1.26)	-0.023 (-1.39)	-0.02 (-1.22)
Competence	-0.02 (-1.95)	-0.026 (-2.50)*	-0.021 (-2.00)*	-0.02 (-0.9)	-0.026 (-1.14)	-0.021 (-0.91)
Age	0.004 (1.16)	0.001 (0.34)	0.002 (0.52)	0.004 (0.51)	0.001 (0.15)	0.002 (0.23)
Sex	-0.008 (-0.24)	-0.004 (-0.1)	-0.014 (-0.39)	-0.008 (-0.11)	-0.004 (-0.05)	-0.014 (-0.19)
Dummy 13	-0.4 (-4.03)**	-0.367 (-3.68)**	-0.384 (-3.84)**	-0.4 (-1.25)	-0.367 (-1.14)	-0.384 (-1.19)
Time 1	0.67 (9.85)**	0.673 (9.72)**	0.673 (9.70)**	0.67 (14.03)**	0.673 (13.89)**	0.673 (13.88)**
Time 2	0.332 (6.22)**	0.333 (6.16)**	0.333 (6.13)**	0.332 (9.21)**	0.333 (9.15)**	0.333 (9.13)**
Time 3	0.301 (5.68)**	0.303 (5.61)**	0.303 (5.61)**	0.301 (8.69)**	0.303 (8.63)**	0.303 (8.63)**
Time 4	0.403 (7.29)**	0.406 (7.16)**	0.406 (7.16)**	0.403 (10.84)**	0.406 (10.71)**	0.406 (10.71)**
Time 5	-0.021 (-0.48)	-0.021 (-0.48)	-0.021 (-0.48)	-0.021 (-0.65)	-0.021 (-0.65)	-0.021 (-0.65)
Time 6	-0.044 (-1.02)	-0.045 (-1.02)	-0.045 (-1.01)	-0.044 (-1.31)	-0.045 (-1.31)	-0.045 (-1.32)
Constant	1.046 (10.11)**	1.156 (11.81)**	1.158 (11.73)**	1.046 (4.66)**	1.156 (5.48)**	1.158 (5.42)**
Observations	462	455	455	462	455	455
R-squared	0.39	0.38	0.38	0.39	0.38	0.38
F test	F(12, 449) = 22.69 [0]**	F(12, 442) = 20.92 [0]**	F(12, 442) = 21.17 [0]**	---------------	-------------	--------------
Wald Chi^2(13)	---------------	--------------	---------------	1801.45 [0]**	1732.36 [0]**	1736.44 [0]**
Number of sub	66	65	65	66	65	65

Columns (1)-(3): Robust t statistics in round brackets. Columns (4)-(6): Robust z statistics in round Brackets. Robust p-values in square brackets. * significant at 5%; ** significant at 1%

Note: Time dummies refer to space partitioning (ABCD, ABH, AED, CDI, AG, FD).

Table 12.1. Decision weights: Lower and Upper Subadditivity

Subject	GROUP	dw	dwprime	Sw
1	1	0.63	0.28	0.09
2	1	0.5	0.33	0.17
3	1	0.7	0.7	-0.4
4	1	0.28	-0.22	0.94
5	1	0.33	0	0.67
6	1	0.3	0.4	0.3
7	1	0.5	0.25	0.25
8	1	0.42	0	0.58
9	1	0.75	1	-0.75
10	1	0.5	0.08	0.42
11	1	0.5	0.33	0.17
12	1	0.42	0.42	0.16
13	1	1.5	0.08	-0.58
14	1	0.17	0	0.83
15	1	0.33	0.25	0.42
16	1	0.32	0.08	0.6
17	1	0.33	0.1	0.57
18	1	0.37	-0.37	1
19	1	0.33	0.42	0.25
20	1	0.5	0	0.5
21	1	0.33	0.25	0.42
22	1	0.5	0.17	0.33
23	1	0.33	0.22	0.45
24	1	0.33	0.48	0.19
25	1	0.33	-0.28	0.95
26	1	-0.08	0.25	0.83
27	1	0.28	-0.22	0.94
28	1	0.83	0	0.17
29	1	0.08	-0.33	1.25
30	1	0.5	0.17	0.33
31	1	0.33	0.25	0.42
32	2	0.42	0.46	0.12
33	2	0.01180556	0.67	0.16
34	2	0.21	0.17	0.62
35	2	0.58	0.25	0.17
36	2	0.42	0.42	0.16
37	2	0.25	0.25	0.5
38	2	0.58	0.33	0.09
39	2	0.33	0.17	0.5
40	2	0.17	-0.17	1
41	2	0.58	0.5	-0.08
42	2	0.38	0.29	0.33
43	2	0.58	0.17	0.25
44	2	0.17	0	0.83
45	2	0.33	0.58	0.09
46	2	0.42	0.33	0.25
47	2	0.42	0.67	-0.09
48	2	0.58	-1.08	1.5
49	2	0.67	0.17	0.16
50	2	0.58	0.42	0
51	2	0.42	0.08	0.5
52	2	0.49	0.18	0.33
53	2	0.5	1.08	-0.58
54	2	0.5	0.5	0
55	2	0.04	0	0.96
56	2	0.33	0	0.67
57	2	0.17	0.17	0.66
58	2	0.25	0.17	0.58
59	2	0.25	0.67	0.08
60	2	0.17	0.08	0.75
61	2	0.13	0.08	0.79
62	2	0.75	0.38	-0.13
63	2	0.75	0.58	-0.33
64	2	0.5	0.17	0.33
65	2	0.33	0.25	0.42
66	2	0.13	0.38	0.49

Table 12.2. Judged Probabilities: Lower and Upper Subadditivity

Subject	GROUP	dp	dpprime	sp
1	1	0.23	0.23	0.54
2	1	0.1	0.6	0.3
3	1	0.7	0.7	-0.4
4	1	0.22	0.02	0.76
5	1	0.7	0.1	0.2
6	1	0.3	0.4	0.3
7	1	0.2	0	0.8
8	1	0.1	0.1	0.8
9	1	0.32	0.6	0.08
10	1	0.3	0.25	0.45
11	1	0.7	0.3	-1.1102E-16
12	1	0.6	0.7	-0.3
13	1	0.1	0.5	0.4
14	1	0.4	0.4	0.2
15	1	0.4	0.4	0.2
16	1	0.3	0.25	0.45
17	1	0.4	0.2	0.4
18	1	0.45	0.45	0.1
19	1	-0.08	0.1	0.98
20	1	0.6	0.35	0.05
21	1	0.25	0.25	0.5
22	1	0.6	0.7	-0.3
23	1	0.35	0.2	0.45
24	1	0.2	0.3	0.5
25	1	0.57	0.7	-0.27
26	1	0.2	0.15	0.65
27	1	0.17	-0.03	0.86
28	1	0.31	0.01	0.68
29	1	0.35	0.3	0.35
30	1	0.5	0.2	0.3
31	1	0.35	0.25	0.4
32	2	0	0.15	0.85
33	2	0.25	0.3	0.45
34	2	0.1	0	0.9
35	2	0.4	0.58	0.02
36	2	0.4	0.5	0.1
37	2	0.2	0.2	0.6
38	2	0.6	0.3	0.1
39	2	0.25	0.35	0.4
40	2	0.45	0.3	0.25
41	2	0.4	0.1	0.5
42	2	0.2	0.4	0.4
43	2	0.4	0.5	0.1
44	2	0.9	0.25	-0.15
45	2	0.25	0.35	0.4
46	2	0.4	0.4	0.2
47	2	0.05	-0.2	1.15
48	2	0.75	0.55	-0.3
49	2	0.3	0.4	0.3
50	2	0.4	0.3	0.3
51	2	0.4	0.05	0.55
52	2	0.3	0.2	0.5
53	2	0.3	0.5	0.2
54	2	0.1	0.7	0.2
55	2	0.2	0.5	0.3
56	2	0.2	0.1	0.7
57	2	0	0	1
58	2	0.2	0.55	0.25
59	2	0.45	0.4	0.15
60	2	0.15	0.2	0.65
61	2	0.6	0.35	0.05
62	2	0.5	0.25	0.25
63	2	0.25	0.2	0.55
64	2	0.15	0.05	0.8
65	2	0.25	0.15	0.6
66	2	1	0.2	0.7

Table 13. Lower and Upper Subadditivity: median values across subjects

	d	dprime	s
Decision weights	**0.375**	**0.235**	**0.33**
Judged Probabilities	**0.3**	**0.3**	**0.4**

Note: d, lower subadditivity; dprime, upper subadditivity; s=1-d-dprime, global sensitivity.

Table 14.1. Emotion, competence, confidence and bounded subadditivity: decision weights

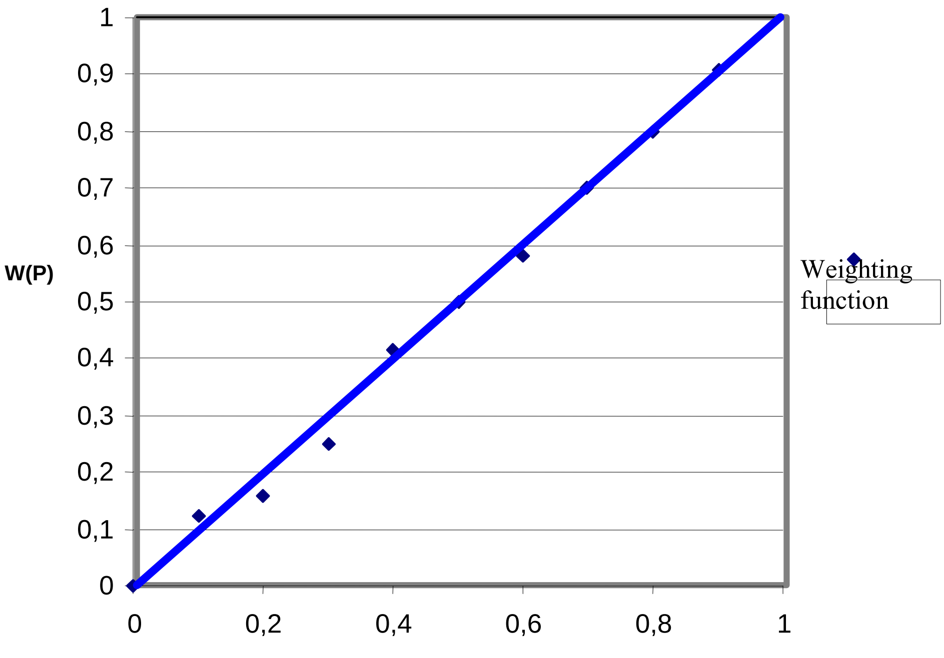
	(1) **dw**	(2) **dw**	(3) **dw**	(4) **dwprime**	(5) **dwprime**	(6) **dwprime**	(7) **sw**	(8) **sw**	(9) **sw**
Positive Emotions	0.013 (2.04)*	-----------	-----------	0.004 (0.25)	----------	-----------	-0.017 (-0.99)	---------	--------
Negative Emotions	-----------	-0.008 (-1.19)	-----------	---------	-0.008 (-0.55)	-----------	----------	0.017 (1)	----------
Net affect	-----------	-----------	0.006 (1.77)	------------	------------	0.004 (0.47)	----------	-----------	-0.01 (-1.18)
Confidence	0.021 (2.78)**	0.023 (2.94)**	0.023 (3.06)**	0.012 (0.58)	0.015 (0.63)	0.013 (0.59)	-0.032 (-1.42)	-0.038 (-1.46)	-0.036 (-1.44)
Competence	0.032 (2.84)**	0.031 (2.44)*	0.032 (2.66)*	0.003 (0.12)	0.006 (0.21)	0.005 (0.15)	-0.034 (-1)	-0.036 (-0.95)	-0.035 (-0.96)
Age	-0.009 (-1.13)	-0.012 (-1.6)	-0.01 (-1.39)	0.003 (0.49)	0.003 (0.38)	0.003 (0.49)	0.006 (0.57)	0.01 (0.9)	0.007 (0.69)
Sex	-0.047 (-1.03)	-0.047 (-0.99)	-0.046 (-0.99)	0.01 (0.1)	0.005 (0.04)	0.01 (0.09)	0.032 (0.28)	0.038 (0.31)	0.032 (0.26)
Dummy13	1.033 (19.53)**	1.051 (19.60)**	1.041 (19.30)**	-0.114 (1.14)	-0.118 (-1.21)	-0.118 (-1.17)	-0.913 (-6.79)**	-0.928 (-7.07)**	-0.917 (-6.80)**
Constant	0.466 (2.41)*	0.618 (3.48)**	0.548 (3.14)**	0.077 (0.45)	0.135 (0.66)	0.087 (0.49)	0.441 (1.6)	0.224 (0.82)	0.348 (1.32)
Observations	66	65	65	66	65	65	66	65	65
R-squared	0.45	0.43	0.44	0.02	0.02	0.02	0.12	0.13	0.13
F-test	F(6,59) = 7.892 [0]**	F(6,58) = 7.367 [0]**	F(6,58) = 7.734 [0]**	F(6,59) = 0.184 [0.9]	F(6,58 = 0.24 [0.9]	F(6,58) = 0.22 [0.9]	F(6,59) = 1.36 [0.25]	F(6,58) = 1.38 [0.24]	F(6,58) = 1.42 [0.22]
Note				Fails normality test at 1%	Fails normality test at 1%	Fails normality test at 5%	Fails normality test at 5%		Fails normality test at 5%
Robust t statistics in parentheses. * significant at 5%; ** significant at 1%									

Table 14.2. Emotion, competence, confidence and bounded subadditivity: judged probabilities

	(1)) dp	(2) dp	(3) dp	(4) dpprime	(5) dpprime	(6) dpprime	(7) sp	(8) sp	(9) sp
Positive Emotions	0.005 (0.57)	----------	---------	0.005 (0.66)	.---------	---------	-0.016 (-1.27)	---------	--------
Negative Emotions	----------	0.002 (0.26)	----------	----------	-0.001 (-0.12)	----------	--------	0.004 (0.33)	---------
Net affect	-----------	----------	0.001 (0.15)	----------	----------	0.002 (0.4)	--------	--------	-0.005 (-0.85)
Confidence	-0.01 (-0.65)	-0.011 (-0.72)	-0.01 (-0.64)	0 (0.03)	0 (0.01)	0 (0.01)	0.017 (-0.66)	0.016 (0.63)	0.015 (0.57)
Competence	-0.012 (-0.62)	-0.013 (-0.71)	-0.011 (-0.58)	0.006 (0.34)	0.006 (0.35)	0.007 (0.41)	0.005 (-0.17)	0.005 (0.17)	0.002 (0.06)
Age	-0.009 (-1.22)	-0.01 (-1.55)	-0.01 (-1.4)	-0.001 (-0.23)	-0.003 (-0.42)	-0.002 (-0.36)	0.004 (0.4)	0.008 (0.74)	0.006 (0.61)
Sex	-0.078 (-1.36)	-0.08 (-1.3)	-0.084 (-1.38)	-0.069 (-1.21)	-0.074 (-1.26)	-0.076 (-1.29)	0.17 (1.85)	0.183 (-1.89)	0.187 (1.96)
Dummy13	-0.257 (5.89)**	-0.246 (5.99)**	-0.252 (6.05)**	0.194 (3.56)**	0.2 (3.76)**	0.195 (3.56)**	0.053 (0.62)	0.032 (0.39)	0.047 (0.56)
Constant	0.645 (3.47)**	0.693 (5.26)**	0.695 (4.44)**	0.345 (2.05)*	0.4 (2.59)*	0.387 (2.56)*	0.162 (0.6)	-0.015 (-0.06)	0.033 (0.14)
Observations	66	65	65	66	65	65	66	65	65
R-squared	0.12	0.12	0.12	0.05	0.05	0.05	0.12	0.11	0.12
Ftest	F(6, 59) =1.39 [0.26]	F(6,58) =1.3 [0.27]	F(6,58) =1.29 [0.27]	F(6, 59) = 0.55 [0.76]	F(6,58) = 0.52 [0.78]	F(6,58) = 0.54 [0.76]	F(6,59) =1.33 [0.25]	F(6,58) = 1.17 [0.33]	F(6,58) = 1.26 [0.28]
Note	Fails normality test at 5%	Fails normality test at 5%	Fails normality test at 5%						
Robust t statistics in parentheses. * significant at 5%; ** significant at 1%									

Figures

Figure 1. Weighting function under risk



Note: the weighting function under risk, W(P), corresponds to the 45 degree line in the Alessandria experiment and to the squared dots for the Milan experiment. Each point represents more than one subject.

Figure 2. Target events for pricing questions

A: ***0-43***
(0-21)
|-----------

B: ***43-48***
(21-25)
|--------------

C: ***48-53***
(25-29)
|---------------

D: ***53-100***
(29-100)
|---------------|

E: ***43-53***
(21-29)
|------------------------------

F: ***0-53***
(0-29)
|---

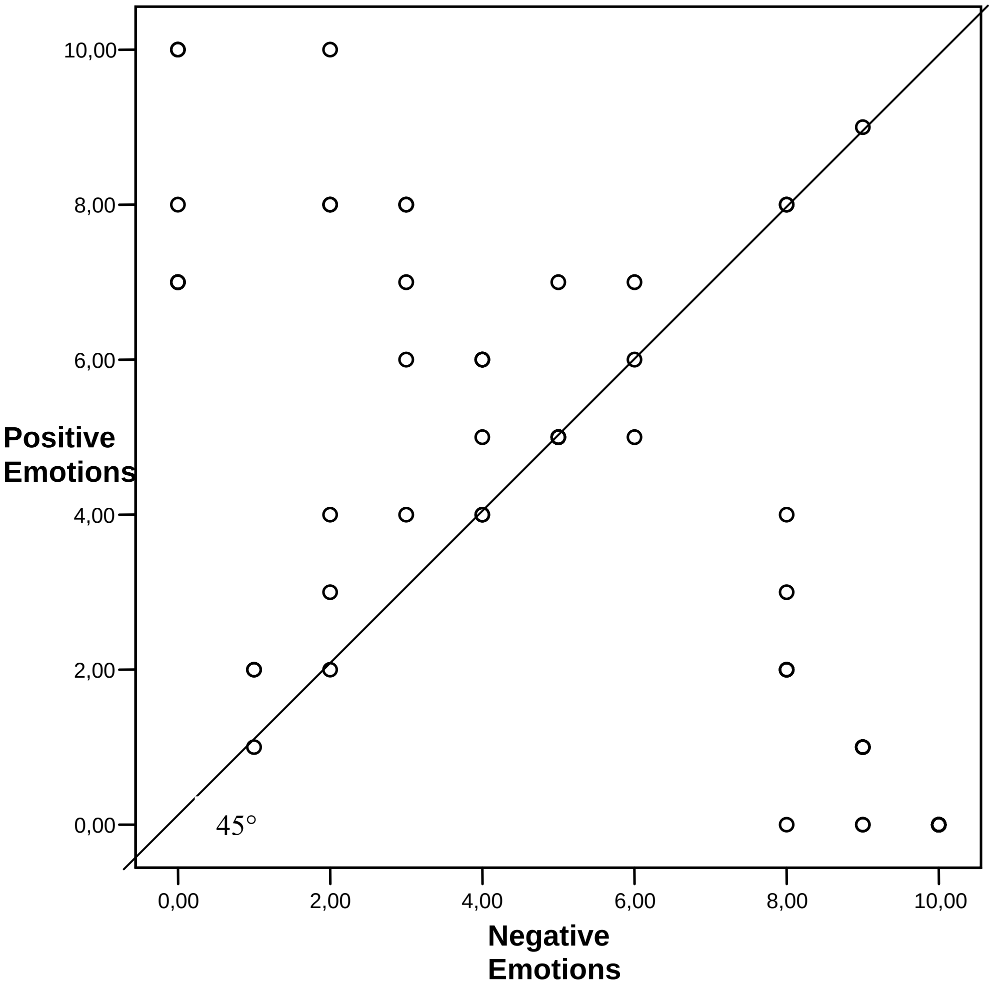
G: ***43-100***
(21-100)
|--|

H: ***48-100***
(25-100)
|--------------------------------|

I: ***0-48***
(0-25)
|------------------------

Note : Event space for prospects based on the proportion of votes received by either the Casa delle Libertà in the 2001 Italian political elections (shown in italics) or by Forza Italia in the 2004 European parliamentary elections (shown in round brackets).

Figure 3. Emotions



Note: Points above (below) the 45 degree line show subjects with positive (negative) net affect, where net affect is defined as the difference between self-reported positive emotions and negative emotions, on a scale from 0 to 10, for each subject. Each point may represent more than one subject.

Figure 4 Tests for bounded subadditivity

Weighting functions

Tests for lower subadditivity (7)

DW(A,B)1= w(IA) +w(IB)-w(II)
DW(A,B)2= w(IB)+w(IC)-w(IE)
DW(A,B)3=w(IC)+w(ID)-w(IH)
DW(A,B)4=w(II)+w(IC)- w(IF)
DW(A,B)5=w(IA)+w(IE)-w(IF)
DW(A,B)6=w(IE)+w(ID)-w(IG)
DW(A,B)7=w(IB)+w(IH)-w(IG)

Tests for upper subadditivity (3)

DWprime1(A,B)=1-w(IG)-w(II)+w(IB)
DWprime2(A,B)=1-w(IG)-w(IF)+w(IE)
DWprime3(A,B)=1-w(IH)-w(IF)+w(IC)

Judged probabilities

Tests for lower subadditivity (7)

Dp1= ISB+ISA-ISH
Dp2= ISC+ISB-ISI
Dp3=ISD+ISC-ISG
Dp4=ISH+ISC-ISE
Dp5=ISA+ISI-ISE
Dp6=ISI+ISD-ISF
Dp7=ISB+ISG-ISF

Test for upper subadditivity (3)

Dpprime1=1-ISF-ISH+ISB
Dpprime2=1-ISF-ISE+ISI
Dpprime3=1-ISG-ISE+ISI