

COMMENTS ON NEUROECONOMICS

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Neuroeconomics is examined critically using data on the response times of subjects who were asked to express their preferences in the context of the Allais Paradox. Different patterns of choice are found among the fast and slow responders. This suggests that we try to identify types of economic agents by the time they take to make their choices. Nevertheless, it is argued that it is far from clear if and how neuroeconomics will change economics.

1. THE BOTTOM LINE

Let me start with the bottom line: Neuroeconomics will remain a hot topic in economics during the coming decade, probably one of the hottest. This is not because of any truth that is waiting to be discovered or some urgent real-world problem that needs to be solved. Rather, the evolution of economics (and probably other disciplines as well) is subject to forces similar to those that dictate the emergence of any other fashion trend.

The rise of neuroeconomics is coming at a point in time when economic theory is not producing any exciting insights. The game-theoretical revolution in economics is complete – it has probably even gone too far by pushing aside other economic models. It is a time in which economists have already recognized the limits of rationality and are increasingly interested in models of Bounded Rationality. However, these models are due almost entirely to introspection and modelling convenience and as such are perceived as arbitrary. Neuroeconomics is offering us the illusion that results achieved through introspection can be supported with hard evidence. For many economists, who are obsessed with the desire to become scientists, this is an opportunity to become associated with real science.

I am not a big fan of neuroeconomics. I heard about it for the first time in the autumn of 2000 at a small conference organized at Princeton

University. Even then I was assigned the role of critic. However, my attitude to neuroeconomics is more complicated than that and in some ways I actually find neuroeconomics to be appealing. I believe in judging academic work by a subjective criterion: whether or not it is interesting and neuroeconomics certainly meets that criterion. So why do I find it difficult to accept neuroeconomics? I can think of two reasons. The first is my position on the mind-body problem. I fear the approach in economics in which decision makers become machines with no souls. The second reason (discussed in Rubinstein 2006, and Harrison 2008) is neuroeconomics' style and rhetoric. Conclusions are hastily drawn on the basis of scanty data. Lack of knowledge and uncertainty are swept under the rug. Colourful diagrams, which mean nothing to economists, are presented as clear evidence. To me, they look like a marketing gimmick like those used to sell a new product in the supermarket. The statistics used are not well understood by the vast majority of the users. Brain researchers are rushing to use economic terms without fully understanding their subtleties. The field suffers from a lack of self-criticism and a reluctance to discuss "details". In informal chats following a seminar, I hear considerable scepticism – which I didn't hear in the seminar itself. I have attended dozens of seminars and read probably a hundred papers on neuroeconomics and I almost always have the feeling of being (unintentionally) manipulated. My sense is that tough competition has led to low standards. A researcher knows that if he doesn't publish a new "discovery", then someone else will and the stakes in a new field are very high.

However, let's put aside the problems of style, rhetoric and pretension for a moment and assume the following scenario: We are able to map all brains onto a canonical brain. The functions of the different areas of the brain are crystal clear to us. The machines used in experiments are cheap enough that thousands of subjects can be experimented on. And finally the data are clear and double-checked. The question would still remain: what is the potential role of brain studies in Economics?

When I read Neuroeconomics papers, I don't get the impression that those who make claims for Neuroeconomics know how it will change Economics (McCabe 2008 states this quite explicitly). Part of the problem is that many brain researchers misunderstand the meaning of economics. Imagine that brain studies were to discover that there is a centre of the brain that determines whether we prefer Bach to Stravinsky or Stravinsky to Bach and that currently 1% of the general population prefer Stravinsky. This would be a really momentous discovery. It would also be a really important piece of information for a manufacturer of Stravinsky discs, but not all neuroeconomists understand that it would have no significance for economics.

It seems that even neuroeconomics researchers with a good understanding of economics are in the dark about how it will

re-shape economics. A year ago, I challenged several ardent supporters of neuroeconomics to show me even one neuroeconomics paper that is likely to change economics. I have yet to receive a satisfactory response. Nonetheless, I'm not going to argue that neuroeconomics will have no effect on economics but just that the neuroeconomics literature does not help us to imagine what that effect will be.

2. WHAT THEN CAN NEUROECONOMICS DO?

The standard way in which we model a decision maker in economics is by a choice function c that attaches to every choice problem A , in the relevant domain, a unique element $c(A) \in A$. The statement $c(A) = a$ means that the decision maker chooses a when the set of available alternatives is A .

Some of us study a somewhat richer structure in which the choice function receives as input not only the set of alternatives A , but also additional information f , which is irrelevant to the mental preferences of the decision maker. In Salant and Rubinstein (2008), we called such information a *frame*. A frame can be, for example, the ordering by which the elements in A are presented or a default alternative. The statement $c(A, f) = a$ means that when the choice problem A is presented to the decision maker framed by f , the element chosen by the decision maker is a .

In the world of neuroeconomics, a decision maker is presented with a choice function that receives as input a choice problem A and produces as output a pair (a, x) consisting of an alternative $a \in A$ and an array of parameters x . The statement $c(A) = (a, x)$ means that the decision maker who confronts the choice problem A will choose a and will produce a vector x of indicators measured and recorded during the period between the moment he was presented with the choice set and the moment he "pushed the button to select a " (and probably even after that).

Current research in neuroeconomics takes x to be a very long vector of numbers that represent the activities in various areas of the subject's brain during the deliberation period. But x can have other meanings as well. For example, there are those who take x to be a description of the subject's eye movements while staring at a screen where the choice problem is being presented. In order to assess neuroeconomics' research agenda, we follow Rubinstein (2007) and look at another, even simpler case, in which x is a single number representing the decision maker's response time.

The platform for the experiments was my didactic website <http://gametheory.tau.ac.il>. Thousands of students in game theory and microeconomics courses in about 30 countries have used the site, where they were confronted with decision problems and game situations. In addition to the choice made, the computer also recorded *response time* (RT), i.e. the time that elapsed from the moment the server sent the question until the moment the answer was received. This type of research has some

obvious merits: it is cheap and facilitates the participation of thousands of subjects from a much broader than usual population. On the other hand, research of this type has a major disadvantage in that response time is a noisy variable (although so are the brain indicators measured through fMRI). Nevertheless, the huge sample size seems to smooth things out.

The basic hypothesis states that response time is an indicator of the way people think about a problem. Assume that decision makers are to choose between *A* and *B* and that their response times in choosing *A* are concentrated around 20 seconds, whereas the length of time it takes them to choose *B* is about 40 seconds. We can then conclude that the choice of *A* is more instinctive whereas the choice of *B* involves more deliberation and is more cognitive.

As an example, we will use results of an experiment based on the Allais paradox. Subjects were asked to make two hypothetical choices as presented by Kahneman and Tversky (1979). First, they were asked to respond to Question 1:

Imagine you are to choose one of the following two lotteries:
 Lottery A yields \$4000 with probability 0.2 and \$0 with probability 0.8.
 Lottery B yields \$3000 with probability 0.25 and \$0 with probability 0.75.
 Which lottery would you choose?

Question 2 followed:

Imagine you are to choose one of the following two lotteries:
 Lottery C yields \$4000 with probability 0.8 and \$0 with probability 0.2.
 Lottery D yields \$3000 with probability 1.
 Which lottery would you choose?

The following table summarizes the results.

n = 2737	C	D	Total	MRT
A	20%	44%	64%	49 s
B	5%	31%	36%	34 s
Total	25%	75%	100%	
MRT	31 s	19 s		

A majority of subjects chose *A* and an even larger majority chose *D*. Those who chose *A* and *D* or *B* and *C* (49% of the subjects who answered the two questions) violated expected utility theory. Note that although in this case the two questions were presented to the subjects one after the other, they were not very different from those reported in Kahneman and Tversky (1979) in which a group of subjects was randomly divided into two subgroups and each of the subgroups answered only one of the two

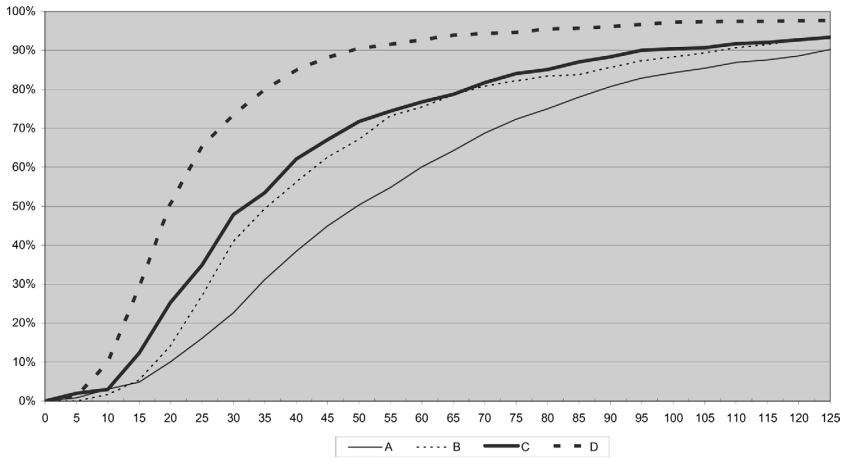


FIGURE 1. Distributions of RT for the choices A, B, C, D.

questions. The Median Response Time (MRT) of the subjects who chose *A* in Question 1 (49 seconds) was significantly longer than that of the subjects who chose *B* (34 seconds) and the MRT of the subjects who in Question 2 chose the risky lottery *C* (31 seconds) was much longer than the MRT of those who chose *D* (19 seconds).

Further information regarding the subjects' response times is presented in figure 1. The graph plots the cumulative distribution of response time for each of the four choices.

The fact that the response time for Question 2 is dramatically shorter than for Question 1 might be an outcome of the order in which the subjects responded to the two questions. Nevertheless, I believe that it is also due to the fact that Question 2 is simpler. There is evidence for this conjecture in the data on the small group (consisting of 86 subjects) who answered only Question 2: their median response time was 32 s which is far shorter than that of the group who answered only Question 1. This could easily be checked by reversing the order in which the questions are presented. It was not done since the site is used for pedagogical purposes and therefore I felt it would not have been correct to do so.

We observe that the choice of *C* requires much more time than the choice of *D*. The interpretation of this result is quite clear: Taking a risk requires more time for consideration. It is less clear how to interpret the differences in response time between those who chose *A* and those who chose *B*. I can conceive of two explanations for the choice of *A*: (i) Lottery *A* has a higher expectation than lottery *B* or (ii) Subjects view a lottery as a two-dimensional vector and when comparing between two vectors they try to "eliminate" one of the two dimensions in which the

parameters are “approximately the same” and then make the decision according to the relative magnitudes of the values in the other dimension. (When comparing the pairs $A = (\$4000, 0.2)$ and $B = (\$3000, 0.25)$, some subjects find the probabilities to be similar and choose A after comparing the dollar amounts.) Both explanations require attention and calculations that require time.

Measuring response time does not allow us to distinguish between the two explanations. The importance of the distinction lies in the fact that if subjects who chose A maximize expected value, then the assumption of the existence of a preference relation over the space of lotteries of the type (x, p) is not rejected. On the other hand, if subjects used the second procedure, it was argued in Rubinstein (1988) that intransitivities are likely to result.

This is a task for which neuroeconomics might be suited. In a study I am conducting with Amos Arieli of the Weizmann Institute, we track the eye movements of subjects who are facing a screen showing the following four numbers:

\$4000		\$3000
with prob. 0.2		with prob. 0.25

The detection of vertical eye movements would support the theory that subjects multiply the prize by its probability in each lottery. The detection of horizontal movements is more consistent with the “similarity” procedure.

One potentially important task for the neuroeconomics approach is to identify “types” of economic agents, namely to determine characteristics of agents that predict their behaviour in different choice problems. It is difficult to do this simply by observing behaviour. If the choices in Problem 1 and in Problem 2 were independent, then given the distributions of answers to the two problems, we would expect to obtain the following distribution of joint choices:

Expected	C	D
A	16%	47%
B	9%	29%

In the experimental results we observe only a slight (though significant) increase in the proportion of subjects who chose the combination $A + C$ or $B + D$. Thus, the data on the choice on its own is not

Allais RT Percentile Scatter Plot
Correlation: 0.59

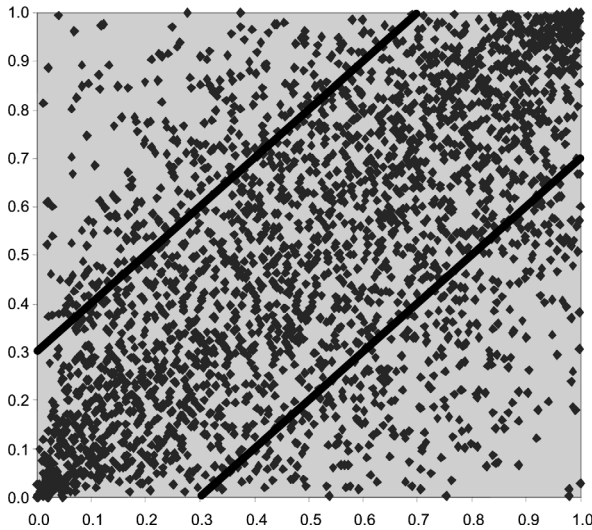


FIGURE 2. Allais Paradox TR Percentill Scatter Plot.

sufficient to identify types of agents. The response time data, however, can help us to do so. A point in the graph in Figure 2 stands for a subject. His coordinates (x,y) indicate that $x\%$ of the population responded faster than he did to question 1 and $y\%$ responded faster than he did to question 2.

The correlation between the two variables is quite high (0.58). The two bold lines divide the unit square into two equally sized areas. The vast majority of subjects fall into the centre half.

What is the difference in terms of behaviour between the slow and the rapidly responding types?

In preparing the following table, the population of respondents was divided into four classes according to RT on Question 2 (similar results are obtained when the RT for Question 1 is used as the base): very fast (the bottom 10%), fast (range of 10–50%), slow (range of 50–90%) and very slow (the top 10%). The more thought the decision maker puts into the problem, the greater the tendency for him to choose option C. While 85% of those in the lower half of the distribution chose the safe alternative D, the subjects in the slowest 10% of the distribution were divided almost equally between the two alternatives.

n = 2737	Fastest 10%	Fast 10%–50%	Slow 10%–50%	Slowest 10%
A = (\$4000, 0.2)	55%	59%	69%	73%
B = (\$4000, 0.25)	45%	41%	31%	27%
C = (\$4000, 0.8)	15%	15%	32%	47%
D = (\$3000, 1)	85%	85%	68%	53%

Another interesting result is obtained by comparing the distribution of choices among the faster half of the population to that among the slower half (as measured by RT on Question 2):

Distribution of choices among the faster half:

n = 1369	C	D	Total
A	11%	48%	58%
B	4%	38%	42%
Total	15%	85%	100%

Distribution of choices among the slower half:

n = 1368	C	D	Total
A	29%	41%	70%
B	5%	24%	30%
Total	35%	65%	100%

Longer response time contributes little to consistency. Whereas 49% of the fastest subjects were consistent, no more than 53% of the slowest ones were. However, the composition of the consistent subjects was dramatically different. While almost 80% of the fastest consistent subjects chose *B* and *D*, only a minority of the slowest chose this combination. Thus, here is a case in which the “neuroeconomics” data were necessary to provide support for the conjecture that subjects are divided into types (fast and slow respondents) and that there are significant differences in their behaviour.

3. THE BOTTOM LINE (ONCE AGAIN)

The grand vision of neuroeconomics is to use the additional information obtained from brain studies, combined with the choice made by the decision maker, in order to better understand the deliberation process

and to use the results to improve economic models. However, it is far from being clear if and how this can be accomplished.

An analogy which I have in mind when thinking about neuroeconomics is of an intelligence agency that tracks enemy activity by continuously monitoring vehicle movements or radio signals. Discovering correlations between enemy tactics and a high level of activity in a particular area or detecting a sequence of high levels of activity at different sites allows the intelligence agency to understand the structure of the enemy's army (such as, where the command centres are located, through what channels the enemy transmits information and so on). This will enhance its understanding of the enemy's decision process. It might also allow the anticipation of the enemy's moves and the prediction of a surprise attack. Does neuroeconomics also work in this manner? Not really. Whereas an intelligence agency is interested in only one "brain", that of the enemy, neuroeconomics is interested to understand all brains. While good intelligence provides data about the enemy in real time, current techniques (fortunately!) don't allow us to gather real-time data on decision makers (and if they did we would live in an entirely new world which presumably have also new economics).

As I demonstrated in the previous section, neuroeconomics' approach could probably be useful in two ways: first, once we have enriched economic models of bounded rationality, it would make sense not to simply invent procedures from off the top of our heads but to use models based on our understanding of the mind (see Rubinstein 1998). In this respect, I imagine that reliable neuroeconomics data could serve a purpose by providing us with information on how widespread the use is of a particular decision-making procedure. Second, one could imagine that brain studies will allow us to identify types of individuals who share modes of behaviour for a wide range of decision scenarios. If this is indeed the case, we would be motivated to construct models in which the distribution of types is a primitive of the model. Using such models, we would probably be able to derive stronger analytical results. But, the proof is by doing and we are far from showing that any of those could yield new economic ideas.

To conclude, brain studies are of course fascinating and although I have yet to come across a single relevant insight produced by these studies it may be that they will eventually change economics. At the end of the day, neuroeconomics will probably influence economics because economics is a culture and not a science. By "culture" I mean a collection of accepted ideas and conventions that are used in our thinking. Cognitive psychology and behavioral economics have changed economics by introducing concepts and conventions that have become part of the mainstream discourse in economics. I would not be surprised if neuroeconomics infiltrates economics in a similar fashion. If, in addition, neuroeconomics makes

less pretentious claims and adopts greater precision, it may become more than just an entertaining sideline.

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Tracking decision makers under uncertainty

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Abstract:

Eye tracking is used to investigate human choice procedures. We infer from eye movement patterns in choice problems where the deliberation process is clear to deliberations in problems of choice between two lotteries. The results indicate that participants tend to compare prizes and probabilities separately. The data provide little support for the hypothesis that decision makers use an expected utility type of calculation exclusively. This is particularly true when the calculations involved in comparing the lotteries are complicated.

Key-words: Decision Making, Expected Utility, Eye tracking, Neuroeconomics, Similarity.

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1. Introduction

How do people choose between lottery 1 which yields the prize $\$x_1$ with probability p_1 and lottery 2 which yields the prize $\$x_2$ with probability p_2 ? There are two types of procedure that come to mind:

Holistic (H-)procedures: In this type of procedure, the decision maker treats the alternatives holistically. For example, he evaluates the certainty equivalent of each of the alternatives and chooses the one with the higher certainty equivalence. Or, he computes the expectation of each of the two lotteries and chooses the one with the higher expectation. More generally, he might have functions g and v in mind and choose the lottery with the higher $g(p_i)v(x_i)$. A canonic formula for such a procedure would assume the existence of a function u such that lottery 1 is chosen if $u(x_1, p_1) > u(x_2, p_2)$.

Component (C-)procedures: The decision maker compares prizes and probabilities separately. In the case that one of the lotteries yields a larger prize with a higher probability he will choose that lottery. Otherwise, he checks for similarity between the prizes and between the probabilities and uses that similarity to make the choice. If, for example, the prize x_1 is much larger than the prize x_2 and the probabilities are similar, even though p_2 is higher than p_1 , he would choose lottery 1. A canonic procedure of this type would assume the existence of functions f , g and h , such that lottery 1 is chosen if $h(f(x_1, x_2), g(p_1, p_2)) > 0$.

The research is motivated by the bounded rationality approach to decision making which focus on the choice procedures used by individuals. We believe that experimental evidence about how people choose between lotteries may change the way in which decision making under uncertainty is modeled. In particular, the research provides a test for the similarity-based approach to choice between simple lotteries suggested in Rubinstein (1988).

2. The Research Concept

The method of using eye-tracking to uncover procedures used by decision makers first appeared in research done in the 70s and was recently revisited.¹ Eye tracking complements MouseLab. In

¹ Using early eye tracking techniques, Russo and Rosen (1975) studied multi-alternative choice and Russo and Doshier (1983) investigated multi-attribute binary choice. They concluded that feature-by-feature comparisons make ...

MouseLab (see Payne et al. (1993)), the participant accesses the information hidden behind boxes on the computer screen by moving the cursor over the boxes.² One advantage of eye tracking over MouseLab is that it records natural unconscious movements while the need to move the mouse in MouseLab requires an unnatural information acquisition strategy (see Lohse and Johnson (1996)).

In our study, participants³ were asked to respond to a sequence of simple virtual choice problems. The participants were paid only a show-up fee of \$12. Participants were not paid for choices made. There is ample evidence that the lack of monetary incentives does not significantly affect subjects' choices (see Camerer and Hogarth (1997)). In any case, note that we are interested only in the choice process that led participants to make their particular choices and not in the choice distributions themselves, which are reported only for the sake of completeness.

In each problem, a participant was asked to choose between two alternatives, Left (*L*) and Right (*R*), by clicking on the mouse. Each decision problem was presented on a separate screen (Figure 1), in which two parameters, *a* and *b*, describe the *L* alternative and two parameters, *c* and *d*, describe the *R* alternative⁴.

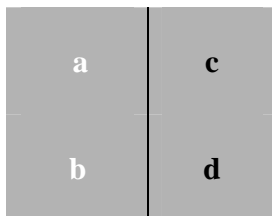


Figure 1: Schematic representation of the screen shown to the participants.

up much of the decision procedure. More recently, Wang et al. (2006) investigated behavior in a sender-receiver game and Reutskaja et al. (2008) studied choice of snack foods under time pressure and option overload.

² The site <http://www.mouselabweb.org> demonstrates the method and allows one to try it out.

³ The participants (24 males and 23 females; average age of 27) all had normal or corrected-to-normal vision and were students (in fields other than economics) in Rehovot, Israel. Participants signed an informed consent form in accordance with the Declaration of Helsinki.

⁴ We did not alternate the sides on which the alternatives are presented. In order to check whether presenting alternatives on the left side (white letters) or on the right side (black letters) makes any difference, we calculated the distribution of response time over all the problems for participants who chose *L* (N=902) and participants who chose *R* (N=805). We found that the average response times of the two groups were practically identical (5.81 sec and 5.75 sec; T-test p-value of 42.5%).

No time restrictions were imposed on the participants and a typical median response time was eight seconds.

Our focus is on the case in which L is a lottery that yields \$a with probability b (and \$0 with probability 1-b) and R is the lottery yielding \$c with probability d (see Figure 2).

$\$X_1$ With probability p_1	$\$X_2$ With probability p_2
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Figure 2: Scheme for choice under uncertainty problems.

We concentrate on comparing the intensity of horizontal and vertical eye movements. Our hypothesis is that decision makers who follow H-procedures will show intensive vertical eye movements while decision makers who follow C-procedures will show intensive horizontal eye movements.

3. The Method

An eye-tracking system⁵ was used in order to continuously record a subject's point of gaze. Analyzing the huge amount of recorded data was not straightforward. We first transformed it into movies showing the path of eye movement on the screen. However, there were only a few cases in which the choice procedure was discernable from the movie (a sample movie can be watched at <http://arielrubinstein.tau.ac.il/ABR09/>). Thus, we needed to develop a measure of the intensity of horizontal and vertical movements.

We divided the screen into four quarters: Top Left, Top Right, Bottom Left and Bottom Right. Eye movements between two sections of the screen are classified into six categories: Left-Vertical, Right-Vertical, Top-Horizontal, Bottom-Horizontal, Descending-Diagonal and

⁵ We used a high-speed eye-tracking system (iView) made by SensoMotoric Instruments (SMI) which is based on an infrared light camera. It captures (at a sampling frequency of 240Hz or one sample every 4.2 milliseconds) a high-resolution image of the pupil and corneal reflection.

Ascending-Diagonal. For each problem and each participant, we calculated the proportion of time spent in each of the six categories of eye movements. Averaging over all participants produced a vector α on which our analysis is based.⁶ (The six components of α sum up to 100%.)

We omitted any period of time for which the eye tracker did not identify the eye position, which was usually the result of blinking. In addition, in order to identify diagonal movements, which always pass briefly through another section of the screen, we omitted any period of time in which the participant's gaze stayed in a particular section for less than 100 msec. Cases in which the above omissions exceeded 20% of the response time were excluded from the sample.

High α -values for the two vertical eye movements will imply that participants' choices were largely based on relating to each alternative as a unit and comparing them as such. High α -values for the horizontal eye movements will indicate that participants based their decisions heavily on comparing each of the features of the alternatives separately.

We suspected that the α -values are sensitive to variation in the level of difficulty in understanding the question's parameters (e.g., if one of the parameters takes a long time to read, this will lengthen the duration of the movement into and out of that section of the screen). Therefore, we also produced a similar vector β for the number of transitions in each type of eye movement. We found that the two measures produced almost identical results.⁷

⁶ Given a choice problem, the exact calculation of the vector α is done as follows:

- (i) For each participant i , let 0 be the point in time at which the problem is first presented and T be the point in time at which the participant clicked on the mouse.
- (ii) Denote the transition times between sections of the screen by: $t_1, t_2, \dots, t_k, \dots, t_n$.
- (iii) Divide the segment of time $[0, T]$ into n intervals: $[0, (t_1 + t_2)/2], [(t_1 + t_2)/2, (t_2 + t_3)/2], \dots, [(t_{n-1} + t_n)/2, T]$. Credit the duration of the k 'th interval ($k=1, \dots, n$) to the total for the type of eye movement that occurred at t_k .
- (iv) Divide the time credited to each type of eye movement by the total of all the eye movements to obtain a vector $\alpha(i)$ (for participant i), which consists of six numbers representing the proportion of time spent in each type of movement.
- (v) Average the vectors $\alpha(i)$ over all participants. Denote the vector of averages as α .

⁷ Russo and Rosen (1975) and Russo and Doshier (1983) based their analysis on counting movements from one section of the screen, X, to another, Y, and back to X. In contrast, we base our analysis on counting movements from X to Y even if there is no return to X. In problems where the response time is relatively long, the two approaches yield the same qualitative results. In problems where the response time is relatively short, their method does not yield sufficient data to make significant inferences.

4. Results

The basic results are presented in Table 1, which shows the α -values in four lottery choice problems.







	The lotteries		N	% of choices		α -values					
	$L = (x_1, p_1)$	$R = (x_2, p_2)$		%L	%R						
U1	(\$3000, 0.15)	(\$4000, 0.11)	35	60%	40%	24% (2%)	23% (2%)	18% (2%)	28% (2%)	4% (1%)	3% (1%)
U2	(\$1700, 0.4)	(\$1300, 0.5)	35	51%	49%	20% (2%)	25% (3%)	25% (2%)	23% (2%)	4% (1%)	2% (1%)
U3	(\$637, 0.649)	(\$549, 0.732)	41	41%	59%	17% (2%)	18% (2%)	29% (2%)	30% (2%)	2% (1%)	4% (1%)
U4	(\$13600, 0.31)	(\$15500, 0.27)	35	37%	63%	16% (2%)	18% (2%)	33% (2%)	28% (2%)	4% (1%)	2% (1%)

Table 1: α -values in lottery choice problems (estimates standard deviations are in parenthesis, bold percentages emphasize the difference in α -values between a problem in which the expected payoff calculation is easy and one in which it is difficult).

Our first conclusion is drawn from the comparison of problems U1-U2 and problems U3-U4 which differ in the difficulty of calculating the expectation. For U3-U4 (which involves a difficult calculation) the average proportion of horizontal movements is 59-61% as compared to only 45-47% for U1-U2 (which involves an easy calculation). We infer that when the expectation calculation is relatively difficult participants tend to use a C-procedure.

Our main interest is in the procedure used in problems like U1 and U2. In order to interpret the results, we compared them to results in two other types of problem in which the deliberation process is transparent.

In D1 and D2, participants were asked to indicate which difference is larger (a-b or c-d). Results are summarized in Table 2:

	The differences		N	% of choices		α - values					
	$L = a - b$	$R = c - d$		%L	%R						
D1	251 222	187 153	38	24%	76%	38% (2%)	44% (2%)	13% (1%)	3% (1%)	2% (1%)	1% (0.3%)
D2	983462 718509	983501 718499	37	22%	78%	18% (3%)	22% (2%)	35% (3%)	20% (2%)	3% (1%)	3% (1%)

Table 2: α 's for problems in which differences were compared.

In D1, the most straightforward procedure involves computing the differences using vertical eye movements. And indeed, vertical eye movements accounted for 82% of the time spent on this problem. In D2, the easiest way of making the choice is to calculate horizontal differences and indeed the share of vertical eye movements declined to 40%. Figure 3 presents the eye movements of two typical participants; both of them used vertical eye movements almost exclusively in D1 while in D2 horizontal eye movements dominated.

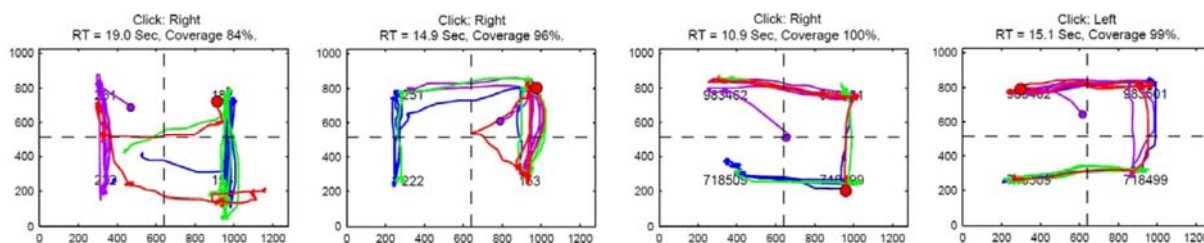


Figure 3: Eye movements for two participants while responding to D1 (left two boxes) and D2 (right two boxes).

In T1, T2 and T3, participants were asked to choose between receiving a sum of money on a particular date and a different sum of money on another date. The results are summarized in Table 3.

	The alternatives		N	% of choices		α - values					
	$L = (x_1, t_1)$	$R = (x_2, t_2)$		%L	%R						
T1	\$351.02 On 20-Jun-2009	\$348.23 On 12-Jul-2009	39	92%	8%	16% (1%)	15% (1%)	24% (1%)	39% (2%)	3% (1%)	4% (1%)
T2	\$467.39 On 17-Dec-2009	\$467.00 On 16-Dec-2009	38	58%	42%	13% (1%)	14% (2%)	36% (2%)	30% (2%)	5% (1%)	2% (1%)
T3	\$500.00 On 13-Jan-2009	\$508.00 On 13-Apr-2009	39	74%	26%	13% (2%)	14% (2%)	25% (3%)	42% (2%)	3% (1%)	2% (1%)

Table 3: α 's for time preference problems. Experiments took place during June-September 2008.

In this case, it is hard to imagine that any of the participants made a "present-value-like" computation which would have involved vertical eye movements. Indeed, we found that 2/3 of eye movements were horizontal. Thus, participants clearly used a C-procedure; in other words, they based their decisions on comparing sums of money and delivery dates separately.

We are now ready to compare the eye movements in problems U1 and U2 with those observed in problems involving the comparison of differences (D1 and D2) and time preferences (T1, T2, T3). For convenience, in Figure 4 we present the α -values of the participants in problem U1 alongside their α -values in D1 and T3.

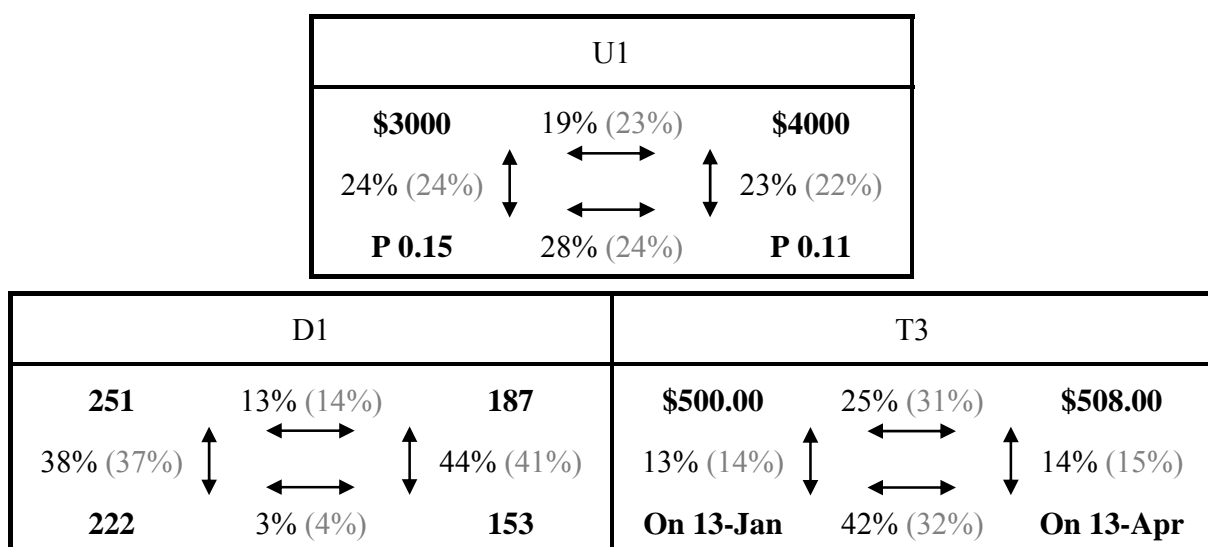


Figure 4: α 's (and β 's) for participants in U1, D1 and T3.

We find that α -values in U1 and U2 fell in between those of the other two problems. The proportion of vertical eye movements in the problems involving choice under uncertainty were well below those in a problem like D1 and well above those in problems involving time preferences, such as T3, in which it is clear that participants use a C-procedure. In each of these problems, the distribution of the frequency of horizontal movements is relatively concentrated around the average⁸. Therefore, we conclude that most participants in the lottery problems U1 and U2 use procedures that are largely, but not solely, based on the comparison of components.

In another group of problems, we switched the locations of the probability and the dollar amount on the right side of the screen (see Figure 5):

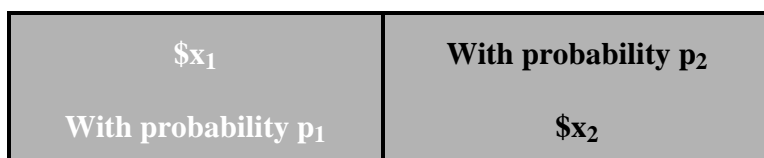


Figure 5: Choice under uncertainty problem: diagonal layout.

In all the problems apart from those in this group, the α -values of the diagonal movements were negligible. In contrast, diagonal movements were used intensively here (see Table 4).

⁸ The distribution of the horizontal movements shows a single peak with standard deviation of 13%.







	The lotteries		N	% of choices		α -values					
	$L = (x_1, p_1)$	$R = (p_2, x_2)$		%L	%R						
U5	\$5000 0.16	0.11 \$7000	37	57%	43%	21% (2%)	21% (2%)	16% (2%)	10% (1%)	9% (1%)	23% (3%)
U6	\$2468 0.26	0.53 \$1234	36	6%	94%	19% (2%)	22% (2%)	16% (2%)	8% (1%)	14% (2%)	21% (3%)
U7	\$4947 0.640	0.638 \$4952	38	61%	39%	17% (2%)	17% (2%)	12% (2%)	8% (1%)	23% (2%)	24% (2%)
U8	\$621 0.87	0.82 \$652	38	68%	32%	16% (1%)	19% (2%)	13% (2%)	10% (1%)	19% (2%)	23% (2%)

Table 4: α values in lottery choice problems with diagonal layout.

We conclude that participants are heavily involved in comparing prizes and probabilities separately when making the choice between two lotteries.

5. Conclusion

The aim of this study was to use eye tracking in order to shed light on the procedures used by decision makers in the context of decision making under uncertainty. We conclude that when the numbers which specify the prices and probabilities of two lotteries made the expectation calculation difficult, they rely almost exclusively on separate comparisons of prizes and probabilities. In the other cases, it appears that they are involved in a hybrid of C- and H-procedures.

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