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Games and Economic Behavior 52 (2005) 257–282
GAMES and Economic Behavior
www.elsevier.com/locate/geb

A brain imaging study of the choice procedure

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Received 8 June 2004

Available online 10 December 2004

Abstract

We study the behavior of subjects facing choices between certain, risky, and ambiguous lotteries. Subjects' choices are consistent with the economic theories modeling ambiguity aversion. Our results support the conjecture that subjects face choice tasks as an estimation of the value of the lotteries, and that the difficulty of the choice is an important explanatory variable (in addition to risk and ambiguity aversion).

The brain imaging data suggest that such estimation is of an approximate nature when the choices involve ambiguous and risky lotteries, as the regions in the brain that are activated are typically located in parietal lobes. Thus such choices require mental faculties that are shared by all mammals, and in particular are independent of language. In contrast, choices involving partial ambiguous lotteries additionally produce an activation of the frontal region, which indicates a different, more sophisticated cognitive process.

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0899-8256/$ – see front matter
doi:10.1016/j.geb.2004.08.005

JEL classification: D81

Keywords: Brain imaging; Decision theory; Ambiguity; Procedural choice

1. Introduction

> "*The mental operations by which ordinary practical decisions are made are very obscure, and it is a matter of surprise that neither logicians nor psychologists have shown much interest in them* (Frank Knight, 1921, Chapter 7)".

1.1. Risk and uncertainty

In *Risk, Uncertainty and Profit*, Frank Knight (1921) introduced a distinction between risk and uncertainty. He called a choice environment *risky* if the outcome is random, but the person making the choice can reasonably attach a numerical probability to each event. He called it *uncertain* if the subject cannot define uniquely and precisely such numerical probability. For example, if the probability of the events are described "objectively," [1] as in tossing a coin or rolling a die, then it is natural to expect that the subject will attach probabilities to events equal to the objective ones. On the other hand, in a situation of uncertainty the subject may have no reasonable estimate of the frequency of the events, say, because the event or choice he is asked to consider is a of a unique, once-and-for-all nature.

The basis of the difference derives in Knight's view from the way in which estimates of probabilities are derived. In the case of risk, the probability distribution over possible outcomes is known. This may be due to an a priori calculation (as in the case of the roll of a die) or frequency estimation. On the other hand, this knowledge is not available in the case of uncertainty, either because no obvious list of equally likely and exhaustive basic alternatives is available or "because the situation is in high degree unique" (Knight, 1921, Chapter 8).

This point of view may seem outdated in view of the rise, in the years to follow Knight's book, of the subjectivist approach to probability of Ramsey, de Finetti and Savage.[2] In the classical theory of choice under uncertainty called "Subjective Expected Utility" (SEU for short)—the most complete treatment of which is the axiomatic formulation by L.J. Savage (1954)—such distinction vanishes. In SEU theory, it is assumed that the subject is able to provide a subjective probabilistic estimate of the relative probability of each event. Once he has done that, the evaluation of a lottery (or, more generally, a state-contingent payoff function) is the same under risk or uncertainty: It is the expected value, computed with respect to this probability. Therefore, in terms of the Knightian distinction, according to SEU theory all uncertainty can be reduced to risk.

[1] Knight (1921, Chapter 8) states that the terms objective and subjective are equivalent to those of risk and uncertainty, but this identification may be confusing today.

[2] The first draft of the book was Knight's doctoral dissertation at Cornell, 1915–1916.

However, in their actual behavior human subjects may fall short of the expectations of theorists. Indeed, among scholars of economics and decision making there has been a resurgence in the interest on Knight's distinction motivated by a very interesting critique of SEU theory formulated by Daniel Ellsberg (1961). Moreover, we will argue in this paper that the distinction may acquire more interest in light on the surging attention on the mental process that the subject follows to formulate his estimate of the likelihood of events.

1.2. Ellsberg's "paradox"

Ellsberg (1961) begins with the Knightian distinction, using the now more customary term *ambiguity* instead of Knight's "uncertainty." Rather than trying to base the distinction on the way in which the probabilities are estimated, he accepts the purely subjective view of Ramsey, de Finetti and Savage: "The degree of a belief is the extent to which we are prepared to act upon it" (Ramsey, 1926). That is, whether subjects are able to attach numerical probability or not to two events can only be measured by their choices over acts based on these events. If subjects are willing to give us an answer to every choice we propose them, and provided that their answers are consistent, this measurement is unambiguously defined.

His classical thought experiment is the first attempt to test whether there is a significant difference between ambiguity and risk. In his experiment, subjects face the choice among lotteries, where the outcome is described by draws of balls from an urn. For an urn with Red, Black and Yellow balls, I can define a lottery as three numbers, assigning, say, a monetary amount to each of the three outcomes. The proportion of the balls, however, is not completely specified: For example, in his classical design, an urn has 90 balls, of which 30 are Red and 60 are Black and Yellow, with the relative number of Black and Yellow balls unspecified. So the subject is not provided with an objective probability: Does he always provide his own, well-specified, subjective probability over the different outcomes, as SEU theory requires?

Ellsberg's experiment:[3] The experimenter tells the subject that an urn has the composition of Red (R), Black (B) and Yellow (Y) balls as described above. Then, the subject is asked to choose between the lotteries a and b whose payoffs (in dollars) are determined according to the following table:

	R	B	Y
a	100	0	0
b	0	100	0

After the subject has made this choice, the experimenter asks him to choose between the lotteries c and d defined by the following:

[3] Though Ellsberg by his own admission tried his experiment under "absolutely non-experimental conditions," this pattern of choices has been observed in a multitude of properly conducted experiments. See, e.g., Luce (2000) for references to this vast literature.

	R	B	Y
c	100	0	100
d	0	100	100

Most subjects choose a in the first pair of lotteries, and d in the second. This is a violation of SEU theory. The intuitive reason is clear: If you are a SEU decision maker, and choose a in the first choice you must think that the outcome Yellow ball is more likely. But then this fact should make you choose c, not d in the next choice.

Thus, the typical subject of Ellsberg's experiment does not form a subjective probability for each event, even upon reflection, and even after interrogation or prodding by unsympathetic critics.[4] In fact, if the assumption that the subject estimates the different alternatives on the basis of some form of expectation is maintained, his choices show that such unique subjective probability cannot exist. When this occurs, we say that the subject's choices display *ambiguity aversion* (*or love*). Clearly, it is the absence of a well-defined objective probability in the experimental design that provides the conditions for ambiguity aversion/love to manifest itself.

The inability of subjects to form an estimate of the probability of different events was, until recently, a controversial issue mainly for scholars in economics. It may acquire larger interest now that neuro scientists have entered into this specific arena. A basic assumption of their program is that the two fundamental operations defining expected utility (the estimate of a probability and the estimate of value) have a neural basis. These are physical computations, performed by neurons. If subjects reveal with their choices that a unique probability does not exist, how can this operation have a neural basis? What is ambiguity aversion telling us about the psychological and neurological processes underlying decisions? Note that subjects in Ellsberg's experiments typically *do* choose one of the lotteries. So some decision process must have taken place. If the outcome is not consistent with the evaluation of expected utility with respect to a probability distribution, what was the process? For example, when Ellsberg introduces ambiguity as an explanation of his experimental observations, he explicitly notes it as a third component, in addition to probability and value, in the evaluation of a possible action.[5]

In light of the experimental robustness of ambiguity aversion, economists have developed extensions of SEU theory which incorporate this third component in a subject's decision rule. One of the most popular extensions is the so-called "Maxmin Expected Utility with multiple priors" (MEU for short) model of Gilboa and Schmeidler (1989). According to this model, the subject's beliefs are given by a *set* of probabilities (equivalently, the subject's beliefs on each event are given by an interval, rather than point, estimate).

4 These are called "deliberate violators" by Ellsberg (1963). Among them, Ellsberg reports, L.J. Savage.

5 He says (Ellsberg, 1961, p. 657):

"Responses from confessed violators indicate that the difference is not to be found in terms of the two factors commonly used to determine a choice situation, the relative desirability of the possible payoffs and the relative likelihood of the events affecting them, but in a third dimension of the problem of choice: the nature of one's information concerning the relative likelihood of the events."

The subject chooses the action whose worst-case expected utility evaluation (the minimum expected utility ranging over the set of possible probabilities) is highest.[6]

1.3. The psychological nature of ambiguity aversion

Ellsberg's paradox suggests that the Knightian distinction is substantial—and moreover that not all uncertainties can be reduced to risk—by proving that there is a difference in the behavior of subjects in choices under risk and choices under uncertainty. While the existence of the difference seems demonstrated, some still doubt its substance and importance. For instance, they argue that subjects might be confused. Deliberate violators might give up their violations facing a tighter experimental design (for instance, with an urn placed in front of their eyes during the entire experiment). Or, in the experimental situation in which ambiguity aversion appears, subjects might be simply exhibiting mistrust toward the experimenter.

The question we address in this paper is to determine experimentally whether there is a fundamental psychological difference between the two. We do this by analyzing the decision process; i.e., the sequence of different activities that are performed in taking a decision.

1.4. Decisions and emotions

Evidence from neuroscience suggests that choices under risk and ambiguity might be fundamentally different from the psychological point of view. In a series of classical papers and books, Antonio Damasio and his group have suggested that emotional components enter ambiguous choices in a crucial way. The evidence for this statement, which is reviewed more in detail later, is both clinical and experimental.

The clinical evidence is provided by a set of human subjects with lesions in the prefrontal cortex. These subjects are well known to have difficulties both in expressing and forming emotions, as well as in taking decisions. However they are not in any significant way impaired in their intellectual, cognitive and memory abilities.

Human subjects choosing a deck out of a set of card decks provide the experimental evidence. A payoff, real or hypothetical, is associated with each card, according to a probability that is not completely specified to the subjects. They are asked to choose one of the card decks; once they choose, they draw a card from the deck, examine the card, and discover the payoff of that card. Then, they proceed to the next choice. Just as in the case of the Ellsberg's urn, the experimenter does not provide the subject with a complete description of the stochastic process he is facing. The truth is that some of the decks have higher gains, but also higher losses, while others have lower gains as well as lower losses. The expected value of the first is lower than the second. The observation is that normal subjects tend over time to switch to the safer decks, while the choices of patients with frontal lesions converge to the first. Test of the emotional reactions to choices are also revealing: in the moments preceding the choice of the risky decks normal subjects show an active Galvanic

[6] In Ellsberg's experiment, a subject whose set of probabilities is given by all Ps such that $P(R) = 1/3$ and $P(B) \geqslant 1/4$ would make the typical ambiguity averse choices.

Skin Response (a measure of emotional reactions), while patients do not. The conclusion is also supported by brain imaging studies of subjects while making choices in the card decks experiment. Decision making, as Antoine Bechara and Antonio Damasio conclude (Bechara and Damasio, 2003), is a process driven by emotions.

1.5. Choices and emotions

On the other hand, subjects in the card deck experiment are performing several tasks at the same time they are choosing between alternatives: but they are also learning about the environment that they are facing, and they are receiving, after every choice, a feedback on their wins or losses. The involvement of emotional factors might therefore occur for any of these three different reasons.

Our experimental design aims at separating the choice from the learning and the payoff feedback, and tests the processes that are active in the presence of ambiguity. Our conclusion is that choice is a process driven by cognitive factors, even within those subjects that in the experiment unambiguously display ambiguity aversion.

1.6. Our experiment

The long-term aim of the research reported here is to identify and test a theory of how subjects actually reach their decisions. We think it is advisable, in this first phase of the research, to focus on the analysis of simple decisions, based on the choice between pairs of economic stimuli. Consequently, we chose a decision problem in line with the original Ellsberg's thought experiment (Ellsberg, 1961). We did not expect the choice behavior of subjects to be different from that predicted by existing "as if" theories of choice under risk and ambiguity, like the MEU model mentioned above. In fact, the analysis of the choice data in section below shows that they were not.

A second element in our choice of design was the introduction of a *partially* ambiguous lottery. In a risky lottery the subject knows the objective probability of outcomes, in an ambiguous lottery he has no information on this probability. In a partially ambiguous he has *some* information. The partially ambiguous lottery is located, *from a choice-theoretic point of view*, in an intermediate position between risky and ambiguous lottery. We will argue, however, that from a procedural point of view it has a very specific nature, so that the behavior of a subject facing a partially ambiguous lottery is very different. This is indeed what the analysis of the data on response times and the imaging data suggest.

1.7. Content of the paper

In Section 2 we describe the experimental design. In Section 3 we present and discuss the behavioral data. More precisely, in Section 3.1 we examine the choices made by the subjects in different conditions, while in Section 3.2 we focus on the response time; namely the time used by the subject to reach each decision. In Section 4 we present and interpret the brain-imaging data in the light of information available in the neuroscience literature on the significance of the different patterns and centers of neural activation. Finally, in Section 5 we draw our conclusions and outline the future research agenda.

2. Experimental design

Subjects were instructed to make a sequence of choices between pairs of lotteries. The pairs were presented in groups of similar choices, and no feedback on the outcome was provided during the test. Outcomes and payments were determined at the end.

2.1. Lotteries

In the entire experiment, four different types of lotteries were used: certain (C), risky (R), partially ambiguous (PA) and ambiguous (A) lotteries. Subjects were informed that the payoff to such lotteries would eventually be determined by the draw of a ball, which could be either blue or red, from an urn containing 180 balls. The number of balls of each color was to be consistent with the information given about the lottery, as specified below. Overall subjects had to make 96 choices. The actual payments were decided at the end of the experiment. First, 4 out of the 96 choices were randomly selected according to a uniform distribution.[7] We then checked which of the two lotteries had been selected in these choices, filled a real urn with balls consistently with the subject's information and asked the subject to pick one of the balls, while keeping the urn above his/her head. The subject was then paid the total of the payments for the four choices.

The pair of lotteries in each choice was presented on a screen, indicating the number of balls for each color and the amount in dollars that (a draw of a ball of) each color would pay. The only exception was the certain lottery, for which the screen simply indicated a fixed amount in dollars. Subjects knew that the urn always contained a total of 180 balls. In the R lottery they were told that the urn would contain 90 balls of each color. For the A lottery no information on the number of balls of either color was given (only that the balls could only be red or blue). Finally, for the PA lottery they were told that the urn would contain at least 10 balls of each color, leaving the composition of the remaining 160 unspecified (but again, that they could only be blue or red).[8]

2.2. Choices

In each choice, it is useful to classify one of the two lotteries as the *main* lottery and the other as the *reference* lottery. The main lottery was either risky, partially ambiguous or ambiguous. Thus, subjects were faced with increasing levels of ambiguity: From no ambiguity in the risky lottery to full ambiguity in the ambiguous one. The main lottery was to be compared to the reference lottery, which could be either risky or certain. We used all possible combinations of main and reference lotteries to obtain six types of choices, the *conditions* in our experiment. Each condition is denoted by the type of its lotteries: For example, the condition PAC faces the subject with a choice between a partially ambiguous

[7] The small number aims at making each subject's choices close to his true preference over the lotteries involved. With a large number, a subject might use a strategy over the entire portfolio of choices that would make the optimal lottery in each choice different from the one he would select if facing that specific choice in isolation.

[8] For the sake of determining a subject's actual payoff, the actual urn compositions in the A and PA case were chosen randomly.

lottery (PA, the main lottery), and a certain lottery (C, the reference lottery). The condition AR faces him/her with the choice between an ambiguous and a risky lottery, and so on. Overall we had three conditions where the reference lottery was of the R type (the R-conditions RR, PAR, AR), and three where the reference lottery was of the C type (the C-conditions RC, PAC, AC).[9]

2.3. *The lotteries*

A detailed description of the different lotteries is provided in Appendix B. Here we point out some specific features of the set of choices we used, because understanding them is essential in the interpretation of the results.

In the C condition subjects are comparing a certain amount (ranging from a minimum of 10 dollars to a maximum of 50) with either a risky, partially ambiguous, or ambiguous lottery. In the R condition the reference lottery is a risky, rather than certain, lottery: this choice may appear more difficult, but not necessarily in the specific setup we adopted. In fact, the reference lottery in fact *dominates* the main lottery, in the following sense. In the RR choice, the main lottery is a mean-preserving (variance-increasing) spread of the reference lottery. For example, the main lottery has payoffs $(64, 0)$, while the reference lottery has payoffs $(60, 4)$, with an equal probability for each type of ball. In the AR and PAR conditions, this negative effect is compounded by the ambiguity associated with the main lottery. For example, the reference lottery has payoffs $(60, 4)$ with fifty–fifty probability, while the main lottery has payoffs $(64, 0)$ for red and blue balls respectively, with an unspecified proportion of red and blue balls.

The joint effect of risk and ambiguity should therefore make the choice of the main lottery look inferior to a subject who is averse to risk and ambiguity. In addition, this comparison should involve simple qualitative reasoning, rather than quantitative comparisons. On the other hand, the choice in the C conditions involves a quantitative comparison, since an estimate of the value of the main lottery is compared with the certain value of a C-type lottery. As we are going to see, this difference between the two R and C conditions is also suggested by our experimental observations.

2.4. *Time sequence*

Each subject experienced the six conditions (RC, PAC, AC, RR, PAR and AR) that we have just described, plus two with Eyes-Closed-Rest (ECR). The conditions and the set of choices in each condition were the same for each subject. The order in which the conditions were presented, and the order of choices within each condition, was determined randomly and independently for each subject.

[9] The names “main” and “reference lottery” are used here for expository purposes only. These names were never used in the experiment, and neither were the labels “certain,” “risky,” “partially ambiguous” and “ambiguous.”

2.5. Imaging technique

The imaging study was conducted using the PET (Positron Emission Tomography) scanning technique. General information on the technique is given in Appendix C, together with a more detailed description of the technique used in the study.

2.6. Implementation

The original sample was composed of 12 young healthy right-handed individuals, chosen among those answering a public announcement posted on campus. One of the subjects had to be excluded from the sample after post experiment interviews determined a state of depression[10]; for a second the data on scanning were lost for technical reasons. Therefore, the data in this study refer to the sub-sample of 10 individuals.

Subjects came in separately, on different days. We first paid each subject 50 dollars in cash. This show-up award was never at risk during the experiment. We then read the instructions. The instructions were very detailed; we also asked the subjects to answer short quiz questions during the presentation to check their understanding. Detailed and careful instructions were intended to make the subject familiar with the four different types of lotteries and the six different conditions. We presented a set of examples, and asked the subject to choose among the lotteries in the example. This also served the purpose of familiarizing the subjects with the method of expressing their choice, a click on the left or right button of a mouse.

After the instructions, the subjects were moved and were positioned in a scanner. Choices were made while the brain activity of the subject was scanned. We had 15 choices for each R condition and 17 choices for each C condition, for a total of 96 choices per subject. A choice appeared on the screen, and subjects had six seconds to decide. The time interval between choices was fixed, and independent from the moment in which the choice was made. A pause of two seconds would follow the end of each choice, and then the next choice would be displayed on the screen (so the overall time interval between choices was eight seconds). The time interval between the different conditions varied between two to four minutes, since a new condition could begin only when the scanner was ready for the next analysis. For each subject, the entire experiment lasted approximately two hours.

3. Behavioral data

3.1. Choices

3.1.1. The C conditions

The observed choices in the C conditions tend to follow a rather regular cutoff policy. Each subject chooses the R, PA or A lottery rather than the C lottery when the certain amount is below a threshold (which varies with the subject), and switches to the C lottery when the threshold is passed.

[10] This is standard procedure: the data from depressed subjects are not considered reliable.

Table 1
Summary statistics for the cutoff in the C conditions

Variable	Obs.	Mean	Std. err.	95% conf. int.
AC cutoff	170	22.7	0.439	[21.83, 23.56]
PAC cutoff	165	21.7	0.3769	[20.95, 22.44]
RC cutoff	153	28.11	0.217	[27.68, 28.54]

Table 2
Choices in the C conditions

Subject	27	29	40	44	52	53	55	59	68	71	Average	Median
Cutoff in RC	25	25	25	33	31	30	28	28	28	*	28.11	28
Deviations from cutoff	0	0	0	2	3	3	3	0	1	*	1.33	
Cutoff in PAC	20	25	15	32	20	30	20	20	15	25	21.7	20
Deviations from cutoff	0	0	0	1	2	0	2	1	0	0	0.6	
Cutoff in AC	20	20	15	31	30	28	20	28	15	20	22.7	20
Deviations from cutoff	0	0	0	2	0	0	0	0	0	1	0.3	
PAC–AC	0	5	0	1	−10	−3	0	−8	0	5	−1	

* Denotes missing data.

Estimates of the cutoff point are summarized in Table 1.[11] The cutoff value is chosen for each subject so as to minimize the number of deviations, for that subject, of the observed choices from the cutoff policy.[12]

Table 2 shows that subjects were consistent in their choices, and that the instances of deviations from the policy implicitly described by the cutoff are small in number.[13]

The bottom row of Table 2 reports the differences in the value of the cutoff for PAC and AC conditions. The differences are zero or small: this indicates that the choices of the same subject are consistent across conditions. The "Mean" column of Table 1 and the last row of Table 2 show that the values of the cutoffs in the two conditions PAC and AC are similar.

3.1.2. The R conditions

Table 3 reports the number of times each subject chose the risky reference lottery in the R conditions. Subjects chose the riskier lottery (the one with the greater spread) most frequently (but still only 14.7 percent of the times) in RR, and less frequently in PAR and AR (approximately the same in the two conditions).

3.1.3. Summary of the analysis of choices

Overall, the observed choices of the subjects are those predicted by widely accepted theories of choice in risky and ambiguous environments, like the MEU model. Between

[11] Some of the data are missing because either the subject did not choose in the amount of time available, or because of an error in recording the answer, for subject number 71.

[12] More precisely, the cutoff has been determined according to the following rule. A c-policy is the policy of choosing the C lottery if its value is larger or equal to c. For each of the possible values of c, determine the number of deviations from the c-policy in the observed choices of the subject. Choose the c that minimizes the number of deviations. If the value of this c is among the values at which the subject expressed indifference, choose the middle if the number of such values is odd, and the next one in ascending order if the number is even.

[13] Subjects are indicated by the classification number in data archive of the Veterans Affairs Medical Center.

Table 3
Choices of the main lottery in the R conditions

Subject	27	29	40	44	52	53	55	59	68	71	total	%
RR	0	4	0	3	0	6	1	6	2	*	22	14.7
PAR	1	0	0	4	0	1	1	4	1	0	12	8
AR	1	2	0	2	2	3	1	3	0	0	14	9.3

* Denotes missing data.

two lotteries, where one is a mean-preserving spread of the other, the subjects chose consistently and almost exclusively the lottery with smaller variance. Subjects were also ambiguity averse. This is hard to detect in the R conditions where the choice is already almost entirely of the lottery with smaller variance. But in the C conditions, the mean cutoff is six to seven dollars higher when the main lottery is R than it is when the main lottery is A or PA (see Table 1).

3.2. *Response times*

The *response time* (RT) is the length, in 1000th of a second (msc), of the time interval between the moment in which the stimulus (the two lotteries) appears on the screen and the moment in which the subject clicks on the mouse making the choice. Tables 4 and 5 below present the first surprise. They show the average response time, taken over subjects and different choices in the same condition, together with some summary statistics.[14]

The response time is approximately half of a second (that is, 25 percent) longer in the R conditions than in the C conditions. Among the C conditions, the fastest decisions were made in the AC and PAC conditions. The slowest decisions were made in the corresponding R conditions, namely AR and PAR. This disparity in response time suggests that subjects approached the two conditions with different mental processes.

Table 4
Average response times (RT) in the R conditions

Variable	Obs.	Mean	Std. err.	[95% conf. interval]
RT in AR	147	2776.95	87.24	[2604.52, 2949.37]
RT in PAR	165	2741.74	94.58	[2554.85, 2928.64]
RT in RR	148	2723.27	92.00	[2541.45, 2905.10]

Table 5
Average response times (RT) in the C conditions

Variable	Obs.	Mean	Std. err.	[95% conf. interval]
RT in AC	170	1947.60	65.98	[1817.34, 2077.85]
RT in PAC	165	2196.72	76.32	[2046.01, 2347.42]
RT in RC	153	2534.43	84.38	[2367.70, 2701.16]

[14] The number of observations is different across conditions. This happens for two reasons. First, some of the observations were lost for technical reasons. Second, the number of choices in the R condition were 15, and 17 in the C condition.

3.2.1. Difficult decisions and learning

Several factors may affect the length of time a subject needs to make a choice. Some insight into the determinants of this time (and hence on the decision process itself) can be obtained by a simple regression. A detailed report of these results is presented in Tables A.1 and A.2.

3.2.2. Learning in C

Consider first the C conditions. We use two variables. The variable *discut* is defined as the absolute value of the difference between the value of the certain lottery and the cutoff point that we have estimated for the subject. When the distance is very small, the subject is probably almost indifferent between the two alternatives, so in terms of the utility to the subject the decision is less important. On the other hand, the conclusion that s/he is indifferent is the outcome of a real life decision process, rather than its starting point. To reach this outcome, the subject might need less time when the value of the certain lottery is farther from the cutoff point, since in this case even an approximate estimate of the value of the main lottery will suffice. This finding, that response time increases as the certain value gets closer to the cutoff, is in line with what a procedural model of choice would predict.

A second variable is the integer-valued *order*, describing the order in which the choice has been presented to the subject in the same condition. If some form of learning takes place, then the response time will fall as the subject is facing choices that are becoming familiar.

The coefficient for the distance from the cutoff point (*discut*) is significant in the three C conditions, and has a negative sign. This is what we would expect to see if the task of deciding involves a significant comparison of two quantities, in our case the value of the certain lottery and some estimate of the value of the main lottery. This is also in agreement with the findings in purely cognitive studies. A strong non-linearity, with the response time increasingly in steep way as the term of comparisons are closer is well documented in cognitive psychology and neuro psychology (see for instance Pinel et al., 2001).

There are some interesting differences among conditions. Both *discut* and *order* have significant coefficients in the regression for the PAC condition. The coefficient for the variable *discut* is -56 msc per dollar, (with a p-value < 0.0001), the coefficient for the *order* variable is -21 per unit (p-value < 0.039). On the other hand, there is no significant difference in the latter coefficient if one estimates separately the initial and later choices. This indicates a regular, progressive learning, rather than a two-stage process—with an initial stage where subjects decide a policy in the form of a cutoff and a second stage in which they simply implement the policy. The *discut* variable has a significant coefficient in the AC and RC conditions as well, but the coefficient in AC is significantly smaller than in the PAC condition. The *order* variable is less significant, or insignificant, in the RC and AC cases respectively.

3.2.3. Learning in R

Here we consider three variables. The first is *value*, the expected value of the reference lottery, which ranged in the experiment between 30 and 40. The second is *order*, with the same meaning as in the previous section. The third and last is *variance*, a dummy variable with values $-1, 0, 1$ indicating the low, medium and high variance in the reference lottery.

Only the variable *variance* is significant, at least in the PAR and in the RR condition. The lack of learning is in agreement with the idea that the conditions where R is the reference lottery are easier. However, it makes the length of the response time in these very conditions even more surprising.

3.2.4. What operations do the subjects do?

The average value of the response time and the way it changes over the course of the trial can give some information on the type of operations subjects are performing. It is useful to compare our data with those for subjects performing a "pure" cognitive task.

In Spelke and Tsivkin (2001), the authors conduct a careful study of the response time for addition of two-digit integer numbers.[15] They study both approximate and exact operations. In the exact addition treatment subjects had to decide between the right answer and a distractor where the tens place was increased or decreased by 1. In the approximate addition treatment the problem was the same, but the candidate answers were multiples of 10, with the most distant answer 30 units more distant than the value closest to the correct answer. The average response time in both cases is (before training) between 4 and 4.5 seconds, a quantity much larger than we observe.[16]

On the other hand, the coefficient for the variable *discut* is large when compared to estimates of the effect of the difficulty of the problem induced by the proximity of the quantities to be compared. Consider for instance the finding in Pinel et al., 2001. In that study subjects had to perform a numerical comparison task: Specifically, they had to decide whether a visually presented number was larger or smaller than a fixed reference number, 65. The *numerical distance effect*,[17] namely the effect of the distance from 65 of the number presented to subjects on their response time, was estimated. The average response time was 600 msc for far numbers, slightly larger for moderately distant numbers, and 700 msc for the close numbers.[18]

4. Imaging results and analysis

4.1. Technical premise

We present the basic concepts necessary to understand the brain images. A more detailed explanation of the PET technique and of the statistical analysis underlying the study is given in Appendix A.

[15] For example, in the exact addition treatment the subjects had to add a first addend, which was ranging from 22 to 86, to a second addend ranging from 18 to 86 with the sum ranging from 40 to 172.

[16] No specific details are given in the study, but it seems that subjects had no time constraint.

[17] This effect is defined and discussed in detail in Dehaene et al. (1998). A second effect, the *number size effect*, was also documented in (Dehaene et al., 1998): For equal numerical distance, the discrimination of two numbers worsens as their numerical size increases.

[18] Numbers close to 65 were in the intervals 60–64 and 66–69; numbers moderately distant 50–59 and 70–79; numbers far 30–49 and 80–99. These times are much shorter than we observed: but the task of these subjects was a simple comparison of two numbers.

A point in the brain is defined by a triple of coordinates (x, y, z), with x the coordinate in the right to left direction, y the coordinate in the front to back direction, and z in the top to bottom direction. A positive x value denotes a position on the right, a positive y in the anterior part, and a positive z a position in the top part of the brain. The origin of this system of coordinates is roughly in the middle of the brain. Together, the triple (x, y, z) defines a point in a standardized three-dimensional model of the brain. The very small volume of brain around each such point is called a *voxel*.

Our observations are N vectors of rCBF (regional Cerebral Blood flow, Appendix A), one for each volume described by the three coordinates (x, y, z) in the brain of each of the N subjects. As different subjects have brains of different shape and size one of the first steps in data reduction to map the observations for the different subjects into a single standardized brain.

A statistical test is then used to estimate the probability that the different levels of rCBF in two conditions (for instance, in the PAC and the AC condition) at a specific point labeled by a triple (x, y, z) is different from zero. It is possible that two different conditions have a rCBF significantly different from the ECR condition, but also that the levels are so similar that the difference is not significant. The Z score is the statistic we use to report the probability that the difference is different from zero. The test is based on the assumption of normality and independence of the error, even in voxels that are very close.

There is a Z score for each voxel (and for each pair of conditions). The data can be more easily interpreted if a map of the difference score is presented in a picture.[19]

The images in the figures present the Z score for each voxel, associating different colors to different scores. First, only the voxels where the value of the Z score is above 2 are shown in color. A green color denotes a value between 2 and 3, yellow between 3 and 4, red between 4 and 5. All regions with value above 5 are white in color. In the images, the top part of each section corresponds to the front (rostral) part of the brain, the left part to the *right* part of the brain.

The values of the three coordinates are given here in millimeters (mm). The images show horizontal (also called transversal) sections of the standard brain, with the Z scores overlaid in color. The sections begin with the top and descend to the bottom. The numbers report the value of the z section, in millimeters. The standard model of the brain is that reported in the Talairach and Tournoux (1988) atlas.

4.2. *The evidence from brain images*

4.2.1. *Overview*

The activation is mostly in cortical areas, particularly frontal and parietal. There is no significant activation of areas (like the medial orbito frontal—or in general orbito frontal—and the limbic system, in particular the amygdala) that have been associated with the effect of emotions on decision making. The significance of this finding is discussed in detail in Section 5.3.1. The images support the idea that the procedure selecting the choice is mostly

[19] Colors are essential for the interpretation of the images, so a color printer is necessary. A copy of the images can be downloaded at http://www.econ.umn.edu/~arust/neuroecon.html.

of a cognitive nature, possibly involving some approximate computation (this hypothesis is discussed in detail in Section 5.2.2).

The R and C conditions are qualitatively different: the R conditions have modest activation compared to the C conditions. This finding supports the conjecture that the process involved in the choice in R conditions is simpler than the one in the C condition. These issues are discussed in detail in Section 4.2.2.

Among the C conditions, AC and RC differ from PAC. The first two have activations concentrated in parietal areas. The PAC condition has activations of the parietal and frontal areas. So the PAC condition plays a special role. In fact, the subtraction PAC–RC seems a weaker version of PAC–AC. This is particularly surprising in view of two facts. First, considered as a decision problem the difference between the AC condition and the PAC condition seems very small. The decision maker is told that the number of balls of each type can be anywhere in the interval $[0, 180]$, while in the second it can be anywhere in the interval $[10, 170]$, an apparently minor difference. Second, two sets of behavioral data suggest a similarity between PAC and AC as compared to RC. The cutoff point is in all subjects very close in the first two conditions, and rather different in the last. Also, the response times in the PAC and AC are similar, and different from the RC condition.

4.2.2. C conditions versus R conditions

As we observed above, the most active contrasts are in the C conditions. This is particularly true if one considers the difference between the various treatments and the ECR condition.[20] Among the C conditions, the most active is PAC. Similarly, among the R conditions the most active is PAR.

A large active region common to many of the differences between the C condition and the ECR is in the occipital lobe, lingual gyrus, with a peak around $(1, -75, 3)$. This region is for example active in PAC–ECR and RC–ECR. Interestingly, it is considerably less active in AC–ECR. This is the primary visual cortex (V1). The activity is due to increased visual attention. The higher activity in the C conditions is indirect evidence that this task induces a relatively greater amount of visual scanning of the main lottery for the purpose of defining the cutoff that is subsequently compared to the constant reference lottery.

4.2.3. The PAC condition

The two differences PAC–AC and PAC–RC have similar patterns. The main areas of activation in the two differences PAC–AC are:

(1) a region in the right frontal lobe, middle frontal gyrus, with peak at $(42, 50, -2)$, with a Z score 4.59;
(2) a region in the parietal lobe: in the subgyrus, with two peaks: one at $(25, -55, 42)$, with a Z score 4.42, and the other at $(34, -55, 33)$, with a Z score 4.11; also in the parietal lobe, precuneus, with peak at $(1, -37, 42)$, with a Z score 3.89;

[20] See Gusnard and Raichle (2001) for a recent illuminating discussion on the role and interpretation of the "baseline" conditions in brain imaging.

(3) a region in the occipital lobe, lingual gyrus, with peak at $(-15, -91, -14)$, with a Z score 4.1;
(4) a region in the left frontal lobe, superior frontal gyrus, with peak at $(-15, -13, 63)$, with a Z score 4.1.

The frontal and occipital activations have a weaker mirror image in the opposite hemisphere.

The region of activation in the difference PAC–RC are similar to the ones above. More specifically, the most active areas are:

(1) a region in the frontal lobe, lower than that observed in PAC–AC, with a peak at coordinates $(46, 39, -9)$, with a Z score 4.46;
(2) a region in the occipital lobe with a peak at $(-10, -91, -14)$, with a Z score 4.37;
(3) a region in the parietal lobe, precuneus, with a peak at $(15, -42, 50)$, with a Z score 4.11.

In contrast, it is clear from the tables for the AC–RC and RC–AC that there is little differential activation in these two cases.

In summary, the PAC condition provides qualitatively different activation than the AC and RC conditions. This finding stands in surprising contrast with the reasonable idea that a partially ambiguous lottery is an intermediate state between a totally ambiguous and a risky lottery. But it is consistent with the idea that the PAC condition is a less familiar experience for our subjects.

4.2.4. Frontal areas

There seems to be no strong activation of the higher frontal regions. More precisely, there is no difference displaying a strong and significant level of frontal activation in the levels above $z = 11$ mm. With one exception that we discuss later, this is also true in the differences PAC–AC and PAC–RC. In the first case, the frontal activation we have already reported is in the z interval between $+11$ and -11 mm. The same area is found in the difference RC–AC, but not in the PAC–RC difference.

The mentioned partial exception in the PAC–AC treatment is the region in the superior frontal gyrus of the left frontal lobe reported earlier (peak at $(-15, -13, 63)$). A similar activation is in the PAC–RC difference. In this case the peak is at $(-12, -8, 61)$, in the medial frontal gyrus of the left frontal lobe. The z coordinate is -4.7 mm, the highest in the PAC–RC difference.

It is worth observing that the pre-frontal cortex (PFC)[21] does appear prominently among the regions that are activated. The PFC is associated with planning, namely the ability to organize cognitive behavior in time and space. [22]

[21] This is the pole of the frontal lobe. It corresponds to the Brodmann areas 9, 10, 11.

[22] This is by now a classic finding. It has first been suggested by lesion studies (see for example the early studies of Shallice, 1988). These early results have been confirmed by brain-imaging studies. See, e.g., Zalla et al. (2000), Koechlin et al. (1999, 2000). However, the literature on this is very large: a useful review is Cabeza and Nyberg (2000). Owen (1997) offers a detailed review of definition and properties of planning ability in human subjects.

4.2.5. Orbito frontal ventromedial areas

There seems to be no strong activation of the ventromedial sections of the frontal lobes. That is, of areas known to mediate the processing of somatic and emotional reactions. A partial exception is an area that appears the RR–PAR difference; the peak is at $(6, 19, -18)$, right cerebrum, frontal lobe, medial frontal gyrus. The score is $Z = -3.47$, $p < 0.00027$. This is the only significant exception: the relative activations in AC–AR at $(1, 32, -22)$ and in RC–RR at $(-1, 8, -18)$ are likely to be artifacts, since they are at the extreme outer boundary of the brain.

5. Conclusions

We conclude by first summarizing the findings of greatest significance (in Section 5.1), and then by providing these findings with a provisional interpretation (in Section 5.2).

5.1. Summary of findings

(1) In their choices, subjects behave as predicted by models of risk and ambiguity aversion; their ambiguity aversion is consistent across the PAC and AC conditions.
(2) The time to decide is shorter in the C conditions. Among those, the minimum is attained in the PAC and AC conditions.
(3) Learning seems to occur in the PAC condition, less so in the other C conditions, and is almost absent in the R conditions.
(4) In the PAC condition, a larger distance from the cutoff point of the certain value makes the decision faster.
(5) The regions with most intense activation are observed in the C conditions, particularly in the difference between PAC and AC.
(6) There is low activation of ventromedial regions.
(7) There is low activation of the high frontal and pre-frontal regions.
(8) The only important frontal activation is in the PAC condition.
(9) There is high activation in the parietal regions in the C conditions.

5.2. Interpretations

5.2.1. A possible choice procedure

The results we have reported strongly suggest that a computational model of decision making might give a more accurate model of the behavior of decision makers.[23]

Here is procedure which gives an account of the observed behavior of subjects in the C condition. In all three cases (whether the main lottery is R, or PA, or A), the subjects are comparing the certain value with some estimate of the value of the main lottery. When this lottery is R the estimate is in substance a sum of the two outcomes, perhaps followed by a simple division. In the A case, the subject considers the best and worst possible scenarios.

[23] A similar idea is developed in Dickhaut et al. (2003).

In the best scenario, all balls are of the "good" color (the one that gives the largest payoff), and in the worst scenario they are all of the "bad" color. In both cases, the corresponding lottery is degenerate, yielding with certainty the prize associated with the only type of ball existing in the urn. So it is easy to evaluate. The situation is more difficult in the PA condition. In this case, the same process of reduction to the best and worst case yields two non-degenerate (true) lotteries: one yielding the high prize with probability $1/18$, the other with probability $17/18$. The subjects then use some rule that takes into account this best and worst case evaluations to estimate the main lottery.[24] Notice that according to this procedure, the PA condition is the hardest of the C conditions, and it is not intermediate between the other two, as it may appear from other perspectives.[25]

We note that in our experiment the choices are similar to those predicted by economic theory. This is not necessarily going to happen in general. We expect that as decisions become more complex, the constraints on the procedure delivering choices will become increasingly important, and affect in a systematic way the decision itself.

The procedure we have outlined may not be consciously followed by the subjects. There is however a substantial difference in the response time in our experiment (always less than three seconds) and that observed in simple computational problems (for example in the cited studies by Dehaene and co-authors). This difference suggests that the procedure in our study does not involve explicit calculations and may be partially automatic. We consider this issue important because automatic processes need not be mediated by consciousness. As a consequence, they are likely to produce relatively inflexible behavior that differs from the repertoire produced by conscious or planned thought. Clearly, more research is needed in this arena.

5.2.2. Approximate and exact estimates

The evidence we have presented suggests that subjects develop their decision process trying to provide some quantitative estimate of the lotteries, but that these estimates are approximate rather than exact. This conclusion is suggested first by the short response time, particularly short in the harder tasks, and it is supported by the observation that the computational aspects of the estimates used in the decision are located in the parietal, rather than frontal lobe.

This statement is significant and informative only inasmuch there is a qualitative difference between exact and approximate processes. For example, a difference in the cerebral networks activated by the two types of processing. This is precisely the conclusion reached by a set of recent studies by Dehaene and different co-authors (see Dehaene et al., 1996, 1999; also see Pugh et al., 1996 and Jonides et al., 1999). These studies argue for the exis-

[24] An example of one such rule is the so-called "α-MEU" rule, according to which an action is ranked via a convex combination of the best and worst case evaluations (α is the weight given to the "min" component, a measure of the subject's ambiguity aversion; see Ghirardato et al. (2002) for details and an axiomatic treatment of this rule).

[25] For instance, in terms of the amount of information available to the decision maker. There is only one possible composition of the urn in the risky lottery; in the partially ambiguous one, there is a set of possible compositions, and in the ambiguous one there is an even larger set. Or consider the point of view of a decision maker who is evaluating lotteries according to the MEU model. The worst case in the risky lottery is better than it is in the partially ambiguous one, and this is in turn better than it is in the ambiguous one.

tence of a specialization for processing *approximate* numerical quantities that is common to humans and animals, particularly mammals.[26] In addition, exact and approximate processing are associated with activity in different cerebral locations. For example in (Dehaene et al., 1999, p. 971) the authors note that

> "[...] the bilateral parietal lobe showed greater activation for approximation than for exact calculation. The active areas occupied the banks of the left and right intra parietal sulci, extending anteriorly to the depth of the post central sulcus and laterally into the inferior parietal lobule [...] Activation was also found during approximation in the right precuneus, left and right pre central sulci [...]"

These two regions also relate differently to language centers. In behavioral and brain-imaging studies exact calculations are shown to be language dependent, while approximations rely on a visuo-spatial cerebral network.[27]

As we have seen, the PAC condition has a comparatively strong activation of the frontal lobe, which extends over a large part of the middle frontal gyrus. This is one of the findings that sets the PAC condition apart from the others, including the AC and RC conditions. There are two possible interpretations of this difference. The first is that some exact calculation is taking place when subjects are considering a partially ambiguous lottery. This is partially in agreement with the finding of Dehaene et al. (1999), but is not entirely convincing in view of the short response time in this condition. A second interpretation appears more convincing on the basis of the evidence we have presented so far: more general higher cognitive functions become involved over the course of the trial, as subjects try to arrive at a satisfactory method to evaluate the PA lottery. Again, further research is necessary here.

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[26] For instance, in (Dehaene et al., 1999) the authors state that

> "Within the domain of elementary arithmetic, current cognitive models postulate at least two representational formats for number: a language-based format is used to store tables of exact arithmetic, and a language-independent representation of number magnitude, akin to a mental 'number line.' "

See, e.g., Dehaene (1992) for a review of these findings.

[27] See Dehaene et al. (1999) and Spelke and Tsivkin (2001). In the Spelke and Tsivkin's (2001) study, subjects were familiar with the two languages (Russian and English). They were trained to execute mathematical tasks either approximately or exactly. The performance after training improved, so training was effective. However, the crucial test was the performance on new tests. When tested on the problems to be solved exactly, the performance was significantly better when the test was administered in the same language in which it had been taught, independently of whether it was English or Russian. On the contrary, the performance on approximate tests was independent of the language. In the authors' words:

> "[...] a specific, natural language contributes to the representation of large, exact numbers but not to the approximate number representation that humans share with other mammals. Language appears to play a role in learning about exact numbers in a variety of contexts [...]"

5.2.3. The response times

Let us recall the two facts that stand out. First, response times are longer in the R than in the C conditions. Second, among the C conditions, response time is shortest in the PAC condition. At first blush, these facts seem to directly contradict our procedural explanation's claim that the choices in the C conditions are harder, and that among them the PAC condition is the hardest. If this is the case, then why do the subjects not take more time in examining the more complex choices, and seem to do the opposite?

Consider this argument more carefully. It is based on two implicit assumptions: (1) that the allocation of attentional effort is in some way optimal, and (2) that subjects make at the beginning of the choice process a single decision on the amount of effort to be devoted to decision making.

The first assumption is reasonable, but its implications are richer than just that longer time will be used for harder problems as long as attentional effort is not costless. If it is costly, then the cost of such effort—which may be different in different conditions—will be compared to its effectiveness. The data on activation seem to indicate that the effort in the C conditions is more intense, hence perhaps more unpleasant. (Moreover, it is also possible that this effort is less effective that it is in the R condition.)

On the other hand, the second assumption is clearly false: Subjects monitor their own decision process, and they likely get a feedback on the effectiveness of their thinking process. This is a common assumption in models of attention (see, e.g., Bundesen, 1990, where attention produces a sharpening of the information, until the subject decides that it is optimal to decide).

Summarizing these considerations, it seems to us that in a realistic model of optimal allocation of attention, the time actually devoted to choice in hard conditions might actually be *shorter*, rather than longer. Thus, we do not think that the data on response times are necessarily at odds with the choice procedure suggested above. Moreover, it is worth remarking that the additional time in the R conditions *vis à vis* the C conditions might be also explained by the fact that in the C conditions only one of the two lotteries (the non-degenerate one) needs to be evaluated.

5.3. Decisions and emotions

5.3.1. The Somatic Marker hypothesis

The interpretation we have provided views the process of choice essentially as a cognitive process. This view contrasts with an interpretation suggested in the last decade—and based largely on neuro psychological and clinical observations—that “decision making is a process guided by emotions” (see, e.g., Bechara and Damasio, 2003).

This latter interpretation is centered around the Somatic Marker hypothesis (SMH; Damasio, 1994; Damasio et al., 1991). The initial insight for this hypothesis is provided by William James’ theory of emotions. Let us first distinguish between *emotion* as the set of somatic reactions induced by an outside event (like the appearance of a snake) and *feeling* as the subjective perception of the events (both external to the subject and internal to the subject, as somatic reactions). In James’ theory, the feeling is induced by the somatic reaction to outside events: in his beautiful expression, we are sad because we cry, we do not cry because we are sad.[28] The SMH extends this idea to decision making. According to the hypothesis, “an emotional (that is, somatic) mechanism rapidly signals the prospective consequences of an action, and accordingly assists in the selection of an advantageous response option” (Bechara and Damasio, 2003).

The centers in the brain where such response is located are the orbito-frontal cortex and the amygdala. As we have seen, neither of these two centers is activated in our subjects. These two regions are routinely observed in studies conducted with the same scanner and techniques, so the failure to observe is almost certainly due to a lack of activation. [29]

The SMH has been tested in a standard laboratory experimental setup, in particular in the Card Deck Test (Bechara et al., 2000). In this test, subjects choose one deck of cards out of a set of four for a number of periods (usually one hundred). After they choose a deck they pick the top card, and a monetary amount associated to each card, which can be positive (gain) or negative (loss), is revealed. Normal subjects tend to choose, after an initial number of periods, decks that have positive expected return, even if the positive amounts are smaller. Patients with lesions in the orbito frontal region or in the amygdala tend to choose, even in later periods, deck that have larger positive amounts but compensated by even larger negative returns, so that the expected return for the deck is negative (Bechara and Damasio, 2003, Fig. 4). These results support the hypothesis that the orbito frontal cortex and amygdala are involved in decision processes, and they have been confirmed by imaging studies (see, e.g., O’Doherty et al., 2001).

There are several differences between the two experimental setups that can explain this difference. First of all, our subjects do not receive any information on the consequences of their choices during the experiment (no feedback), so they do not experience gain or losses. Second, our subjects do not learn anything about the distribution of the outcomes in addition to what they know at the beginning of the experiment. That is, we study specifically choice, rather than learning and choice. In contrast in the Card Deck Test subjects experience incremental learning: they are informed of the outcome in each period, and can use this information in the following choices. Finally, our subjects have only gains, while subjects in the Card Deck test have gains and losses. It is interesting to note that in a study (Dickhaut et al., 2003) with a structure similar to the present study, but involving losses, an orbito frontal activation appears in the comparison between gain and losses.

[28] More precisely:

> “[. . .] the more rational statement is that we feel sorry because we cry, angry because we strike, afraid because we tremble, and not that we cry, strike, or tremble, because we are sorry, angry, or fearful, as the case may be” (James, 1884).

[29] For example an orbito frontal activation appears clearly in the study (Dickhaut et al., 2003), conducted with the same devices and techniques. In the images of the present study, a clear example of a ventromedial orbito frontal activation can be found in any of the subtractions from ECR of any of the conditions. A particularly clear instance is for example in the ECR–AR subtraction, between the vertical coordinates 0 to -13 (see the set of images ECR in http://www.econ.umn.edu/~arust/neuroecon.html). A comparative activation of this region in the ECR condition is a standard—although not yet well understood—finding.

5.3.2. Reward anticipation and outcomes

Very similar differences appear between the setup of our study and recent studies focusing on the neuro anatomical and neuro chemical mechanisms underlying the evaluation of rewards, and in particular on the separation between expectancy and experience of reward and loss (see Breiter et al., 2001, but also Breiter et al., 1997), or reward anticipation and the reward outcome (see Knutson et al., 2001).

In these studies, the experimental sessions consist of a sequence of trials, where subject observe a cue that may signal the delivery of a reward or the lack of reward (or of a loss). Immediately after the arrival of the cue and possibly of their response, subjects know whether a reward is given in that trial. Different regions are activated in the different cases (with Nucleus Accumbens, Ventromedial Frontal Cortex and Orbito Frontal Cortex the main regions in the various cases). These studies provide the foundation for a mechanistic explanation of the processes that go from delivery of reward or lack thereof, to subject's evaluation of the outcome. However, they are not a study of the process leading to choice.

Further studies, with a careful analysis of brain activation, are needed to test the hypothesis that choice separated from immediate reward requires different brain processes, and to understand how emotions enter the decision process. It seems, though, that the black box of the decision process is slowly beginning to yield.

Acknowledgments

We thank a large number of colleagues that have listened to formal and informal presentations of these results, for comments and insights; in particular, the participants of the Minnesota Conference on Neuroscience and Economics. This research was financed in part by the NSF Grant 0136556 to Aldo Rustichini.

Appendix A. Regression tables

Table A.1
Regression on response times for the C conditions

Variable	Coeff.	Std. error	t	$P > t$	95% conf. interval
Response time for AC on discut and order					
Discut	−34.68	7.77	−4.46	0.000	[−50.03, −19.32]
Order	−3.91	12.68	−0.31	0.758	[−28.95, 21.12]
Constant	2411.67	165.70	14.55	0.000	[2084.53, 2738.81]
Response time for PAC on discut and order					
Discut	−56.71	8.44	−6.71	0.000	[−73.39, −40.03]
Order	−20.99	13.46	−1.56	0.121	[−47.58, 5.59]
Constant	3106.25	172.11	18.05	0.000	[2790.70, 3417.4]
Response time for RC on discut and order					
Discut	−53.61	12.61	−4.25	0.000	[−78.53, −28.69]
Order	−29.35	16.28	−1.80	0.074	[−61.53, 2.82]
Constant	3286.75	188.70	17.42	0.000	[2913.89, 3659.62]

Table A.2
Regression on response times for the R conditions

Variable	Coeff.	Std. error	t	$P > t$	95% conf. interval
Response time for AR on value, order and variance					
Value	4.24	12.04	0.35	0.725	[−19.58, 28.07]
Order	−11.01	20.51	−0.54	0.592	[−51.60, 29.58]
Variance	219.26	108.28	2.02	0.045	[5.005, 433.51]
Constant	2470.72	890.28	2.78	0.006	[709.15, 4232.29]
Response time for PAR on value, order and variance					
Value	21.98	12.89	1.700	0.091	[−3.53, 47.49]
Order	−1.21	22.02	−0.06	0.956	[−44.78, 42.36]
Variance	311.23	117.17	2.66	0.009	[79.42, 543.04]
Constant	1333.62	917.55	1.457	0.147	[−481.52, 3148.77]
Response time for RR on value, order and variance					
Value	12.46	13.22	0.94	0.348	[−13.69, 38.62]
Order	−8.48	22.70	−0.37	0.709	[−53.41, 36.44]
Variance	251.10	120.21	2.09	0.039	[13.26, 488.94]
Constant	1915.64	968.55	1.98	0.050	[−0.667, 3831.95]

Appendix B. The lotteries

All lotteries were built on the basis of an urn containing 180 balls, that could be either red or blue. The different lotteries were described by different proportions of red and blue balls in the urn, different information and different value associated with each ball. In all treatments, the color of the ball with the high value outcome changed over the different choices in that treatment.

B.1. Reference lotteries

The certain lottery C was a degenerate lottery: a single value would appear on the screen, ranging from a minimum of 10 to a maximum of 50.[30]

In the risky lottery R the urn had 90 blue and 90 red balls; the outcomes had expected values ranging from 30 to 40.[31] For each of the different expected values, we had three different lotteries, with different variance. For instance for the expected value 40 we had (80, 0), (58, 12) and (48, 32) as possible outcomes.

B.2. Main lotteries

In the R lottery, the urn had 90 blue and 90 red balls, and the monetary payoffs were fixed to be $(60, 10)$.

In the partially ambiguous lotteries (PA), the urn contained at least 10 balls of each color, while the others could be of either color. In the ambiguous lotteries (A), *all* the balls could be of either color.

[30] Precisely: 10, 15, 20, 25, 28, 30, 31, 32, 33, 34, 35, 36, 38, 40, 42, 45, 50.
[31] Precisely: 30, 32, 35, 38, 40.

In the PAC condition, the payoffs were fixed to be (60, 10); only the attribution to one or the other color was changed across lotteries. The same values, (60, 10) were used for the A lotteries in the AC condition. In the PAR and AR conditions, the PA and A lotteries had a simple outcome structure: five different pairs of outcomes. One was always equal to zero, the other ranged from 60 to 80.[32]

In the implementation of the lottery in the final stage of the experiment (when the payment to the subjects was decided), the actual composition of the urns used for the ambiguous and partially ambiguous lotteries were drawn from a uniform distribution over the number of blue balls.

Appendix C. PET

PET measures the amount of *regional Cerebral Blood Flow* (rCBF) to specific regions of the brain. The procedure begins with the slow injection of a lightly radioactive liquid into an arm vein. The scanning begins almost immediately after the injection.

C.1. What PET detects

In a PET study, a subject is administered by injection a radioisotope emitting positrons (positively charged electrons). The isotope then circulates through the bloodstream to reach, among others, the brain tissue. Positrons are positively charged electrons, emitted from the nucleus of radioisotopes that are unstable because they have an excessive number of protons and a positive charge. When a positron comes in contact with an electron, the two particles annihilate turning the mass of the two particles into two gamma rays that are emitted at 180-degree to each other. These gamma rays easily escape from the human body and can be recorded by external detectors. The tomography detects these coincident rays, which indicates that positron annihilation has occurred somewhere along that coincidence line. The scanner then reports the amount of radiation from all different positions in the brain on average over the period in which the scan is taken. When the gamma rays interact with scintillation crystals, they are converted into light photons in the crystals. The scintillation events can be compared among all opposing detectors along many coincidence lines.

The procedure is reliable, accurate, and gives a complete picture of the brain, with a uniform precision for deep and superficial structures. However, it is necessary to take averages of rCBF over a relatively long period (on the time scale of the experiment) and the technique is therefore not suitable to detect changes that take place in short time intervals. (See, e.g., Phelps, 1992 for details.)

C.2. Method in our study

In our study, PET was used together with a tracer (H215O) to estimate rCBF, a standard indicator for brain activity. The rCBF was estimated from tissue radioactivity (after

[32] Precisely: 60, 64, 70, 76, 80.

correction with measured two-dimensional attenuation) using a Siemens ECAT 953B scanner (Knoxville, TN USA) with septae retracted; i.e., three-dimensional acquisition. An arm vein was used for access. The participant's head position was stabilized with a vacuum-molded pillow. A slow-bolus of H215O was injected intravenously (9.25 MBA or 0.25 mCi/KGB initially, infused at a constant speed over 30 s). Data acquisition (correcting for random decay and electronic dead time only) commenced upon arrival of activity into the head as evidenced by consistently rising true counts. Each experimental scan of 90 seconds contained data from one type of lottery, e.g., CGS or RG. The interval between scans was about 10 minutes. Images were reconstructed by filtered back projection including non-orthogonal angles to a final image resolution of 10 mm full-width at half-maximum.

C.3. Statistical analysis

An exposition of the conceptual and statistical foundations of the analysis is given in Frackowiak et al. (1997). For each individual and each treatment, we have a four dimensional vector (x, y, z, rCBF) recording the rCBF at the location described by the (x, y, z) coordinates.

C.3.1. Normalization

The data are for each individual subject, with brains of possibly different size and shape. The data are normalized onto a standard brain, so that a point in the standard brain corresponds to the same point in different brains.

We then analyze each pair of treatments separately, subtracting at each voxel the rCBF of the two activations, and then subtracting from this number, one for each subject, the average over subjects. A two-sided test gives the probability that the difference is larger than zero under the null hypothesis that the treatment is not influential.

References

Bechara, A., Damasio, A.R., Damasio, H., 2000. Emotion, decision making and the orbito frontal cortex. Cerebral Cortex 10, 295–307.

Bechara, A., Damasio, A.R., 2003. The Somatic Marker hypothesis: A neural theory of economic decisions. Games Econ. Behav. Special issue on Neuroscience and Economics.

Breiter, H., Aharon, I., Kahneman, D., Dale, A., Shizgal, P., 2001. Functional imaging of neural responses to expectancy and experience of monetary gains and losses. Neuron 30 (2), 619–639.

Breiter, H., Gollub, R., Weisskopf, R., Kennedy, D., Makris, N., Berke, J., Goodman, J., Kantor, H., Gastfriend, D., Riordan, J., Mathew, R., Rosen, B., Hyman, S., 1997. Acute effects of cocaine oh human brain activity and emotion. Neuron 19 (3), 591–611.

Bundesen, C., 1990. A theory of visual attention. Psychol. Rev. 97, 523–527.

Cabeza, R., Nyberg, L., 2000. Imaging cognition II: An empirical review of 275 PET and fMRI studies. J. Cognitive Neurosci. 12 (1), 1–47.

Damasio, A.R., 1994. Descartes' Error: Emotions, Reason and the Human Brain. Grosset Putnam, New York.

Damasio, A.R., Tranel, D., Damasio, H., 1991. Somatic Marker and the guidance of behavior: Theory and preliminary testing. In: Levin, H.S., Eisenberg, M.H., Benton, A.L. (Eds.), Frontal Lobe Function and Dysfunction. Oxford Univ. Press, New York.

Dehaene, S., 1992. Varieties of numerical abilities. Cognition 44 (1–2), 1–42.

Dehaene, S., Dehaene-Lambertz, G., Cohen, L., 1998. Abstract representations of numbers in the animal and human brain. Trends Neurosci. 21 (8), 355–361.
Dehaene, S., Spelke, E., Pinel, P., Stanescu, R., Tsivkin, S., 1999. Sources of mathematical thinking: Behavioral and brain-imaging evidence. Science 284 (7), 970–974.
Dehaene, S., Tzourio, N., Frak, V., et al., 1996. Cerebral activations during number multiplication and comparison: A PET study. Neuropsychologia 34, 1097–1106.
Dickhaut, J., McCabe, K., Nagode, J., Rustichini, A., Smith, K., Pardo, J., 2003. The impact of the certainty context on the process of choice. Proc. Nat. Acad. Sci. 100 (6), 3536–3541.
Ellsberg, D., 1961. Risk, ambiguity, and the Savage axioms. Quart. J. Econ. 75, 643–669.
Ellsberg, D., 1963. Risk, ambiguity and the Savage axioms: Reply. Quart. J. Econ. 77 (2), 336–342.
Frackowiak, R., Friston, K., Frith, C., Dolan, R., Mazziotta, J., 1997. Human Brain Function. Academic Press.
Ghirardato, P., Maccheroni, F., Marinacci, M., 2002. Differentiating ambiguity and ambiguity attitude. J. Econ. Theory 118, 133–173.
Gilboa, I., Schmeidler, D., 1989. Maximin expected utility with a non-unique prior. J. Math. Econ. 18, 141–153.
Gusnard, D., Raichle, M., 2001. Searching for a baseline: Functional imaging and the resting human brain. Nature Rev. Neurosci. 2, 685–694.
James, W., 1884. What is an emotion? Mind 9, 188–205.
Jonides, J., Schumaker, E., Smith, E., et al., 1999. The role of parietal cortex in verbal working memory. J. Neurosci. 18, 5026–5034.
Knight, F.H., 1921. Risk, Uncertainty and Profit. Houghton Mifflin, Boston.
Koechlin, E., Basso, G., Pietrini, P., Panzer, S., Grafman, J., 1999. The role of the anterior frontal cortex in complex goal-directed behavior. Nature 399, 148–151.
Koechlin, E., Corrado, G., Pietrini, P., Grafman, J., 2000. Dissociating the role of the medial and lateral anterior prefrontal cortex in human planning. Proc. Nat. Acad. Sci. 97, 7651–7656.
Knutson, B., Fong, G., Adams, C., Varner, J., Hommer, D., 2001. Dissociation of reward anticipation and outcome with event-related fMRI. Brain Imaging 12 (17), 3683–3687.
Luce, R.D., 2000. Utility of Gains and Losses. Lawrence Elbaum Associates, London, UK and Mahwah, NJ.
O'Doherty, J., Kringelbach, M., Rolls, E.T., Hornak, J., Andrews, C., 2001. Abstract reward and punishment representations in the human orbito frontal cortex. Nature Neurosci. 4 (1), 95–102.
Owen, A.M., 1997. Cognitive planning in humans: Neuropsychological, neuroanatomical and neuropharmacological perspectives. Progress Neurobiol. 53, 431–450.
Phelps, M.E., 1992. Positron emission tomography. In: Mazziotta, J., Gilman, S. (Eds.), Clinical Brain Imaging: Principles and Applications. Davis.
Pinel, P., Dehaene, S., Riviere, D., LeBihan, D., 2001. Modulation of parietal activation by semantic distance in a number comparison task. Neuroimage 14 (5), 1013–1026.
Pugh, K., Shaywitz, S., et al., 1996. Auditory selective attention: An fMRI study. Neuroimage 4, 159–173.
Ramsey, F.P., 1926. Truth and probability. In: Braithwaite, R.B. (Ed.), The Foundations of Mathematics and Other Logical Essays. Harcourt Brace, New York.
Savage, L.J., 1954. The Foundations of Statistics. Wiley, New York.
Shallice, T., 1988. From Neuro-Psychology to Mental Structure. Cambridge Univ. Press, Cambridge, UK.
Spelke, E., Tsivkin, S., 2001. Language and number: A bilingual training study. Cognition, 45–88.
Talairach, J., Tournoux, P., 1988. Co-Planar Stereotaxic Atlas of the Human Brain. Thieme, New York.
Zalla, T., Koechlin, E., Pietrini, P., Basso, G., Aquino, P., Sirigu, A., Grafman, J., 2000. Differential amygdala responses to winning and losing: A functional magnetic resonance imaging study in humans. Europ. J. Neurosci. 12, 1764–1770.