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An experimental test of the absentminded driver "paradox"

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Abstract

Absentmindedness is a special case of imperfect recall which according to Piccione and Rubinstein (1997a) leads to time inconsistencies. Aumann, Hart and Perry (1997a) question their argument and show how dynamic inconsistencies can be resolved. The present paper explores this issue from a descriptive point of view by examining the behavior of absentminded individuals in a laboratory environment. Absentmindedness is manipulated in two ways. In one treatment, it is induced by cognitively overloading participants. In the other, it is imposed by randomly matching decisions with decision nodes in the information set. The results provide evidence for time inconsistencies in all treatments. We introduce a behavioral principal, which best explains the data.

| *Keywords*:	imperfect recall, absentmindedness,
	dynamic inconsistency, experiment
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1   Introduction

Dynamic consistency is a compelling fundamental tenet of rational behavior: once a decision maker makes a plan, she should carry it out as long as there is no relevant change in the decision environment. Notwithstanding its normative appeal, the principle of dynamic consistency has been systematically invalidated by empirical evidence, therefore calling for a revision of the normative theories, as in the case of decision-making under risk (e.g. Kahneman and Tversky, 1979) or ambiguity (e.g. Gilboa and Schmeidler, 1989; Epstein and Schmeidler, 2003). Conversely, Piccione and Rubinstein (1997a; henceforth PR) have drawn attention to a particular case of dynamic inconsistency that arises exactly from standard rational theory. PR considered a specific type of imperfect recall, which they termed "absentmindedness", where a single history passes through two decision nodes in an agent's information set. They showed that in the analysis of decision problems featuring absentmindedness, traditional game theory yields time inconsistencies.

Absentmindedness and the paradoxical results associated with it are most usefully illustrated by the problem of the "absentminded driver", a simplified version of which is presented in Figure 1's game tree.[1]

Figure 1: The absentminded driver problem
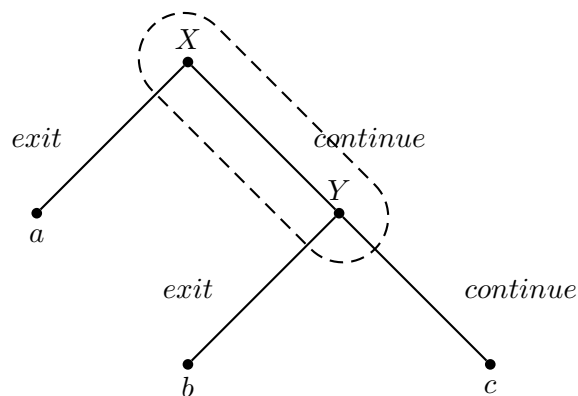
The absentminded driver starts her journey at node X where she can either "exit" (for a payoff of a) or "continue" to Y where she faces the same choice. If at Y she exits, she gets a payoff of b; if she continues beyond Y, she earns c. The driver suffers from absentmindedness in the sense that

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[1]We speak of game (rather than decision) tree to stay in the framework of game theory.

she is unable to distinguish between nodes X and Y, both of them being in the same information set. PR demonstrated that if the highest payoff is at the second intersection (i.e., $b > a$; c),[2] an agent's plan before she starts her journey (the *planning stage*) is inconsistent with her beliefs once she reaches a decision node (the *action stage*) as long as she assigns some positive probability to being at Y. In other words, the decision maker is tempted to change her initial plan when the time comes to make a decision.[3] This observation was termed by PR "the absentminded driver paradox".

In the same issue of *Games and Economic Behavior*, Aumann, Hart and Perry (1997a; henceforth AHP) replied to PR. AHP argued that optimization at the information set should be carried out with respect to the strategy at the current decision node while considering the rest of the play as fixed. AHP showed how in this case the planning-optimal decision is also action-optimal, thus resolving the paradox.[4]

Notwithstanding having been brought out more than a decade ago, the absentminded driver paradox and the theoretical controversy surrounding it have not yet been settled. Game theory has proven unable to provide a general normative prescription because different game-theoretical approaches lead to conflicting results. Indeed, while AHP argue for the planning-optimal strategy as the unique normative prescription, Binmore (1996) considers any non-committing plan irrelevant to the analysis.

Unlike previous studies, in this paper we explore the paradox from a descriptive point of view.[5] Accordingly, we implement the problem depicted

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[2]Throughout the paper we use the terms 'exit', 'intersection', and 'node' interchangeably.

[3]Note that the highest payoff b can never be reached through pure or mixed strategies. The following analyses therefore always consider *behavioral strategies*, allowing the decision maker to randomize over her actions, independently at X and at Y. Thus, the behavioral strategy is a distribution over the possible actions available at the information set. An action is chosen independently according to the behavioral strategy each time the information set is reached.

[4]This notion is mathematically equivalent to a modified multiselves approach (where a person is viewed as consisting of different temporal selves).

[5]Theoretical discussions of the paradoxes arising under absentmindedness can be found in Battigali (1997), Gilboa (1997), Grove and Halpern (1997), Halpern (1997), Aumann, Hart, and Perry (1997b), and Lipman (1997), which are summarized and countered in Piccione and Rubinstein (1997b), Binmore (1996), and Board (2003). So far the experimental studies of absentmindedness did not attempt a direct test of the absentminded driver paradox. Huck and Müller (2002) tested a related game which is comparable only to the action stage, while Deck and Sarangi (2009) aimed to show the possibility of inducing absentmindedness in an experimental setting and do not provide a systematic test of the paradox.

in Figure 1 in an experimental environment and study how decision makers actually behave when put in a state of absentmindedness. We can thus explore whether they exhibit inconsistencies (as postulated by PR's paradox) or act as if they consisted of "multiple selves" therefore letting the paradox disappear (as argued by AHP).

To these two approaches we add a third one rooted in behavioral considerations. The theoretical analyses of PR and AHP assume that a decision maker is able to perform sophisticated calculations over the distribution of beliefs about the states of the world. We argue instead that an absentminded individual, not knowing where she is during the journey, brings to mind a specific contingency, such as being at the second intersection, and is inclined to act accordingly. Thus, the individual would tend to exit more than dictated by her planning strategy because of the occurrence of "being at the second intersection" in her mentally constructed hypothetical state of the world, rather than because of sophisticated optimization over beliefs.

Our experiment is constructed in a way which enables us to juxtapose the predictions of the three approaches. Each participant in the experiment goes through both a planning stage and an action stage. In the planning stage, the participants choose only one behaviorial strategy to be independently implemented at both exits. In the action stage, the participants choose two behavioral strategies, one for each exit. Absentmindedness in the action stage is manipulated in two different ways, which we term "induced absentmindedness" (henceforth IND treatment) and "imposed absentmindedness" (henceforth IMP treatment). To gain insight into the underlying process, namely to distinguish between PR optimization and our cognitive explanation, we ask participants in the action stage of both the IMP and IND treatments to guess and bet on which intersection their current decision applies to. If decision makers construct a mental hypothetical state of the world, we predict that they will base both their guesses and their game decisions on this mental state. Thus, time inconsistencies, if any, should be correlated with the guesses in the sense that participants should exit more when they believe to be at the second exit. Since eliciting beliefs may change people's behavior (e.g., by creating a demand to choose a strategy consistent with the stated beliefs) we control for this by running treatments without belief elicitation.

To induce absentmindedness we build upon an innovative procedure re-

cently introduced by Deck and Sarangi (2009). The procedure is based on the divided attention technique (see, e.g., Deutsch and Deutsch, 1963; Kahneman, 1973) by which participants' cognitive resources are overloaded with multiple tasks. The method relies on cognitive overload (resulting from information abundance) to make participants forget their own past decisions.[6]

In our experiment, similar to Deck and Sarangi (2009), we cognitively overload participants by asking them to consider and decide on many driving "maps", with each map representing an independent payoff-earning game of the type depicted in Figure 1. Compared to Deck and Sarangi (2009), we enlarge the set of maps presented to the participants both by increasing the number of game trees (defined by the payoffs a, b, and c) and creating four maps per game tree by using different colors. In order to recognize a map, a participant therefore must remember not only the payoffs, but also the color and the combination thereof. The use of different colors also contributes to the reliability of the strategies' estimation, as each participant essentially makes each decision four times. Additionally, we do not impose any time limit on choices, although we strongly encourage participants to make each decision rather fast.

In the IND treatment, the order in which exits appear throughout the action stage corresponds to the natural one. Namely, for each map, the second exit always appears after the first one, with at least one other map in between. Keeping the exits to the natural order has the drawback that first decision nodes X are more likely to appear early in the stage. Therefore, timing can serve as a signal for the current node: a participant, although absentminded, may conjecture to be at X, and consequently decide to "continue" with high probability, during the early part of the stage switching this strategy sometime midway through the stage. This participant would emulate the behavior of a non-absentminded individual and show contingencies between guesses and actual nodes.

To control for this experimental artifact, we introduce the IMP treatment, in which participants make their two decisions knowing that a decision is randomly matched to one exit in order to determine the payoff. More

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[6]When people must process large amounts of information within a short time span, the limited capacity of their short-term memory causes cognitive overload (see, e.g., Kareev and Warglien 2003). Short-term memory capacity refers to the number of items that an individual can retain at one time and is classically estimated to be 7 ± 2 (Miller 1956; Shiffrin 1976; Kareev 2000; but see Cowan 2001 for a lower estimate).

specifically, with probability 0.5 the first decision applies to decision node X and the second decision to decision node Y, and with probability 0.5 the order of the nodes is reversed. Although it imposes absentmindedness by definition, this treatment may alter the optimal strategy as participants can increase their expected payoff by choosing "continue" at one decision node and "exit" at the other (this argument is elaborated in Section 6(e) of AHP). To circumvent this issue, we use the same procedure in the IMP treatment as in the IND treatment. This procedure precludes the use of the above strategy since the cognitive overload makes it difficult to identify different instances of the same map, and therefore to employ different strategies at the two different nodes.[7]

Our results generally indicate significant time inconsistencies across treatments and paradox trees, in line with PR. The belief data supports our cognitive interpretation of the effect.

The remainder of the paper is organized as follows. The next section presents the formal arguments of PR and AHP. In Section 3 we develop our behavioral approach. Section 4 details the experimental design and experimental implementations of imperfect recall. Section 5 discusses our experimental results, and Section 6 has some concluding remarks.

2 Theoretical background

Consider the absentminded decision problem shown in Figure 1. Denote the probability of "continue", which defines the behavioral strategy, by p. At the planning stage, the decision problem is to maximize $(1-p)a+p(1-p)b+p^2c$ over p. Straightforward computations show that the optimal behavioral strategy is

$$(1) \qquad\qquad p^* = \frac{b-a}{2(b-c)}.$$

Take now into account the action stage. Once the driver is on the road and arrives at an intersection, she does not know whether this is the first or second intersection. Let α be the probability the driver assigns to being at X, and let $H(p, q, \alpha)$ be the expected payoff given the probability to

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[7]Our data confirms that participants were unable to follow this strategy, which would lead to an overall probability to "continue" of 0.5.

continue p, the strategy at the other decision node q, and the belief α. PR take the probability of "continue" at the current and at the other node as being the same and therefore maximize $H(p, p, \alpha) = \alpha[(1-p)a + p(1-p)b + p^2c] + (1-\alpha)[(1-p)b + pc]$ over p, holding α fixed. Solving this problem yields:

$$(2) \qquad \bar{p} = \frac{\alpha(2b - a - c) + c - b}{2\alpha(b - c)},$$

which is strictly smaller than p^* for any $\alpha < 1$. Thus, in PR's argumentation, unless the driver believes, unreasonably, to be at the first node X with probability 1, her optimal strategy at the action stage is inconsistent with her optimal plan.

AHP claim that PR's analysis is "flawed" (p. 102) in its formulation. They observe that "when at one intersection, he (the driver) can determine the action *only there*, and *not* at the other intersection — where he isn't" and "whatever reasoning obtains at one (intersection) must obtain also at the other" (p. 104). Accordingly, the planning-optimal strategy p^* is also action-optimal if it maximizes payoff at the action stage assuming that p^* is played at the other intersection. In AHP's analysis, the expected payoff at the action stage is

$$(3) \qquad H(p, q, \alpha) = \alpha[(1-p)a + p(1-q)b + pqc] + (1-\alpha)[(1-p)b + pc],$$

where α is not held fixed, but is determined by q; in particular, it is the consistent belief $\alpha = \frac{1}{1+q}$.[8]

Suppose that the strategy at the other intersection is the one prescribed by the optimal plan p^* as defined in (1), i.e., $q = p^* = (b-a)/(2(b-c))$. Then the probability that the current intersection is X is $\alpha = 2(b-c)/(3b-2c-a)$. Substituting q for $(b-a)/(2(b-c))$ and α for $2(b-c)/(3b-2c-a)$ into (3), the expected payoff from choosing "continue" at the current intersection with probability p becomes

$$(4) \qquad H\left(p, \frac{b-a}{2(b-c)}, \frac{2(b-c)}{3b-2c-a}\right) = \frac{b(a+b) - 2ac}{3b - a - 2c},$$

which does not depend on p. Hence $p = p^*$ maximizes (4) and therefore

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[8]For a discussion of consistent beliefs under absentmindedness and their relation to Bayesian updating, see Section 5 in PR.

p^* is both planning- and action-optimal. AHP thus prove that in the absentminded driver problem studied here the planning-optimal strategy is the *unique* action-optimal strategy. Furthermore, the planning-optimal strategy is always action-optimal. Although, in general, there may exist other strategies that are action-optimal, they are not available to the agent at the action stage as q must be taken to be the optimal strategy already determined in the planning stage.

3   Behavioral hypothesis

It is well established that people do not make decisions under uncertainty according to the normative principles of expected utility theory. Among the theoretical models which have been put forth to provide a faithful description of how people think, some maintain that boundedly rational individuals make their decisions on the basis of sampled specific instances (Gilboa and Schmeidler, 1995; 1997; Osborne and Rubinstein, 1998). Experimental evidence supports the view that decisions are driven by a sample drawn from memory or experiences (Fiedler, 2000; Kareev, 2000; Erev et al., 2010). Although in the question at hand there is no experience to sample from, Erev et al. (2008) suggest that the sample used as basis for decisions under uncertainty may come not only from empirical distributions, but also from objective distributions. For decisions under absentmindedness, such an objective probability distribution exists in the form of beliefs about the decision nodes in the information set, as provided by α.

We propose a simple decision process in which one state of the world is sampled from the objective distribution to influence decision making. Such a cognitive process is likely to effect time inconsistencies in a way which is similar, but not identical, to PR. More specifically, we hypothesize that the decision maker uses the probability distribution over the two decision nodes to mentally generate a realization of a possible state of the world. This mental state leads her to act in accordance with that realization. Thus, insofar as the decision maker assigns some probability to being at the second decision node, she will sometimes mentally sample the state of being at Y and tend to exit. We shall refer to this process as case-based time inconsistencies, or CBTI.

To formalize this hypothesis in Figure 1's problem, denote by σ_i the

strategy that the decision maker would like to choose at decision node i ($i \in \{X, Y\}$) if she knew that i would be the actual state of the world. With probability α the absentminded driver mentally samples node X, which induces a tendency to move according to σ_X, and with complementary probability, $1 - \alpha$, she mentally samples Y, which induces a tendency to move according to σ_Y.[9] This tendency should be interpreted as a shift from the planning-optimal strategy p^* to a convex combination of p^* and σ_i where the weight given to p^* is independent of i. Accordingly, the expected observed mean strategy, $\hat{p}$, should lie between p^* and the expected σ_i:

$$\min(p^*, \alpha\sigma_X + (1-\alpha)\sigma_Y) < \hat{p} < \max(p^*, \alpha\sigma_X + (1-\alpha)\sigma_Y).$$

In the following we will show that:

(5) $$\alpha\sigma_X + (1-\alpha)\sigma_Y < p^*,$$

so that $\hat{p} < p^*$, and CBTI indeed leads to time inconsistency, in the same direction as that predicted by PR. First note that the driver always wishes to exit at Y, implying $\sigma_Y = 0$. Therefore inequality (5) reduces to:

(6) $$\alpha\sigma_X < p^*.$$

When $a > c$, it is not obvious what one should do at X because the action-optimal strategy hinges upon the choice at Y. In this case, the strategy at X can be construed to be the same as in the planning stage, i.e. $\sigma_X = p^*$. Condition (6) thus implies that the driver would not like to follow her planning-optimal strategy as long as $\alpha < 1$, therefore exhibiting time inconsistency.

On the other hand, if $c > a$, wishing to continue at the first intersection is a dominant strategy, i.e. $\sigma_X = 1$. In such a case, time inconsistency arises due to the assumption that the states of the world are mentally sampled in relation to α. In our experiment the objective α is 0.5 (each map is indeed presented to the participants twice). Since $c > a$ implies $p^* > 0.5$, inequality

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[9]Here we assume a simple sampling process from the distribution given by α. The predictions of the hypothesis remain qualitatively unchanged if this assumption is somewhat relaxed, insofar as X (Y) is mentally sampled with a probability that is weakly increasing (decreasing) in α, and symmetry holds in the sense that if $\alpha = 0.5$, then each node is sampled with equal probability.

(6) holds.[10]

The case with $c = a$ is somewhat ambiguous because $\sigma_X = 1$ is only weakly dominant. Although it seems still reasonable to take $\sigma_X = 1$, this would imply $\hat{p} = p^* = 0.5$ and hence no time inconsistency. Therefore CBTI has no clear predictions.

4 Experimental design

To disentangle the predictions of the three different approaches presented in the previous sections, the experiment consisted of two phases: the planning stage where participants had to provide their plan *before* starting the "journey", and the action stage in which participants had to indicate their choices *during* the journey. According to AHP, no difference in behavior between the stages should be detected. According to PR, participants should always exit more in the action stage. Finally, according to CBTI, participants should systematically exit more in the action stage only in the periods when they guess to be at the second node.

4.1 Phase 1: Planning stage

The first phase involved sequential decisions. In this phase, participants were shown 14 game trees of the type depicted in Figure 1 in 4 different colors (yellow, green, blue, purple) so that they faced a total of 56 maps.[11] For every map, each participant had to specify her behavioral strategy.

To implement the randomizing mechanism associated with behavioral strategy play, we used a technique similar to that provided by Huck and Müller (2002). Participants were asked to imagine an urn with 100 balls. They could determine the composition of the urn, i.e., how many balls would stand for "exit" and how many for "continue". Once the composition of the urn was decided, the computer randomly drew one ball from the urn (afterwards replaced). If the ball showed "exit", then the participant had to take the first exit and earned a. If the ball showed "continue", then the participant continued to the second exit and the computer randomly drew

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[10]This result remains unchanged if we replace the experimental $\alpha = 0.5$ with the consistent $\alpha = \frac{1}{1+\sigma_X}$.

[11]Recall that a "map" is uniquely identified by both the game tree (and thus the payoffs) and the color.

a second ball. If this was an "exit"-ball, then the participant had to take the second exit and earned b; otherwise, the participant stayed to the end and earned c.

For each of the 56 maps, participants were asked to indicate their desired mixture of "exit" and "continue" balls in two boxes; i.e., they had to enter a number in both the "exit"-box and the "continue"-box, where the two numbers had to add up to 100. We made clear that the strategy chosen by a participant referred to both exits. Although this procedure allowed participants to implement randomized strategies, participants could, if they wanted to, enter 100 in one box and 0 in the other, therefore playing a pure strategy.

To familiarize participants with the task — including both the game form and the randomization procedure — we gave them 15 minutes of practice to experiment with different payoffs and strategies. Participants filled in payoffs in a blank tree and indicated a behavioral strategy, after which they received the resulting probability distributions over outcomes as well as the expected payoff. Next, particular payoff realizations could be obtained by pressing a "travel"-button repeatedly.

4.2   Phase 2: Action stage

The second phase of the experiment corresponds to the action stage. In this phase, participants encountered each map twice, never consecutively. In addition to the 56 maps shown during the planning stage, participants were presented with 16 (4 trees $\times$ 4 colors) filler maps. Given that each of the 72 maps was shown twice, the action stage consisted of 144 game decisions/periods.

For every map, participants had to indicate two strategies, one for each exit. Strategies were elicited employing the same randomization technique as in the first phase.[12] Participants were required to decide twice on each map regardless of their decision the first time they observed the map; i.e., having chosen to exit with certainty at the first exit ($p = 0$) did not exclude making a choice for the second exit. Although this procedure somewhat alters the original game,[13] the theoretical analysis of Section 2 remains valid

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[12]Although people, in reality, can choose only one of the two actions, we allow participants to randomize in the action stage for being consistent not only with the planning stage, but also with the theoretical models (which allow for randomizing).

[13]In the original game, the probability of being at each node depends on the strategy

because the conditional payoff relevant decisions are equivalent to those of the original game.

Depending on how absentmindedness was brought about and on whether beliefs were elicited or not we discriminate among four treatments.

4.2.1 Inducing and imposing absentmindedness

In the IND treatment the payoff for each map was computed in the natural way; i.e., the first time a participant saw a map, her decision applied to the first exit, and the second time she observed the same map, her decision applied to the second exit. Thus, the experiment's timing could have served as a cue for the current exit. To avoid this shortcoming, in the IMP treatment, the payoff for each map was determined by randomly matching decisions with exits. Specifically, the first time a participant saw a map, her decision could apply to the first or second exit with 50% probability each; the second time that map was presented, her decision would apply to the other exit.

When participants start the action stage, their memory is not overloaded yet and thus they might remember the maps that were displayed.[14] Therefore only filler maps were used in the first (and the last) 10 periods.

4.2.2 Belief elicitation

Given the importance of beliefs to disentangling CBTI from PR's argument, we elicited point beliefs about the exit at which a participant thinks to be.[15] Moreover, in the IND treatment (where absentmindedness is achieved by means of cognitive overload), the elicited beliefs serve as a memory test, aimed at verifying how well participants can recall, and thus whether or not they are absentminded.

The elicitation procedure was as follows. In each period, participants were asked to guess whether they were at the first or second exit and to place a bet on their guess being correct. Specifically, participants were asked to choose one of the three options depicted in Table 1. Each option is associated with a gain and a loss depending on the guess being correct

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chosen endogenously by the decision maker.

[14]At the very beginning of treatment IND, participants know with certainty that their decisions are for the first exit.

[15]In the IMP treatment beliefs are tantamount to guessing the outcome of a fair coin toss.

or not. The possibility of gains should incentivize participants to remember maps, even though the concomitant possibility of losses should urge those who suffer from imperfect recall to select option A.[16]

Table 1: Elicitation of beliefs about the current decision node

Your choice	Option	If your guess is *correct* you WIN	If your guess is *wrong* you LOSE
○	A	1	1
○	B	3	5
○	C	5	15

To control for a possible impact of belief elicitation on participants' choices, we conducted both the IMP and IND treatments also without eliciting beliefs. Therefore, our experiment comprises four treatments: IMP with and without belief elicitation (henceforth IMP-With and IMP-Without), IND with and without belief elicitation (henceforth IND-With and IND-Without).

4.3 Experimental game trees

The game trees used in the experiment are shown in Table 2. Trees 1–14 were presented to the participants in both phases. Trees 15–18 were presented in phase 2 only: they are filler trees, which we exclude from all analyses.

In addition to ten *paradox trees*, we included two *optimal exit* and two *optimal stay trees*, where the existence of a dominant strategy excludes time inconsistencies due to absentmindedness. The optimal stay trees have the largest payoff at the end (i.e., $c > a, b$). The optimal exit trees have the largest payoff at the first exit (i.e., $a > b, c$). The unique optimal pure strategy in these trees is "continue" at both stages and "exit" at both stages, respectively. Hence, recall plays no role. Behavior in these trees will provide a check of participants' understanding of the task.

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[16]The numbers in Table 1 are chosen so that the expected payoff from option A exceeds the expected payoff from the other two options whenever the probability assigned to being correct is lower than 2/3. Only if the probability of being correct is greater than 5/6, a risk neutral decision maker should opt for C.

Table 2: Experimental game trees

Tree number	a	b	c	p^*	$\alpha = 1/(1 + p^*)$	$\bar{p}$	Tree type
1	20	50	30	0.75	0.57	0.38	Paradox
2	10	80	30	0.70	0.59	0.35	Paradox
3	0	40	10	0.67	0.60	0.33	Paradox
4	10	50	20	0.67	0.60	0.33	Paradox
5	30	90	40	0.60	0.63	0.30	Paradox
6	30	70	30	0.50	0.67	0.25	Paradox
7	20	80	10	0.43	0.70	0.21	Paradox
8	30	60	20	0.38	0.73	0.19	Paradox
9	30	70	10	0.33	0.75	0.17	Paradox
10	30	50	10	0.25	0.80	0.13	Paradox
11	50	10	30				Optimal exit
12	60	40	20				Optimal exit
13	20	10	50				Optimal stay
14	10	30	60				Optimal stay
15	0	50	10				Filler
16	10	80	40				Filler
17	30	90	50				Filler
18	10	60	20				Filler

4.4 Procedures

The computerized experiment was conducted in the controlled environment of the laboratory of the Max Planck Institute of Economics (Jena, Germany) in April and December 2009. It was programmed in z-Tree (Fischbacher, 2007). The participants were undergraduate students from the Friedrich-Schiller University of Jena. They were recruited using the ORSEE (Greiner, 2004) software. Upon entering the laboratory, the participants were randomly assigned to visually isolated computer terminals. The instructions distributed at the beginning informed the participants that the experiment consisted of two phases, and explained the rules of the first phase only. Written instructions on the second phase were distributed at the end of the first one (a translation of the German instructions for both phases is reproduced in the Appendix). Before starting the experiment, participants had to answer a control questionnaire testing their comprehension of the rules.

We ran two sessions per treatment. Thirty-six students participated in each treatment (so that a total of 144 participants were involved in the

experiment). In all treatments, participants did not know the number of maps (and thus periods) beforehand. Moreover, they did not receive any information on the random draws determining their period-payoff or on the earnings from their guesses until the end of the experiment.

Each session lasted about two hours. Money in the experiment was denoted in ECU (Experimental Currency Unit), where 10 ECU = 7 euro cents. Participants were informed that the sum of all payoffs accumulated during the several periods of the two phases would determine their final monetary payoff.[17] The average earnings per participant were €35.40 (including a €2.50 show-up fee).

5 Experimental results

5.1 Planning stage

We use the data from phase 1 (planning stage) to check whether participants understood the task they were facing and behaved according to the incentives. Since phase 1 is the same for all four treatments, we pool the data across treatments and rely on 144 individual observations.[18]

For optimal stay and optimal exit trees, we expect participants to behave optimally in close to 100% of the decisions. Table 3 shows that, in the planning stage, the proportion of optimal choices for trees 11 to 14 is above 90% and the mean strategy is to take the optimal action with over 0.95 probability (see columns (1) and (3), respectively). The proportion of optimal choices is lower in the action stage, but the mean strategies are close to optimal.

Due to the participants' computational limitations, we do not expect continue choices in the paradox trees to be perfectly aligned with the optimal p^*. Yet, if participants are sensitive to the payoffs they can obtain from each tree, then their choices should be correlated with the optimal strategy across trees. Averaging over the 144 participants for each of the 10 paradox trees, we find that choices in these trees are indeed significantly correlated with p^* ($\rho = 0.906$, $p < 0.001$).

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[17]By paying a small monetary amount over a large number of periods we try to induce risk neutrality.

[18]For each participant and each tree, we take the average over the four colors.

Table 3: Continue choices for the optimal stay and optimal exit trees

	Proportion of optimal choices		Mean Choice	
Tree	Plan	Action	Plan	Action
	(1)	(2)	(3)	(4)
11	92.01%	56.16%	2.071	22.56
12	93.58%	77.60%	1.988	6.858
13	92.36%	84.03%	96.785	94.77
14	92.88%	87.59%	97.500	96.14

5.2   Planning vs. action

The mean strategies by paradox tree, phase and treatment are summarized in Tables 4 and 5. A graphical representation of the same data is provided in Figure 2, where the trees are ordered on the horizontal axis by p^*.

The mean strategies are lower in the action stage than in the planning stage for all 10 paradox trees and in all four treatments (compare column (1) with (2) and column (7) with (8) in Tables 4 and 5). This difference is statistically significant in all but 3 cases, according to Wilcoxon signed rank tests with continuity correction relying on 36 independent observations (see columns (3) and (9) in the tables). Overall, the probability assigned to continue in the action stage is, on average, 85.1% and 69.0% of that assigned in the planning stage, in treatments IMP and IND, respectively.

Table 6 reports the results of two generalized linear random-effects models (based on Poisson distributions) regressing continue choices on *Phase* (which takes values 1 and 2) while controlling for p^*, belief elicitation (BE, which equals 1 for the treatment with belief elicitation and 0 otherwise), and the interaction of BE with p^* and *Phase*.

The estimated coefficient on *Phase* is negative and highly significant in both treatments, thereby confirming that participants tend to continue less in the action stage whatever the manipulation of absentmindedness. In the IMP treatment, continue choices do not depend on belief elicitation (the coefficient on BE is not significant), and are positively correlated with p^* regardless of whether beliefs are elicited or not. Moreover, the negative effect of *Phase* on continue choices is less pronounced when $BE = 1$ (i.e., with belief elicitation). Turning to the IND treatment, continue choices are weakly significantly higher with belief elicitation whereas the other effects

Table 4: Continue choices for the paradox trees in the IMP treatments

		IMP-WITH						IMP-WITHOUT		
Tree	p^*	Plan	Action	_Plan vs. Action_ p-value[a]	Action $\beta = X$	Action $\beta = Y$	$\beta = X$ vs. $\beta = Y$ p-value[b]	Plan	Action	_Plan vs. Action_ p-value[a]
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	75.000	61.458	56.361	0.036	61.617	47.602	0.001	63.882	58.427	0.085
2	70.000	63.181	61.844	0.278	66.753	54.351	0.003	67.840	60.601	0.023
3	66.667	74.076	69.354	0.006	73.907	61.419	0.002	80.007	76.177	0.221
4	66.667	60.722	59.132	0.391	63.324	51.602	0.002	63.840	58.028	0.066
5	60.000	56.667	51.302	0.047	55.918	43.377	0.001	61.028	50.962	0.002
6	50.000	50.653	41.545	0.001	45.244	36.653	0.001	53.250	43.059	0.001
7	42.857	43.174	34.556	0.003	35.727	32.514	0.016	48.035	35.385	0.000
8	37.500	42.389	34.194	0.000	35.888	31.059	0.005	43.778	34.604	0.000
9	33.333	39.215	30.299	0.000	29.965	30.793[c]	0.025	42.917	30.375	0.000
10	25.000	36.993	30.490	0.020	31.849	27.449	0.070	40.875	30.028	0.000

[a] Two-sided Wilcoxon signed rank tests with continuity correction relying on 36 independent observations (averages over the 4 colors for each participant).

[b] Two-sided Wilcoxon signed rank tests with continuity correction. Number of independent observations for each map: $N_1 = 25$; $N_2 = N_3 = 28$; $N_m = 27$ for $m = 4, \ldots, 9$; $N_{10} = 28$.

[c] The lower mean for $\beta = X$, compared to $\beta = Y$, is due to an outlier. The corresponding medians are 30 and 25. Thus, the significant result reflects a difference in the predicted direction.

Table 5: Continue choices for the paradox trees in the IND treatments

		IND-WITH						IND-WITHOUT		
Tree	p^*	Plan	Action	Plan vs. Action p-value[a]	Action $\beta = X$	Action $\beta = Y$	$\beta = X$ vs. $\beta = Y$ p-value[b]	Plan	Action	Plan vs. Action p-value[a]
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	75.000	62.951	42.278	0.000	73.161	33.805	0.000	63.743	49.701	0.000
2	70.000	67.799	41.806	0.000	72.070	28.921	0.000	68.167	50.660	0.000
3	66.667	77.965	44.410	0.000	84.372	29.567	0.000	76.646	53.448	0.000
4	66.667	65.993	40.257	0.000	70.650	28.567	0.000	61.875	48.274	0.000
5	60.000	63.278	39.899	0.000	72.490	23.604	0.000	60.507	43.549	0.000
6	50.000	52.903	35.139	0.000	69.574	18.454	0.000	53.750	35.833	0.000
7	42.857	44.146	29.948	0.001	55.833	15.753	0.000	48.889	33.198	0.000
8	37.500	46.222	30.101	0.000	55.075	20.495	0.000	45.174	35.122	0.000
9	33.333	41.604	29.385	0.000	51.117	18.856	0.000	46.215	32.528	0.000
10	25.000	40.382	31.333	0.000	49.040	19.991	0.000	45.139	30.472	0.000

[a] Two-sided Wilcoxon signed rank tests with continuity correction relying on 36 independent observations (averages over the 4 colors for each participant).

[b] Two-sided Wilcoxon signed rank tests with continuity correction. Number of independent observations for each map: $N_1 = 31$; $N_2 = 26$; $N_3 = N_4 = 32$; $N_5 = 31$; $N_6 = 29$; $N_7 = 27$; $N_8 = N_9 = 30$; $N_{10} = 33$.
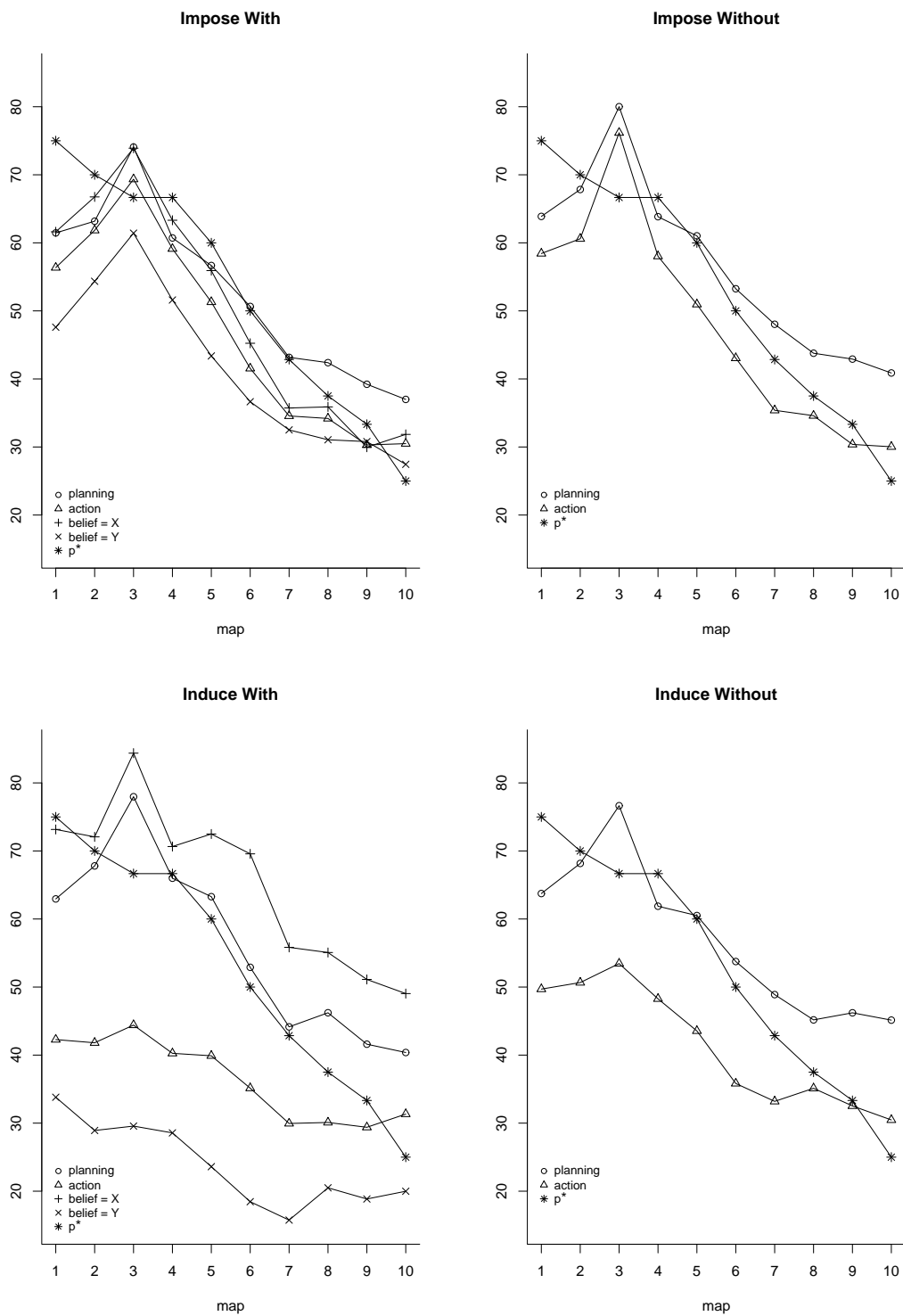
Figure 2: Mean continue choices in the four treatments

Impose With

Impose Without

Induce With

Induce Without

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Table 6: Time inconsistencies: Generalized linear mixed-effects regression on continue choices

	IMPOSE			**INDUCE**		
	Coeff	Std.Error	p-value	Coeff	Std.Error	p-value
Intercept	26.022	2.195	0.0000	49.234	2.701	0.0000
$Phase$	-10.313	0.651	0.0000	-17.094	0.882	0.0000
BE[a]	-0.868	3.085	0.7794	6.433	3.737	0.0896
p^*	0.793	0.017	0.0000	0.488	0.023	0.0000
$BE{\times}Phase$	1.521	0.906	0.0931	-2.824	1.206	0.0192
$BE{\times}p^*$	-0.0658	0.024	0.0067	-0.108	0.030	0.0004

[a] BE is 1 for the treatments with belief elicitation and 0 otherwise.

are as in IMP. We conclude that time inconsistencies exist in the data, in line with PR's argument and in contradiction to the normative analysis of AHP.

The effect of belief elicitation on participants' behavior is also explored via a series of two-sided Wilcoxon rank sum tests comparing the 36 independent continue choices in IMP-With (IND-With) and IMP-Without (IND-Without). The p-values (reported in Table 7) confirm that for all but three trees belief elicitation does not affect behavior.

Table 7: Comparing continue choices with and without belief elicitation in the action stage

Tree	IMPOSE WITH vs. WITHOUT p-value	INDUCE WITH vs. WITHOUT p-value
1	0.681	0.028
2	0.021	0.021
3	0.101	0.101
4	0.636	0.069
5	0.955	0.316
6	0.713	0.761
7	0.933	0.248
8	0.901	0.195
9	0.924	0.305
10	0.831	0.528

5.3 Beliefs

Before addressing the main issue of contingencies between beliefs and game decisions and the effect of timing in the IND treatment, we look at the bets made on the beliefs to ascertain the extent to which the participants *feel* absentminded. Taking the betting choices in treatment IMP as a baseline, we find that, overall, participants were unlikely to choose the risky bets B and C. In fact, participants are even more likely to choose the safe option A in IND compared to IMP (84.2% vs. 79.4%). Choices of the highly risky option C are quite rare in both treatments, although more frequent in IND (4.9% vs. 2.0%), where option B is selected less frequently (10.8% vs. 18.5%). We conclude that, moving from the IMP to the IND treatment, the shift to the cautious option A is larger in magnitude than the shift to the risky option C. This indicates that participants are not systematically more confident about their bets in treatment IND than in treatment IMP, in which they are absentminded by definition.

The mean continue choices by stated beliefs (labelled β) are presented in columns (4) and (5) of Tables 4 and 5. The mean strategy chosen when participants guess to be at node Y is significantly lower than that chosen when participants guess to be at node X for all 10 trees and for both IMP-With treatment and IND-With treatment, in line with the CBTI prediction. To test the correlation between stated beliefs and game strategies while controlling for other variables, we use the generalized linear random-effect models reported in Table 8. The model regresses continue choices on $Belief$, controlling for p^*, $Actual\ node$ and $Period$.

Continue choices are negatively and significantly correlated with the stated beliefs. However, in the IND-With treatment this result can be due to participants not being absentminded, i.e., knowing which decision node they are at. Indeed, in Model 1 of the IND-With panel, strategies are also correlated with the actual decision node, indicating that participants' beliefs are more accurate than expected by chance. Yet, this can happen not only if participants can recall their history, but also if they use the period as a cue. To control for this possibility, we perform Model 2 (which includes $Period$ among the covariates). We find that the effect of the actual node disappears when controlling for $Period$, while the effect of $Belief$ remains unchanged. In line with the unequivocal correspondence between beliefs and decisions observed in the IMP-With treatment, we conclude that, in the IND-With

Table 8: Beliefs-strategies contingencies

	IMP-WITH				IND-WITH			
	Model 1		Model 2		Model 1		Model 2	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Intercept	23.227	0.000	23.667	0.000	83.226	0.000	82.079	0.000
	(2.803)		(2.822)		(2.974)		(2.999)	
Belief	−11.338	0.000	−11.280	0.000	−37.341	0.000	−37.079	0.000
	(0.745)		(0.746)		(0.936)		(0.939)	
p^*	0.755	0.000	0.759	0.000	0.378	0.000	0.388	0.000
	(0.027)		(0.027)		(0.028)		(0.029)	
Actual node	−0.352	0.525	−0.342	0.537	−2.243	0.001	−0.350	0.704
	(0.554)		(0.554)		(0.679)		(0.921)	
Period			−0.012	0.171			−0.048	0.002
			(0.009)				(0.016)	

[Note] Numbers in parentheses are estimated standard errors.

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treatment, the correspondence is, at least in part, not due to an artifact. This observation supports the CBTI hypothesis.

6   Conclusions

The vast majority of theoretical and experimental research effort to understand rational decision making has so far been confined to situations of perfect recall. Nonetheless, imperfect recall is likely to play a significant role in many real-world decision problems. Firms or countries, for example, are often modeled as single players, although different elements in their strategies have to be decided by different agents, sometimes lacking information about the decisions of other parts of the aggregate player (cf. Binmore, 1996). Furthermore, even a single person is likely to suffer from imperfect recall as storing and accessing huge amounts of information is practically impossible.

Some issues arising from imperfect recall are well illustrated by the paradox of the absentminded driver (Piccione and Rubinstein, 1997b).[19] This paper joins the theoretical efforts devoted to the paradox, and complements the theoretical discussions by providing a positive analysis of the problem. Specifically, we report on an experiment designed to compare behavior in a planning stage and an action stage of a decision problem featuring absentmindedness. In the minimal setting, as implemented in our IMP treatment, the decision task is almost identical in the two stages, with the only difference being that in the action stage participants provide two strategies, whereas in the planning stage they provide a single strategy to be implemented twice. Despite the fact that payoff is maximized by the same strategy in both cases, we find that this difference is enough to lead to a systematic variance in behavior, as predicted by Piccione and Rubinstein (1997a). Namely, participants tend to exit more in the action stage than in the planning stage. This result is supported by the findings in the IND treatment, in which absentmindedness is implemented in a more natural way.

Examining the elicited beliefs, we find a significant correlation between stated beliefs and game strategy: participants assign, on average, a lower probability to continue when they guess to be at the second (rather than the

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[19]Other directions of research focus on the analysis of players with bounded complexity (see, e.g., Abreu and Rubinstein 1988; Lehrer, 1988).

first) node. This finding is not consistent with PR's argument, which does not make a normative distinction between different times in which an information set is reached. It is, however, predicted by the "case-based time inconsistencies" hypothesis. According to our interpretation, participants are not cognitively equipped to deal with probabilistic constructs such as distributions, but are able to mentally represent concrete instances. Therefore they generate a deterministic state of the world based on the distribution, and act according to it. This process leads to a contingency between decisions and stated beliefs, as both are based on the same mentally constructed state of the world.

We should note that the contingency between beliefs and strategies is merely correlational, in our design as well as in theory. Therefore we cannot completely rule out alternative explanations. One such explanation is that trembles in the strategy lead to systematically different beliefs driven by a preference for consistency. However, this explanation does not rationalize why planning and action decisions should differ. Hence, it cannot account for the observed difference between plans and actions, which is apparent regardless of belief elicitation. Our interpretation, on the other hand, provides a unified process which fully predicts and organizes the data.

Our results are also related to the theoretical analysis developed by Binmore (1996), who modeled the absentminded driver paradox as a repeated decision problem, somewhat akin to our action stage. It is noteworthy that the behavior we observe in the action stage conforms to the normative prescription of Binmore (1996), although he assumes that the decision maker can remember all her past decisions and thus derive a frequency-based belief over decision nodes. Conversely, our participants did not receive feedback between maps and encountered each decision node twice.

To sum, we provide conclusive descriptive evidence for the existence of the time inconsistencies predicted by PR, and elucidate the process driving these inconsistencies. In this paper we focus on the problem of the absentminded driver, which was at the center of the theoretical debate. We leave it for future research to study the implications of the case-based reasoning theory resented here for more general situations.

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Experimental instructions

This appendix reports the instructions (originally in German) we used for the IND-With treatment. The instructions for the other treatments were adapted accordingly and are available upon request.

<div align="center">INSTRUCTIONS</div>

Welcome and thanks for participating in this experiment. Please remain quiet and switch off your mobile phone. Stow away any reading or writing materials: your table should contain only these instructions. Do not speak to the other participants. Communication between participants will lead to the automatic end of the session with no payment to anyone. Whenever you have a question, please raise your hand and one of the experimenters will come to your place.

You will receive 2.50 euros for having shown up on time. The experiment allows you to earn additional money. Since your earnings during the experiment will depend on your decisions, and may depend on chance, the better you understand the instructions, the more money you will be able to earn.

In this experiment you will not interact with any other participant. The decisions of the other participants will not affect your earnings and, similarly, your decisions will not affect the earnings of the other participants.

During the experiment, we shall not speak of euros but rather of ECU (Experimental Currency Unit). ECU are converted to euros at the following exchange rate: 10 ECU = 7 euro cents.

<div align="center">DETAILED INFORMATION ON THE EXPERIMENT</div>

Imagine yourself driving up the highway as you see in the following picture.
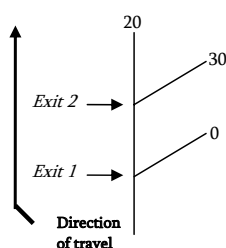
When you approach Exit 1, you have to decide whether you want to continue on the highway or you want to take that exit. If you decide to take Exit 1, then you terminate your journey. Otherwise, you continue to Exit 2, where again you must decide whether to continue on the highway or to exit. The numbers on the highway tell you the amount of money in ECU that you would earn based on where you choose to go. In the example above, you would earn: 0 ECU if you take Exit 1;

<div align="center">28</div>

30 ECU if you continue at Exit 1 and take Exit 2; 20 ECU if you continue at both exits. In this example, your maximum earnings would be achieved by continuing at Exit 1 and then taking Exit 2.

In the experiment, you will be shown several highways differing in the amount of ECU they yield. Each highway will be presented to you in 4 different colors (yellow, green, blue, red). In the following, we shall refer to a highway in a specific color as a map. Highways with the same earnings but different colors correspond to different maps. You can think of the different colors as different days in which you are driving on the same highway. Suppose that you are shown the highway depicted in the above example first in yellow and then in blue. Your travel on the yellow highway takes place on one day and your travel on the blue highway takes places on another day. Therefore, your earnings from the two travels are independent of each other.

The experiment consists of two phases. The instructions for the first phase follow on this page. The instructions for the second phase will be distributed to you at the end of the first phase. This is done to avoid confusion between the two phases. Your payoff from any of the two phases is determined only by what you do in that phase and is not affected by what you do in the other phase.

At the end of today's session, i.e., after the second phase, the amount of ECU you have earned in each period of the two phases will be added up. The resulting sum will be converted to euros and paid to you in cash and privately (i.e., without the other participants knowing your earnings) together with the show-up fee of 2.50 euros.

PHASE 1

There will be a series of periods in this phase. In each period, you will be shown a map (i.e., a highway in a specific color). Like in the example above, it is as though you are starting at the bottom of the map and driving up the highway, and your payoff will depend on where you go. For each map, you must make a single decision that applies to both exits.

For each map, you decide as follows. Imagine an urn with 100 balls. You can determine how many of these balls stand for "continuing" and how many stand for "exiting". Once you have decided the composition of the urn, the computerized program will randomly draw a ball from the urn (and put it back afterward). If the randomly drawn ball shows "exit", then you take the first exit and earn the corresponding amount of ECU. If the ball shows "continue", then you continue to Exit 2 and the program will randomly draw a second ball from the urn. Depending on whether the ball shows "continue" or "exit", you get the corresponding earnings.

To determine the composition of the urn, you must enter a number in each of the two boxes that you will see on the screen below the map. One box is labeled "exit" and the other is labeled "continue". The number you enter in the exit-box

determines the number of exit-balls in the urn. Likewise, the number you enter in the continue-box determines the number of continue-balls in the urn. The sum of the two numbers you enter must be 100.

EXAMPLE 1. If you enter 80 in the continue-box and 20 in the exit-box, then the urn will contain exactly 80 continue-balls and 20 exit-balls. This means that when the program randomly draws the first ball from the urn, you will have 80% chance of continuing on the highway and 20% chance of taking Exit 1. If the first randomly drawn ball shows "continue", then at the second random draw (corresponding to Exit 2) you will again have 80% chance of continuing on the highway and 20% chance of taking Exit 2. Therefore you will have $80\% \times 80\% = 64\%$ chance of continuing beyond Exit 2 and $80\% \times 20\% = 16\%$ chance of taking Exit 2.

EXAMPLE 2. If you enter 40 in the continue-box and 60 in the exit-box, then the urn will contain exactly 40 continue-balls and 60 exit-balls. This means that when the program randomly draws the first ball from the urn, you will have 40% chance of continuing on the highway and 60% chance of taking Exit 1. If the first randomly drawn ball shows "continue", then at the second random draw (corresponding to Exit 2) you will again have 40% chance of continuing on the highway and 60% chance of taking Exit 2. Therefore you will have $40\% \times 40\% = 16\%$ chance of continuing beyond Exit 2 and $40\% \times 60\% = 24\%$ chance of taking Exit 2.

EXAMPLE 3. If you enter 0 in the continue-box and 100 in the exit-box, then the urn will contain only exit-balls. This means that you will take Exit 1 with certainty.

As it is evident from examples 1 and 2 above, you can make a decision that does not mean exiting or continuing with certainty. However, if you wish to make such a decision, you can do so by entering 100 in one box and 0 in the other (like in example 3 above).

During the two phases of the experiment you will have to make many decisions. If you make each decision in 20 seconds, the two phases will last more than one hour. Thus, in order for the experiment to take not too long, we strongly encourage you to decide rather fast.

You will NOT receive any information about the random draws, and thus your earnings, until the end of today's session.

Practice stage

Before the experiment starts you will have 15 minutes of practice to get familiar with your task. This stage is conducted only to help you learn how the experiment works, and does not count towards your payoff. During this time you can choose different highways to practice on, and see the consequences of different choices for each highway.

On your screen you will see a highway with three empty payoff-boxes (A, B, and C in the picture below), one exit-box, and one continue-box.
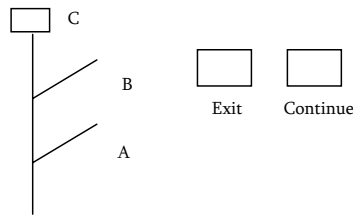
In order to choose a highway to experiment with, you have to enter a number between 0 and 200 in each of the three payoff-boxes A, B, and C. The number you enter in the payoff-box labeled A stands for the ECU you would earn if you take Exit 1. Similarly, the numbers you enter in the payoff-boxes labeled B and C stand for the ECU you would earn if you take Exit 2 or continue at both exits, respectively.

The exit-box and the continue-box allow you to determine the composition of the urn from which the program will make the random draw(s) deciding where you go and thus how much you earn. The numbers you enter in the continue-box and the exit-box must add up to 100.

Once you have entered a number in each of the 5 boxes, if you press the button marked "I want to test this highway and this composition of the urn" you will see on the screen:

- the chances you have to take Exit 1, to take Exit 2, or to continue beyond Exit 2 based on the numbers you have entered in the continue-box and in the exit-box;
- the expected payoff in ECU given your choices.

You can change all or some of the numbers you have entered as many times as you want, and then press the button to know the consequences (as explained above) of your choices.

After you have chosen a highway and a composition of the urn for that highway, you can experience "travelling" along the highway and observing whether you end up in A, B, or C. For that you can press the button marked "Travel". Each time you press this button, the program will make the random draw(s) based on your decision, and show the result. In order to make many travels and see what happens for each of them, you can press the "Travel"-button as many time as you like.

During the 15 minutes of practice, you can repeat all the steps above as many times as you wish. Notice that you can enter a number in the three payoff-boxes only in the practice stage. Thereafter, the payoffs that you can earn are given.

Before the practice stage starts, you will have to answer some control questions to verify your understanding of the rules of the experiment.

Please remain seated quietly until the experiment starts. If you have any ques-
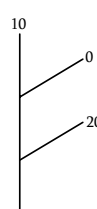
tions please raise your hand now.

PHASE 2

In this phase, you will be asked to imagine yourself travelling along the highway. During your travel you encounter the exits one after the other.

During this phase you will again see a series of maps. But, differently from phase 1, you will see each map exactly twice. Since a map is identified by both a highway with some earnings and a color and since each highway is shown to you in 4 different colors, you will see the same highway $2 \times 4 = 8$ times, but only twice in the same color.

The first time you see a map, your decision applies to Exit 1; the second time you see the map, your decision applies to Exit 2. The maps are displayed in a preselected order and you will never see the same map in two consecutive periods. Hence the map you will see in period 1 will not be used in period 2, but it may appear again in period 3, or period 4, or any other period during this second phase.

Like in phase 1, for each map you must decide how many of the 100 balls contained in an urn should stand for "continuing" and how many for "exiting". Below each map you will again see a continue-box and an exit-box, in each of which you must enter a number. The sum of the two numbers you enter must always be 100.

What is different is that in phase 2, the program will randomly draw only one ball from the urn. The drawn ball will determine your decision for the current exit of the shown map. If, for instance, you are shown a map for the first time and enter 20 in the exit-box and 80 in the continue-box, you will have 20% chance of taking Exit 1 and 80% chance of continuing. On the other hand, if you are shown a map for the second time and enter 50 in the exit-box and 50 in the continue box, you will have 50% chance of taking Exit 2 and 50% chance of continuing. Of course, where you end up depends on the two decisions you make for a particular map as well as on the random draw. The table below shows 3 possible cases.

		First time you see a map (Exit 1 decision)	Second time you see a map (Exit 2 decision)	Earnings
	Case 1	10 in exit-box and 90 in continue-box; a continue-ball is randomly drawn	50 in exit-box and 50 in continue-box; a continue-ball is randomly drawn	10
	Case 2	10 in exit-box and 90 in continue-box; an exit-ball is randomly drawn	50 in exit-box and 50 in continue-box; a continue-ball is randomly drawn	20
	Case 3	10 in exit-box and 90 in continue-box; a continue-ball is randomly drawn	50 in exit-box and 50 in continue-box; an exit-ball is randomly drawn	0

Notice that even though you enter 100 in the exit-box (therefore deciding to exit with certainty) the first time you see a map, you will still be shown the map a second time. In this case it does not matter what decisions you make the second

time.

You do not know how many periods there are in this phase. During the phase you will not be informed of how many periods are left, nor of whether you are at the first or second exit of the current map.

For each map, before making your decision about the number of exit-balls and continue-balls that should be contained in the urn, the computer will ask you to guess whether you think of being at Exit 1 or at Exit 2; that is, whether you think to see the current map for the first time or for the second time. You will have to place a bet on your guess being correct by choosing one of the three options shown below:

Your choice	Option	If your guess is *correct* you WIN	If your guess is *wrong* you LOSE
º	A	1	1
º	B	3	5
º	C	5	15

Note that option B and C offer higher payoffs if you are correct, but also carry higher losses if you are wrong. Therefore you are advised to choose option C only if you are very sure that you are correct, option B if you think that you are probably correct, and option A if you are very unsure that you are correct.

Please remain seated quietly until the experiment starts. If you have any questions please raise your hand now.