The Economic Journal, **112** (*October*), 936–965. © Royal Economic Society 2002. Published by Blackwell Publishers, 108 Cowley Road, Oxford OX4 1JF, UK and 350 Main Street, Malden, MA 02148, USA.

THE COMPLEXITY EFFECTS ON CHOICE WITH UNCERTAINTY – EXPERIMENTAL EVIDENCE*

Doron Sonsino, Uri Benzion and Galit Mador

We present experimental evidence suggesting that human subjects dislike complexity in choice with uncertainty. Our results suggest that the probability of choosing a given alternative decreases with the relative complexity of that alternative. Complexity increases the noise in the choice process and the chances that the (otherwise) inferior alternative will be selected. Our results contradict the predictions of (discounted) expected utility theory and intuitively appealing axioms like 'stochastic dominance' and 'convexity'. These 'complexity effects' may lead to inefficient portfolio selection. The perceived complexity of a given lottery may depend on editing procedures and be subjected to framing effects.

The flourishing experimental research on individual choice over the last two decades has produced a list of anomalies suggesting that human agents' behaviour is frequently incompatible with the formal models traditionally employed in the economic literature.[1] Some of these anomalies – eg the certainty effect of Kahneman and Tversky (1979) – have demonstrated that individual behaviour is inconsistent with the von Neumann Morgenstern *Expected Utility* theory. Alternative models like *Prospect Theory* (Kahneman and Tversky, 1979), *Anticipated Utility* (Quiggin, 1982) and many others have been suggested to resolve the contradictions. Other anomalies – eg, the evidence on hyperbolic discounting presented by Thaler (1981) – have referred to the case of intertemporal choice and suggested that human subjects do not comply with Samuelson's *Discounted Utility* model. Again, attempts have been made to develop alternative models that reconcile the inconsistencies; see, for example, Loewenstein and Prelec (1992).

This paper concentrates on a different anomaly that seems inconsistent with the evaluation models that are typically assumed in the economic literature. The basic 'simple' idea is that human subjects are inclined to avoid 'complicated' lotteries. Accordingly, they sometimes discriminate against complicated lotteries and prefer simple lotteries to complicated ones in cases where the value of the complicated lottery should be higher.

In particular, we demonstrate that complexity affects choice in two ways:

1. The probability of choosing a given alternative (in binary choice tasks) decreases with the relative complexity of that alternative.
2. The noise in the choice process increases with complexity and thus the chances that the (otherwise) inferior alternative will be selected, increase as well.

* We thank Andreas Blume, David Budescu, Ido Erev, Tzhachi Gilboa, Uri Gneezy, Werner Guth, Doron Kliger, Dov Monderer, Rosemarie Nagel, Robin Pope, Ariel Rubinstein, Peter Wakker, Mark Pingle and Lanna Volokh for comments and conversations on different aspects of this project. We thank David de Meza and two anonymous referees for their important contributions. We also thank the fund for the promotion of research at the Technion for its financial support.

[1] For examples, see the survey by Camerer (1995).

We term these effects: *the negative complexity effects in choice with uncertainty*. (See Section 1 for a survey of the preceding literature on the subject.) We use random-effects models to analyse the overall experimental data-set and argue that both effects are significant in our data set.

Lotteries-complexity seems especially relevant in cases where current choices determine the distribution of pay-offs over several (future) periods. In such cases, decision makers have to choose between lotteries over streams of pay-offs.[2] The corresponding decision problems can thus be characterised by two basic dimensions of complexity: the number of periods over which current decisions affect future pay-offs and the probability distribution according to which the realised stream of pay-offs is determined. The existing experimental literature on choice and decision making typically focuses on either 'single-period choice with uncertainty' or on 'intertemporal choice with no uncertainty'.[3] The current study, however, deals with the more complicated, general case of lotteries over streams of deferred pay-offs.

To argue formally that complexity affects choice, we need some complexity measure or at least some axiomatic set-up that will enable us to rank the lotteries under investigation according to their complexity-level. Defining a 'proper' general complexity measure for multi-period lotteries, however, seems like a non trivial challenge. We bypass the problem by adopting a simple complexity measure (closely related to the Payne *et al.* (1993) measure of cognitive effort) that generates an intuitively appealing (complexity-)ranking of the lotteries that are compared in this study. We are then able to show that our pool of subjects indeed discriminates against complicated lotteries while violating the predictions of discounted expected utility theory, rank dependent utility and other evaluation models studied in the literature.

The data for the paper were collected in a series of in-class experiments. To provide incentives, we have told the participants in advance that we will pay them in three deferred cheques payable at the same dates as the pay-offs of the multi-period lotteries under consideration.[4] Subjects were also told that the amount of each deferred cheque will be proportional to their total realised pay-off for the corresponding period.

The complexity effects described above seem intuitively appealing and might have interesting practical implications. Complexity-aversion, for instance, may suggest that real-estate heirs might be willing to sell their bequests in discounted prices to avoid the complexity of renting and maintaining the property in the future. Complexity effects might also show up in choice between different wage-schemes, insurance plans and investment or saving plans. As a concrete example, we demonstrate in the paper that complexity-aversion might explain small-scale

[2] See, for example, the choice problem in Fig. 1.

[3] The two exceptions that we could trace are Prelec and Loewenstein (1991) and Keren and Roelofsma (1995) who study the interaction between anomalies in intertemporal choice and anomalies in (single–period) choice with uncertainty. These studies, however, deal only with special types of 'degenerated' lotteries over streams of pay-offs.

[4] The use of deferred cheques is a common practice in Israel. The banks in the country do not withdraw against a deferred cheque before the pre-specified future payment date posted on the cheque.

diversification and inefficient portfolio selection. We also argue that the perceived complexity of a given lottery might depend on editing procedures and be subjected to framing effects.

The paper is organised as follows: Section 1 briefly reviews the related literature. Section 2 outlines the basic framework and presents our complexity measure. Section 3 outlines the experimental method. Section 4 describe the main results. The results on complexity and inefficient portfolio selection are presented in Section 5. In Section 6, we suggest that framing might affect the perceived complexity of a lottery. Section 7 considers the range of models, while Section 8 describes the results of the econometric analysis. Section 8 concludes.

1. Related Literature

The existing literature on decision and choice contains only a few related references dealing with complexity and decision making. Bruce and Johnson (1996) and Johnson and Bruce (1997*a*, *b*, 1998) study the effect of complexity on actual decision and choice in the UK horse-track betting market. In contrast with our approach, they define the complexity of a choice-problem (while we refer to the complexity of each alternative under consideration). They assume that the complexity of a problem increases with the number of alternatives from which the decision maker has to choose and with the 'list of attributes' that characterise each alternative. The conjecture that complexity adversely affects the accuracy of choice (when accuracy is measured in terms of choosing the alternative with higher expected pay-off) is rejected in Bruce and Johnson (1996).

In an earlier reference, Wilcox (1993) studies the effect of stronger incentives on subjects' performance in simple binary choice tasks versus their effect on subjects' behaviour in complicated choice tasks. The complicated choice problems for that study were constructed from the simple choice problems by splitting each lottery into a two-stage lottery with an equivalent distribution. Wilcox shows that, when incentives are low, complexity decreases the accuracy of decisions. This complexity effect, however, disappears when the incentives are high.

Neilson (1992) generalises the expected utility model by assuming that the utility function employed in the evaluation of a given (single-period) lottery might depend on the number of outcomes in the support of the lottery. In particular, Neilson assumes the existence of a sequence of utility functions $\{U_i(\cdot)\}_{i=1}^n$ where $U_i(\cdot)$ denotes the utility function used in the evaluation of a lottery with i different outcomes and $U_1(x) \geq U_2(x) \ldots \geq U_n(x)$ for all $x > 0$. He shows that the generalised model might explain a generalised common consequence (or certainty) effect.

In a further investigation of Neilson's generalised model, Humphrey (1998) points to the fact that the inclination to penalise lotteries with many outcomes might contradict the experimental evidence on the event-splitting effect. In particular, Humphrey (1998, 2000) formally demonstrates that Neilson's generalised model is incompatible with experimental evidence on the event-splitting effect and with the evidence on violations of transitivity documented by Starmer (1999).

In a recent concurrent study, Hucks and Weizsacker (1999) show (in the context of single-period lotteries) that the frequency of deviation from expected pay-off maximisation in binary choice problems increases with the (maximal) number of possible prizes. Moreover, the subjects reveal a tendency to choose the less complex alternative (ie the lottery with a smaller number of prizes) in such cases.

The experimental study underlying the current paper postulates that complexity should be measured at the primitive level of individual lotteries and not at the higher level of choice problems as in the studies of Bruce and Johnson. Our framework (choice between multiperiod lotteries) is more general than the ones investigated in the references above. Some of the results (eg the ones on inefficient portfolio selection) seem especially strong and suggest that economists should pay more attention to complexity considerations when analysing (or applying) models of choice under conditions of uncertainty.

2. Preliminaries

2.1. *Multi-period Lotteries*

A multi-period lottery is a lottery over streams of pay-offs. In this study, we focus on multi-period lotteries with a finite support (ie a finite number of possible streams of pay-offs) and a finite horizon (ie a finite number of periods in which the lottery pays the prizes). We accordingly define a multi–period lottery L as a tuple $(\mathbf{p}, \mathbf{X})$ where $\mathbf{p} = (p_1, p_2, \ldots, p_m)$ is a probability vector satisfying $p_i \geq 0$ for every $i = 1, 2, \ldots, m$ and $\sum_{i=1}^{m} p_i = 1$, and $\mathbf{X}$ is an $m \times T$ matrix describing the pay-off streams that may result from the lottery L. Thus, p_j denotes the probability with which the T-period pay-off stream from the lottery will be the one given by the jth row of the matrix $\mathbf{X}$; ie x_{j1} at date 1, x_{j2} at date 2, ... and x_{jT} at date T. As a simple example, take the case where

$$\mathbf{p} = (0.4, 0.6) \qquad \text{and} \qquad \mathbf{X} = \begin{pmatrix} 20 & 40 \\ 30 & 50 \end{pmatrix}.$$

In this case, L pays the stream '20 in period 1 and 40 in period 2' with probability 0.4, and the stream '30 in period 1 and 50 in period 2' with probability 0.6. For every two lotteries, $L^1 = (\mathbf{p}^1, \mathbf{X}^1)$ and $L^2 = (\mathbf{p}^2, \mathbf{X}^2)$, we use $\alpha L^1 + (1 - \alpha) L^2$ to denote the (convex combination) lottery that pays the stream of pay-offs described by the jth row of lottery L^1 with probability αp_j^1 and the stream of pay-offs described by the jth row of lottery L^2, with probability $(1 - \alpha) p_j^2$.[5]

2.2. *Preferences on Multi-period Lotteries*

Let $\mathcal{L}$ be a space of multi-period lotteries as described above. Assume that, for every $L^i, L^j \in \mathcal{L}$ and for every $\alpha \in (0, 1)$, $\alpha L^i + (1 - \alpha) L^j \in \mathcal{L}$. Let DM be a decision maker with a complete, transitive and reflexive binary relation $\succeq$ that describes her preferences on $\mathcal{L}$. For every two lotteries L^1 and L^2 in $\mathcal{L}$, we say that DM prefers L^2

[5] For simplicity, assume that the matrices $\mathbf{X}^1$ and $\mathbf{X}^2$ do not have identical rows so that there is no need to sum up probabilities in constructing the convex combination.

on L^1 iff $L^2 \succeq L^1$. We use $\succ$ to denote the strong preference relation induced by $\succeq$; ie, $L^2 \succ L^1$ iff $(L^2 \succeq L^1)$ and not $(L^1 \succeq L^2)$. As a reference point to the experimental results that will be introduced in the following sections, we now suggest three intuitively appealing axioms on $\succeq$. In the proceeding Sections, we argue that complexity effects might lead to violations of each of these axioms.

AXIOM 1: *Convexity If* $L^2 \succ L^1$ *and* $L^3 \succeq L^1$ *then* $\alpha L^2 + (1-\alpha)L^3 \succ L^1$ *for every* $\alpha \in (0, 1)$.

In words, convexity says that if DM strongly prefers L^2 on L^1 and prefers L^3 on L^1 then she should strongly prefer any convex combination of L^2 and L^3 on L^1.

Convexity was assumed (in a single-period context) by Fishburn (1982, 1983*a*, *b*) in deriving several alternatives to expected utility theory. The axiom also holds when decision makers follow some of the other 'alternative' evaluation models proposed in the literature.[6]

In defining the next two axioms, we use $L^i(\tilde{t})$ to denote the single-period lottery that pays (at date 1) according to the marginal distribution of pay-offs at date $\tilde{t}$ in lottery L^i.[7] We assume that if $L^i \in \mathcal{L}$ then $L^i(t) \in \mathcal{L}$ for every $t = 1, 2, \ldots, T$. We say that $L^i(t)$ first-order stochastically dominates $L^j(t)$ when the usual definition holds; ie {The probability that $L^i(t) \leq x$} $\leq$ {The probability that $L^j(t) \leq x$} for every x and the inequality holds strictly for some x.

AXIOM 2: *Stochastic Dominance If* $L^2(t)$ *first-order stochastically dominates* $L^1(t)$ *for every* $t = 1, 2, \ldots, T$, *then* $L^2 \succ L^1$.

In words, first-order stochastic dominance says that if lottery L^2 gives a better pay-off distribution than lottery L^1 in each period t, then DM should prefer L^2 to L^1.

First-order stochastic dominance is considered an intuitively appealing assumption on individual choice. The axiom is satisfied (in the single-period framework) by the expected utility model, anticipated (rank dependent) utility theory, generalised prospect theory and many other evaluation models. Contradictions to stochastic dominance were reported by Tversky and Kahneman (1986), Starmer and Sugden (1993), Humphrey (1995) and others. In these cases, however, the violations of dominance involved event-splitting or coalescing of outcomes. Subjects revealed a preference to stochastically dominated alternatives when these alternatives involved more 'favourable' outcomes. In our experiments, however, subjects reveal a preference for stochastically dominated alternatives when these alternatives are less complicated and, in particular, involve less 'favourable' outcomes than the dominating alternatives. In this sense, the violations of stochastic dominance reported in this paper are different from the ones previously presented in the literature.[8]

[6] See the survey in Camerer (1995) for specific references and for examples to previous experimental studies where the axiom was violated.

[7] In the case of lottery 5(B) (as presented at the beginning of Section 4.2), for instance, $5(B)(2)$ is the lottery that pays 30 with probability 0.6 and 105 with probability 0.4 at date 1.

[8] See also the discussion of Kroll *et al.* (1988*a*, *b*) findings in footnote 20.

Axiom 3: IIP (*Independence of Irrelevant Periods*) *If* L^1 *and* L^2 *are two lotteries that pay the same distribution of pay-offs in all periods except period* $\tilde{t}$ (*so that* $L^1(t) = L^2(t)$ *for every* $t \neq \tilde{t}$), *then* $L^2 \succ L^1$ *iff* $L^2(\tilde{t}) \succ L^1(\tilde{t})$.[9]

In words the axiom says that if L^2 and L^1 are two lotteries that pay the same distribution of pay-offs in all periods except for period $\tilde{t}$ then DM prefers L^2 to L^1 if and only if she prefers the distribution of pay-offs that is generated by lottery L^2 at date $\tilde{t}$ to the distribution of pay-offs that is generated by the lottery L^1 for that date.

The IIP Axiom also seems like an intuitively appealing demand from individual choice. Note that any separable evaluation model of the form

$$V(L) = \sum_{t=1}^{T} \psi(t) V[L(t)]$$

where $\psi(t)$ denotes the (lottery-independent) discount factor for period t and $V(\cdot)$ denotes some (lottery-independent) evaluation model for single-period lotteries, satisfies the IIP axiom. In particular, note that the axiom does not preclude hyperbolic discounting – see, for example, Ainslie and Haslam (1992) – or negative discount rates (Loewenstein and Prelec, 1991). Loewenstein and Prelec (1993, study 2), however, present experimental data suggesting that subjects may violate the IIP axiom while rating 5-period sequences of outcomes.[10] We are not aware of any other documented violations of the axiom.

2.3. *Discounted Expected Utility* (*DEU*)

The DEU model assumes the existence of a (monotonically increasing) utility function $U : \mathbb{R} \mapsto \mathbb{R}$ and a positive discount factor $\delta \leq 1$ such that every lottery $L = (\mathbf{p}, \mathbf{X})$ is assigned a value $V(L)$ according to the formula

$$V(L) = \sum_{i=1}^{m} p_i \left[\sum_{t=1}^{T} \delta^{t-1} U(x_{it}) \right]$$

and $L^1 \succeq L^2$ iff $V(L^1) \geq V(L^2)$.

The discounted expected pay-off (DEP) from lottery L is the discounted expected utility from that lottery when the utility function U is given by $U(x) \equiv x$.

The DEU model serves as a basic building block in modern economic theory. It is assumed by basic models in micro economics, macro economics and finance. Note that the model satisfies our three axioms (Convexity, Stochastic Dominance, IIP) independently of the specific form of the utility function U and the rate of discounting δ. When $T = 1$, the DEU model shrinks into Von Neumann Morgenstern's *Expected Utility*. The experimental evidence described in the sequel

[9] The axiom resembles the independence axiom that is used in deriving the discounted utility model (Koopmans, 1960; Fishburn and Rubinstein, 1982) – in the sense of assuming the irrelevance of those periods where the two alternatives pay the same (distribution of) pay-offs. It also has a flavour of the stationarity axiom in assuming that the irrelevant periods can be 'erased' from the time-scale when we compare the two alternatives.

[10] Note that the complexity of each alternative is fixed in the Loewenstein and Prelec (1993) design.

demonstrates, in particular, that complexity considerations may lead to violations of expected utility theory.

2.4. *Complexity of Multiperiod Lotteries*

To argue formally that human subjects dislike complexity in choice with uncertainty, we need a complexity measure or at least some axioms that will enable us to rank the lotteries under investigation according to their relative complexity. For the sake of this specific study, we adopt a simple complexity measure that generates an intuitively appealing (complexity-)ordering of the lotteries that were presented to our subjects. In particular, we assume that the complexity of a given lottery $L = (\mathbf{p}, \mathbf{X})$ is equal to the product of the number of rows in $\mathbf{X}$ and the number of columns in $\mathbf{X}$. We use $COMP(L)$ to denote the corresponding number. For instance, the complexity of Alternative A in Fig. 1 is 2 while the complexity of Alternative B is 12.

Intuitively, our simple complexity measure seems closely related to different measures of cognitive effort studied in the psychological literature, see Payne *et al.* (1993) for specific examples. It also seems correlated with the formal notions of complexity used in logic and probability theory, see, for example, the discussion in Gilboa (1994). Note, however, that, in general, the problem of defining an 'appropriate' formal complexity measure for multi–period lotteries seems like a non

Payment Dates:

Payment 1: 1/5/1999
Payment 2: 1/11/1999
Payment 3: 1/5/2000

Which of the following two alternatives do you prefer?

Alternative A

Probability	Payment 1	Payment 2
100%	0	100

Alternative B

Probability	Payment 1	Payment 2	Payment 3
50%	30	30	30
12.5%	0	0	0
0.5%	50	100	60
37%	60	60	40

Mark your choice with a $\surd$

I prefer Alternative A to Alternative B
I prefer Alternative B to Alternative A

Fig. 1. *The Structure of a Typical Problem*

trivial challenge. It seems that many different factors other than the size of the pay-off matrix **X** might play a role in determining the complexity of a given lottery. The number of different elements in **X**, the number of different elements in the probability vector **p**, the size of the pay-offs and the probabilities, the 'form' (say, fractions or decimal numbers) in which the pay-offs and the probabilities are presented and many other factors may, in fact, affect the perceived complexity of the lottery. The collection of lotteries examined in the current study, however, is relatively homogeneous, except for the size of the pay-off matrices.[11] We therefore chose to adopt the simple complexity measure outlined above.

3. Method

The data were collected in a series of in-class experiments (henceforth: sessions) that took place at the Faculty of Industrial Engineering and Management at the Technion, Israel Institute of Technology. The subjects were undergraduate (76%) and graduate (24%) students that have passed introductory courses in economics and probability. (The differences in choice frequencies between the undergraduate students and the graduate students were statistically insignificant.)

In the experiment, the subjects were asked to answer 14 choice problems. The problems were presented to the same group of 97 students in three separate sessions with a gap of 1–2 weeks between successive sessions. In each session, the subjects were asked to answer several (4–5) choice problems. The problems were divided across sessions so that similar problems were not presented to the subjects at the same session. Problems 11–13 were also presented to one more group of 23 students so that, altogether, we had 120 observations for these three problems. Detailed information about the experimental sessions is provided in the Appendix (Table A1). The (translated) instructions handed out to the subjects are presented in the Appendix Figure A1. The example in Fig. 1 (that was included in the written instructions) illustrates the structure of a typical problem.

In all of the problems included in the experiment, the payments were made at 6-month intervals; see, for example, the payment schedule of the lotteries in Fig. 1. The maximal number of payments was three but most of the lotteries involved only one or two periods. The first payment was scheduled to the first of the month following the end of the experiment.

We have used six different versions of each problem; three of which starting with one lottery as Alternative *A* and the other three starting with the second lottery as Alternative *A*. The order of rows (in each pay-off matrix) was randomly shuffled across these six versions. The problems were presented to the subjects in an independent, random order.

To provide incentives, subjects were told that, at the end of the experiment, after we process the data, we will give each one of them three deferred cheques: one cheque for each payment-date specified in the lotteries. We also told the subjects that, to determine the amount of these cheques we will draw, for each

[11] In particular, note that all pay-offs are at the range of 40–160 and that the probabilities are always presented in a percentage, decimal form with no more than two digits to the right of the decimal point.

subject, the lotteries that he has chosen (in all of the sessions in which he has participated) and calculate his average realised pay-off for each payment-date. The corresponding three figures will be used to determine the size of the corresponding cheques. The instructions (see Appendix) emphasised that the size of each cheque will increase with the average amount that the subject has earned for the corresponding date.

In the verbal instructions stage, we told the subjects that the exact formula according to which the three payments were determined will be disclosed when we distribute the first cheque. We also promised the subjects a minimum total payment of 30 NIS (approximately 7.5 US dollars at the time of the experiment).

One of the referees was concerned that our incentive scheme might have caused an (expected) wealth effect on subjects' behaviour. To control for that, we have run problems 11–13 on 35 more (different) subjects that were told that their final cheques will be determined by *randomly* choosing one of the three problems at the end of the experiment. The instructions and incentives scheme was identical to the original one in all other respects. The results obtained for these three control problems were not significantly different from those obtained in the original experiment: 71% chose *B* in Problem 11, 60% chose *B* in Problem 12 and 37% chose *B* in Problem 13.[12]

4. The Complexity Effects

4.1. *Single-period Example*

Consider Problems 1–4, as used in Table 1.

Observe that alternative *A* is the same in all four problems. Alternative *B*, however, changes across the problems. In particular, Lottery $3(B)$ is the convex combination $0.3 \times 1(B) + 0.4 \times 2(B) + 0.3 \times 1(A)$. Lottery $4(B)$ is a slight improvement, in terms of first-order stochastic dominance, on $3(B)$.

Convexity (Axiom 1) implies that subjects that prefer *B* to *A* in Problems 1 and 2, should prefer *B* to *A* in Problem 3 as well. Similarly, Stochastic Dominance (Axion 2) implies that subjects that prefer *B* to *A* in Problem 3, should also prefer *B* to *A* in Problem 4. If subjects' behaviour is consistent with these axioms, the percentage of subjects preferring *B* to *A* in Problem 3 should not be significantly lower than 93% and the percentage of subjects preferring *B* to *A* in Problem 4 should not be significantly lower than the percentage of subjects preferring *B* to *A* in Problem 3. The results, which are also presented in Table 1, however, contradict these predictions. The percentage of subjects preferring *B* to *A* decreases significantly as we move from Problems 1 and 2 through Problem 3 to Problem 4.

A closer inspection of subjects' behaviour shows that 17 of our 97 subjects choose the complicated alternative *B* in Problem 3 while reverting to the simple

[12] Note also that Problem 11 (see Appendix) was presented to class I in session 1 while it was presented to class II in session 3. The choice-proportions, however, were not significantly different across the two groups (67% choosing *B* in Class I, 73% choosing *B* in Class II).

Table 1

Problems 1–4

	Alternative A		Alternative B	
Problem 1 ($N = 97$)[13]	Alternative 1(A) ($N = 6$)		Alternative 1(B) ($N = 91$)	
	Probability	Payment 1	Probability	Payment 1
	50%	110	50%	106
	50%	80	50%	96
Problem 2 ($N = 97$)	Alternative 2(A) ($N = 7$)		Alternative 2(B) ($N = 90$)	
	Probability	Payment 1	Probability	Payment 1
	50%	110	50%	130
	50%	80	50%	74
Problem 3 ($N = 97$)	Alternative 3(A) ($N = 19$)		Alternative 3(B) ($N = 78$)	
	Probability	Payment 1	Probability	Payment 1
	50%	110	15%	106
	50%	80	20%	74
			15%	96
			15%	110
			20%	130
			15%	80
Problem 4 ($N = 97$)	Alternative 4(A) ($N = 29$)		Alternative 4(B) ($N = 68$)	
	Probability	Payment 1	Probability	Payment 1
	50%	110	18%	106
	50%	80	11%	74
			15%	130
			4%	81
			12%	96
			15%	110
			11%	80
			9%	75
			5%	131

Choice Results for Problems 1–4	1	2	3	4
Alternative A	6%	7%	20%	30%
Alternative B	94%	93%	80%	70%

alternative A in Problem 4. Only 7 subjects, however, switched from choosing A in Problem 3 to choosing B in Problem 4. The hypothesis that the switch-rates are equal is rejected at a significance level $p \leq 0.065$.[14]

Thus, our subjects' behaviour is inconsistent with expected utility theory. Informally, we also claim that the observed contradictions cannot be naturally resolved by most alternative models suggested in the literature.[15] In particular, note that

[13] Recall that the problems were presented to the subjects in a random order (in each session). For the exposition, we have numbered the problems in the order in which they appear at the paper. Note also that Problems 2–4 were presented to the (same) subjects in different sessions.

[14] The hypotheses that the probability of switching from choosing A in problem $i, (i = 1, 2)$ to choosing B in problem $j, (j = 3, 4)$ is equal to the probability of switching from B to A is similarly rejected at $p \leq 0.05$.

[15] The exception is Neilson (1992) as discussed in the literature review.

over-weighting of small probabilities (as assumed, for instance, by generalised prospect theory) should increase the value of lotteries $3(B)$ and $4(B)$ relative to the fixed alternative A and thus cannot explain the experimental results. Rank-dependent utility (and most other 'alternative' theories) satisfy stochastic dominance and thus cannot explain the significant decrease in the percentage of subjects choosing B in the move from Problem 3 to Problem 4. The same is true for stochastic choice models; see, for example, Hey and Carbone (1995).

We believe, however, that complexity-aversion provides an intuitively appealing explanation to the results above. Our complexity measure implies that lottery $4(B)$ is more complicated than lottery $3(B)$ which, in turn, is more complicated than each of the lotteries $2(B)$ and $1(B)$. The observed decrease in the percentage of subjects choosing B might thus follow from the increase in complexity of this alternative. In the econometric analysis in Section 7, we argue that this 'negative complexity effect' is indeed statistically significant.

Finally, note that the literature on the event-splitting effect (see Section 1) suggests that alternative $4(B)$ with its multiple positive prizes should appear more attractive than alternative $3(B)$ which, in turn, might appear more attractive than each of the alternatives $2(B)$ and $1(B)$. The fact that our subjects run away from alternative B as its complexity increases demonstrates that the complexity effect is stronger than the event-splitting effect in our data.[16]

4.2. *Two-periods Example*

The next three problems (Problems 5–7 in Table 2) involve lotteries over two-periods' streams of pay-offs.

Again, Alternative A is the same in all three cases. Alternative B changes slightly across the problems.[17] In particular, note that the distribution of each payment (1 and 2) in lottery $6(B)$ first-order stochastically dominates the distribution of the corresponding payment in lottery $5(B)$. Similarly, the distribution of each payment in lottery $7(B)$ first-order stochastically dominates the distribution of pay-offs in lottery $6(B)$. Stochastic Dominance (Axiom 2) thus implies that the percentage of subjects preferring B to A should not decrease significantly as we move from Problem 5 through Problem 6 to Problem 7. The results, also in Table 2, however, show that the percentage of subjects preferring B to A has significantly decreased on the move from Problem 5 to Problem 6. Again, the complexity effects provide a possible explanation. Lottery $6(B)$ is more complicated than lottery $5(B)$ so many of our subjects revert to the simpler alternative A.

Yet, given this result, one might expect that the complexity effect would cause a further decrease in the percentage of subjects choosing B in the move from Problem 6 to Problem 7. The results in Table 2, however, show that, in fact, the

[16] In particular, note that since the event-splitting effect may partially offset the complexity effect in our data, the actual complexity effect might be stronger than perceived by the significance levels presented above.

[17] The three problems were presented to the subjects in different sessions; see Table A1 in the Appendix for details.

Table 2
Problems 5–7

Problem 5 ($N = 97$)	Alternative 5(A) ($N = 42$)		Alternative 5(B) ($N = 55$)		
	Probability	Pmt 1	Probability	Pmt 1	Pmt 2
	100%	160	60%	120	30
			40%	115	105
Problem 6 ($N = 97$)	Alternative 6(A) ($N = 49$)		Alternative 6(B) ($N = 48$)		
	Probability	Pmt 1	Probability	Pmt 1	Pmt 2
	100%	160	42%	120	30
			12%	118	108
			28%	115	105
			18%	123	33
Problem 7 ($N = 97$)	Alternative 7(A) ($N = 48$)		Alternative 7(B) ($N = 49$)		
	Probability	Pmt 1	Probability	Pmt 1	Pmt 2
	100%	160	12%	122	32
			18%	123	33
			16%	115	105
			6%	121	13
			4%	116	106
			24%	120	30
			12%	118	108
			8%	117	107
Choice Results for Problems 5–7			5	6	7
Alternative A			43%	51%	50%
Alternative B			57%	49%	50%

percentage of subjects choosing B in Problem 7 was not significantly different from the corresponding percentage for Problem 6.[18]

The evidence for the existence of a complexity effect thus seems weaker in this sequence of problems. The econometric analysis in Section 8, however, provides an intuitive explanation. In the analysis, we show that complexity plays a double role in multi-period lotteries' evaluation. First, subjects penalise lotteries for complexity so that the (expected) *Value Adjusted to Complexity* of lottery L, $VAC(L)$, decreases with the complexity of that lottery ($COMP(L)$). Second, complexity also increases the variance of the (white) noise in the evaluation process, so that the variance of $VAC(L)$ also increases with $COMP(L)$.

Table 2 shows that our subjects were equally split between alternatives A and B in Problem 6. This may suggest that the expected VAC of lottery 6(A) is close to the expected VAC of Lottery 6(B). Now, recall that Lottery 7(B) has a pay-off distribution

[18] Sign tests suggest that the differences in subjects' behaviour in Problem 5 and in each of the Problems 6 and 7 are significant at p = 0.1. The differences in behaviour in Problems 6 and 7 are found to be insignificant. Note, however, that (as explained in Section 4.1) the event-splitting effect might partially offset the complexity effects in these cases.

that is very similar to the pay-off distribution of Lottery 6(*B*). Indeed, the pay-off distribution of 7(*B*) is slightly better than the distribution of 6(*B*) in term of first-order stochastic dominance, but it is slightly worse because of its higher complexity. This suggests that the expected *VAC* of Lottery 7(*B*) might be very close to the expected *VAC* of Lottery 6(*B*). In such a case, the impact of the increase in complexity in the move from Problem 6(*B*) to Problem 7(*B*) on the variance of the white noise is lost in the sense that it does not cause a significant decrease in the percentage of subjects choosing the complicated alternative; see the illustration in Figure 2 (*a*).

For comparison consider the move from Problem 3 to Problem 4. The fact that 80% of the subjects chose *B* in Problem 3 suggests that the expected *VAC* of lottery 3(*B*) is significantly higher than the expected *VAC* of lottery 3(*A*). In such a case, the increase in complexity in the move from Lottery 3(*B*) to the (otherwise similar) Lottery 4(*B*) on the noise-variance might indeed cause a significant decrease in the percentage of subjects choosing the complicated alternative *B*; see the illustration in Figure 2(*b*).

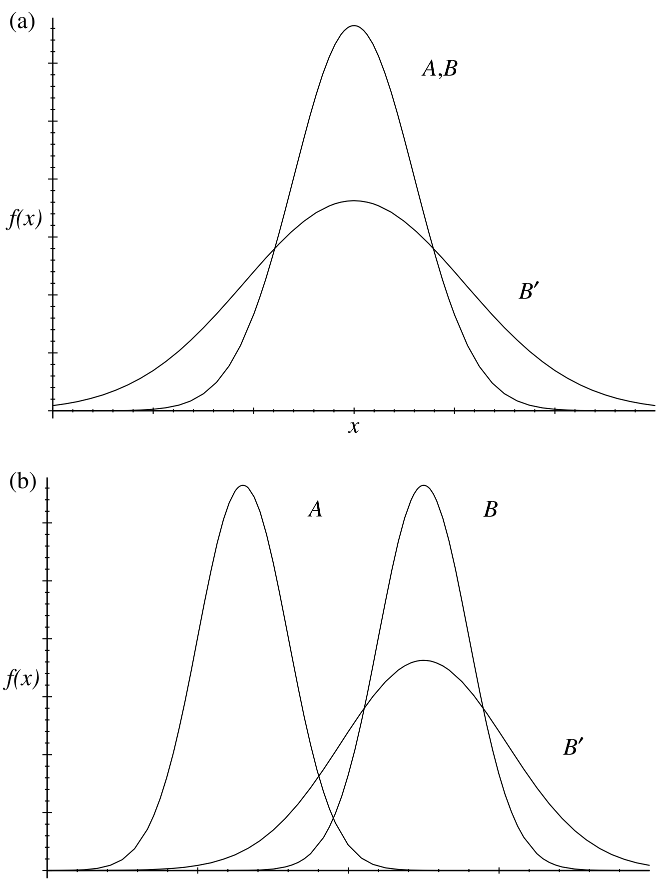

Fig. 2.

4.3. *Violations of IIP*

Consider next Problems 8–10 (Table 3).

Note that the distribution of payment 2 in Problem 9 is the same as the distribution of payment 1 in Problem 8 (for each alternative). The distribution of payment 1 is the same in both alternatives: $9(A)$ and $9(B)$.

Similarly, the distribution of payment 3 in Problem 10 is the same as the distribution of payment 1 in Problem 8 (for each alternative). The distribution of payments 1 and 2 are the same in both alternatives: $10(A)$ and $10(B)$.

The IIP Axiom (Axion 3) implies that every subject that has preferred alternative B to A in Problem 8 should also prefer B to A in Problems 9 and 10. In our experiment, however, the percentage of subjects preferring B to A has decreased from 80% in the case of Problem 8 to 69% in the case of Problem 9 and to 41% in the case of Problem 10.[19]

The results, as shown in Table 3, clearly demonstrate that our subjects do not conform with the IIP Axiom. In particular, the observed behaviour sharply contradicts the predictions of the DEU model and any evaluation model of the separable from

$$v(x) = \sum_{t=1}^{T} \psi(t) v[L(t)]$$

Note, however, that since the values of alternatives A and B become closer as we move from Problem 8 through Problem 9 to Problem 10 (because the difference in pay-off distributions is postponed to later periods), the results might also be explained by a standard stochastic choice model – as, for example, in Hey and Carbone (1995) – without referring to any complexity effects. The analysis in Section 7 suggests that the noise in the process of choosing between two alternatives A and B increases with the complexities of the underlying lotteries ($COMP(A)$, $COMP(B)$). Thus, it seems that the complexity effect interacts with the noisy choice process to produce the strong results obtained for this set of problems.

5. Complexity and Rejection of Efficient Portfolios

In this Section, we claim that the complexity effects may explain inefficient portfolio selection.[20] To test this conjecture, we have first used the next two choice problems: 11 and 12 (Table 4).

Problem 11 was designed to test the risk preferences of our subjects in the relevant pay-off region. Alternative A in that problem is composed of a simple

[19] All differences are significant at $p \leq 0.01$.

[20] Earlier experimental evidence on violations of the efficient-portfolio hypothesis was presented by Kroll *et al.* (1988*a*, *b*). In Kroll's experiments, however, subjects received statistical information on the risky assets (and the riskless interest rate) and were asked directly to choose an investment portfolio. A significant portion of the chosen portfolios were inefficient (which might be considered another violation of the dominance axiom discussed in Section 2.2). Note, however, that the Kroll *et al.* (1988*a*, *b*) set-up is very different and much more 'complicated' than the binary-choice design used in the current experiment. In this sense, the current manifestations of inefficient portfolio selection seem more compelling.

Table 3
Problems 8–10

Problem 8 ($N = 97$)	Alternative 8(A) ($N = 19$)				Alternative 8(B) ($N = 78$)			
	Probability	Payment 1			Probability	Payment 1		
	50%	110			18%	106		
	50%	80			20%	74		
					12%	96		
					15%	110		
					20%	130		
					15%	80		
Problem 9 ($N = 97$)	Alternative 9(A) ($N = 30$)				Alternative 9(B) ($N = 67$)			
	Probability	Pmt 1	Pmt 2		Probability	Pmt 1	Pmt 2	
	50%	50	110		18%	60	106	
	50%	60	80		20%	50	74	
					12%	60	96	
					15%	50	110	
					20%	60	130	
					15%	50	80	
Problem 10 ($N = 97$)	Alternative 10(A) ($N = 57$)				Alternative 10(B) ($N = 40$)			
	Prob.	Pmt 1	Pmt 2	Pmt 3	Prob.	Pmt 1	Pmt 2	Pmt 3
	50%	40	73	110	18%	60	50	106
	50%	60	50	80	20%	40	73	74
					12%	60	50	96
					15%	40	73	110
					20%	60	50	130
					15%	40	73	80

Choice Results for Problems 8–10	8	9	10
Alternative A	20%	31%	59%
Alternative B	80%	69%	41%

lottery; alternative B pays the expected pay-off of that lottery with probability 1. Previous experimental evidence – see, for example, Kahneman and Tversky (1979) – suggests that most subjects will prefer the risk-free alternative B in this case; 69% of the subjects have conformed with this hypothesis.[21]

Lottery 11(A) was then used to construct Problem 12 as follows: Alternative 12(A) is a copy of lottery 11(A). We now think of this lottery as representing the return $R(X)$ on some tradeable security X. Alternative 12(B) then represents the distribution of returns on a portfolio that is composed of equal shares in two independent copies of X; that is, it represents the random variable $\frac{1}{2}R(X_1) + \frac{1}{2}R(X_2)$, where X_1 and X_2 are two independent copies of X. If subjects conform with expected utility theory and are risk averse (so that they prefer alternative B to alternative A in Problem 11) then they should prefer B to A in the case of

[21] Note however that alternative B is also less complicated than Alternative A in this case, so that the preference for A might also follow from complexity–aversion.

Problem 12 as well. Thus, the data for Problem 11 suggest that at least 69% of the subjects should prefer *B* to *A* in Problem 12. In fact, only 53% of our subjects have preferred *B* to *A* in Problem 12 (a statistically significant difference at $p \leq 0.05$). Moreover, even when we restrict the sample to those subjects that have acted risk aversively (i.e. chosen alternative *B*) in Problem 11, we still find out that only 53% of the subjects chose the efficient alternative *B* in Problem 12. These results might again be explained by invoking the negative complexity effect. Risk-averse subjects are avoiding the diversified portfolio because of its higher complexity.

Note, however, that when we restrict the sample to those (risk-seeking) subjects that have chosen alternative *A* in Problem 11, we find that 52.6% of these subjects acted risk aversively by choosing *B* in Problem 12. This might be explained by claiming that the choice process is very noisy. It then follows that some of the shift of risk–averse subjects from 11(*B*) to 12(*A*) was also triggered by that noise. In Section 7, we argue that the noise in the choice process increases with the complexity of the underlying problem, so that (as suggested in §4.3) the two forces interact to produce the observed results.

In Problem 13, we have tested the negative complexity effect on diversification in a multi-period context. The alternatives presented in this problem refer to a ‘stock’ that pays 9 or 12 with equal probabilities, in periods 1 and 2, independently across periods. Alternative *A* (no diversification) applies to the case where the subject holds 8 shares of the stock in period 1 and 10 shares in period 2. Alternative *B* (diversified) applies to the case where there are two independent copies of that stock and the investor diversifies by equally splitting his investment among the two. In period 1, he holds 4 shares in each company. In period 2, he increases his investment to 5 shares of each company.

DEU theory clearly implies that risk averse investors should prefer lottery *B* to *A* in this application. The data for Problem 11 thus suggest that at least 69% of the subjects should prefer *B* to *A* in this case. In practice, only 40% of the subjects preferred *B* to *A* in this case. The percentage of risk-averse subjects (i.e. subjects that chose *B* in Problem 11) that have chosen the efficient portfolio in the current problem was only 42%. (The data for Problems 11–13 is summarised in Table 4).

6. Independent vs Correlate Framing

In Problem 14 (Table 5), we have asked the subjects to choose between two similar alternatives. Alternative *B* was constructed from alternative *A* in two steps:

1 Changing the framing from two independent lotteries (one for each period) to a single two-period lottery
2 Increasing some the pay-offs slightly (by 1 or 2 NIS) to generate a first-order stochastically dominating alternative.

The ‘reduction of compound lotteries’ axiom – see, for instance, Segal (1990) – implies that alternative *B* should be preferred to *A* under DEU-maximisation and under any other model that satisfies the Dominance Axiom. Still, 34% of our subjects have violated the prediction of the axiom and preferred *A* to *B*. One possible explanation is that our subjects violate the reduction of compound

Table 4

Problems 11–13

	Alternative 11(*A*) ($N = 37$)			Alternative 11(*B*) ($N = 83$)		
Problem 11 ($N = 120$)	Probability	Payment 1		Probability	Payment 1	
	30%	150		100%	107	
	40%	80				
	30%	100				
Problem 12 ($N = 120$)	Alternative 12(*A*) ($N = 56$)			Alternative 12(*B*) ($N = 64$)		
	Probability	Payment 1		Probability	Payment 1	
	30%	150		24%	115	
	40%	80		9%	150	
	30%	100		16%	80	
				9%	100	
				24%	90	
				18%	125	
Problem 13 ($N = 120$)	Alternative 13(*A*) ($N = 72$)			Alternative 13(*B*) ($N = 48$)		
	Probability	Pmt1	Pmt2	Probability	Pmt1	Pmt2
	25%	96	90	6.25%	96	120
	25%	72	120	12.5%	72	105
	25%	96	120	6.25%	96	90
	25%	72	90	25%	84	105
				12.5%	84	90
				12.5%	96	105
				6.25%	72	90
				12.5%	84	120
				6.25%	72	120

Complexity Effects in Efficient Portfolio Selection	11	12	13
% preferring the low–risk alternative *B*	69	53	40
% preferring the riskier alternative *A*	31	47	60
% of risk averse choosing *B*	100	53	42

Table 5

Problem 14 ($N = 96$)

Alternative 14 (*A*) ($N = 34$)*				Alternative 14 (*B*) ($N = 62$)		
Lottery 1 (Payment 1)		Lottery 2 (Payment 2)				
Probability	Payment	Probability	Payment	Probability	Payment 1	Payment 2
50%	80	30%	150	15%	82	151
50%	120	30%	80	20%	120	80
		30%	100	20%	80	81
				15%	120	150
				15%	120	100
				15%	81	101

*Participation in two lotteries (1 and 2) where lottery 1 will take place at date 1 and will determine payment 1 and lottery 2 will take place at date 2 and will determine payment 2.

lotteries axiom (in a multi-period type of application). Alternatively, we suggest that complexity considerations might have caused this framing effect. In particular, the independent concise framing of alternative A might have been perceived by many subjects as less complicated than the correlated framing of alternative B.[22] These subjects therefore choose A in spite of the fact that it should not be difficult to observe that B is stochastically dominant.

7. Analysis

To summarise the data quantitatively and demonstrate that complexity has the anticipated effects on subjects' behaviour in our study, we have tested several alternative models that can be distinguished by the following criteria:

7.1. *Differential vs Proportional Model*

The differential model basically assumes that the value assigned by subject i to alternative A in Problem j ($j = 1, 2 \ldots 14$), takes the form

$$VAC_i(A_j) = \beta_i^0 + \beta_i^V V(A_j) + \beta_i^C COMP(A_j) + \epsilon_i(A_j)$$

where A_j denotes alternative A in problem j, $VAC_i(A_j)$ denotes the realised *Value Adjusted to Complexity* of A_j to subject i, $V(A_j)$ denotes the value of that lottery according to some standard evaluation model that does not take complexity directly into account (details on the estimation of V are presented in the sequel), $COMP(A_j)$ denotes the complexity of A_j as defined in Section 2, and $\epsilon_i(A_j)$ denotes a random error with a distribution that may depend on the specific characteristics of lottery A_j.

Similarly, the value assigned to Alternative B in Problem j takes the form

$$VAC_i(B_j) = \beta_i^0 + \beta_i^V V(B_j) + \beta_i^C COMP(B_j) + \epsilon_i(B_j)$$

The differential model then assumes that subject i chooses B_j iff

$$VAC_i(B_j) > VAC_i(A_j)$$

Using P_i to denote the corresponding probability, we have

$$\begin{aligned} & P_i\,[VAC_i(B_j) > VAC_i(A_j)] \\ & = P_i\,\{\beta_i^V[V(B_j) - V(A_j)] + \beta_i^C[COMP(B_j) - COMP(A_j)] + \epsilon_i^* > 0\} \end{aligned}$$

where ϵ_i^* now presents the noise in the choice process.

Setting $V_j = V(B_j) - V(A_j)$, $C_j = COMP(B_j) - COMP(A_j)$, and assuming that $\epsilon_i^* \sim \mathrm{N}(0, \sigma_j^2)$, we find that the probability p_i that player i will choose B in Problem j satisfies

$$p_i = \Phi\left(\frac{\beta_i^V V_j + \beta_i^C C_j}{\sigma_j}\right)$$

[22] In the econometric analysis that follows, we set $COMP(A) = 5$ (which is the sum of the complexities of Lottery 1 and Lottery 2) and $COMP(B) = 12$.

for each subject i, so that

$$\Phi^{-1}(p_i) = \frac{\beta_i^V V_j + \beta_i^C C_j}{\sigma_j}.$$

For the *proportional model*, we now assume that

$$VAC_i(A_j) = \beta_i^0 V(A_j)^{\beta_i^V} COMP(A_j)^{\beta_i^C} \mathrm{e}^{\epsilon_i(A_j)}$$

and that

$$VAC_i(B_j) = \beta_i^0 V(B_j)^{\beta_i^V} COMP(B_j)^{\beta_i^C} \mathrm{e}^{\epsilon_i(B_j)}.$$

So that,

$$\frac{VAC_i(B_j)}{VAC_i(A_j)} = \left[\frac{V(B_j)}{V(A_j)}\right]^{\beta_i^V} \left[\frac{COMP(B_j)}{COMP(A_j)}\right]^{\beta_i^C} \mathrm{e}^{[\epsilon_i(B_j)-\epsilon_i(A_j)]}$$

and

$$\ln\left[\frac{VAC_i(B_j)}{VAC_i(A_j)}\right] = \beta_i^V \ln\left[\frac{V(B_j)}{V(A_j)}\right] + \beta_i^C \ln\left[\frac{COMP(B_j)}{COMP(A_j)}\right] + \epsilon_i^*.$$

Thus,

$$\begin{aligned} P_i\left[VAC_i(B_j) > VAC_i(A_j)\right] &= P_i\left[\frac{VAC_i(B_j)}{VAC_i(A_j)} > 1\right] = P_i\left\{\ln\left[\frac{VAC_i(B_j)}{VAC_i(A_j)}\right] > 0\right\} \\ &= P_i\left\{\beta_i^V \ln\left[\frac{V(B_j)}{V(A_j)}\right] + \beta_i^C \ln\left[\frac{COMP(B_j)}{COMP(A_j)}\right] + \epsilon_i^* > 0\right\}. \end{aligned}$$

Using the first-order Taylor approximation of $\ln(x) = x - 1$ (around the point $x = 1$), and assuming again that $\epsilon_i^* \sim \mathrm{N}(0, \sigma_j^2)$, we find that the probability p_i that i will choose B in Problem j satisfies

$$p_i = \Phi\left[\frac{\beta_i^V \dfrac{V(B_j) - V(A_j)}{V(A_j)} + \beta_i^C \dfrac{COMP(B_j) - COMP(A_j)}{COMP(A_j)}}{\sigma_j}\right]$$

for each subject i, and

$$\Phi^{-1}(p_i) = \frac{\beta_i^V \tilde{V}_j + \beta_i^C \tilde{C}_j}{\sigma_j}$$

where

$$\tilde{V}_j = \frac{V(B_j) - V(A_j)}{V(A_j)} \quad \text{and} \quad \tilde{C}_j = \frac{COMP(B_j) - COMP(A_j)}{COMP(A_j)}.$$

7.2. *Fixed vs COMP-dependent Variance*

We have tested three alternative specifications of the noise-variance σ_j^2:

$$\sigma_j^2 = k^2 \quad (1)$$

$$\sigma_j^2 = k^2[COMP(A_j) + COMP(B_j)] \quad (2)$$

$$\sigma_j^2 = k^2[COMP(A_j)COMP(B_j)]. \quad (3)$$

7.3. *Fixed Effects vs Random Effects*

Fixed-effects models ignore heterogeneity across subjects and formally assume that $\beta_i^V = \beta^V$ and $\beta_i^C = \beta^C$ for each subject i.

Since each one of 97 subjects has made 14 different binary-choices along the experiment, the right statistical model should acknowledge possible heterogeneity across subjects. Technically, this can be done by estimating a random-effects model assuming that the individual parameters β_i^V and β_i^C are independently drawn from some given distributions for each subject i. In particular, we have examined the case where

$$\beta_i^V \sim \mathrm{N}[\beta^V, \sigma(V)^2] \quad \text{and} \quad \beta_i^C \sim \mathrm{N}[\beta^C, \sigma(C)^2].$$

Since, however, we had only 14 observations per subject, we had to simplify the estimation a lot (see details in Section 8.2) to obtain convergence of the NLMIXED procedure with the two random effects described above. In the next Section we therefore describe the results of estimating the (comprehensive) fixed-effects models first and only then briefly refer to the results obtained in estimating the random-effects models.

8. Results

8.1. *Results – Fixed Effects Models*

Altogether, the two different specifications of the basic model (§7.1) and the three alternative specifications of the noise variance, (1)–(3), generate six alternative basic models for estimation.

To represent the value of lottery L before the adjustment to complexity, $V(L)$, we have assumed that the utility of money takes the form $U(x) = x^\alpha$. Using δ to denote the periodical (exponential) discount rate, we may then represent $V(L)$ by the expression

$$V(L) = \sum_{i=1}^{m} p_i \left[\sum_{t=1}^{T} \delta^{t-1} (x_{i,t})^\alpha \right].$$

The parameters α and δ were estimated (together with the other coefficients of the model: β^V and β^C) on SAS8 using the NLMIXED procedure. Table 6 gives the results of the estimation for each of the six models. The table also gives the Akaike's (1974) Information Criterion (henceforth AIC) scores for each model.

The lowest AIC score was obtained for the proportional model with noise variance of the form $\sigma_j^2 = k^2[COMP(A_j) + COMP(B_j)]$; see model (2). The estimated parameters for this model, together with the standard deviations and the corresponding (one tail) significance levels, are included in Table 7.

Table 6

Estimate Parameters[23]

The Model		α	δ	β^V	β^C	AIC (lower is better)
Differential Models						
Version	(1)	0.68	0.38	1.35	−0.03	1,697.8
Version	(2)	0.65	0.36	3.96	−0.05	1,695.3
Version	(3)	0.65	0.35	4.2	−0.04	1,702.6
Proportional Models						
Version	(1)	0.57	0.30	36.7	−0.05	1,698.5
Version	(2)	0.58	0.32	84.8	−0.09	1,694.0
Version	(3)	0.62	0.34	84.8	−0.07	1,699.6

The estimated exponent α (0.588) suggests that the subjects are (on average) moderately risk-averse. The estimated periodical discount rate (0.316) is surprisingly low. This might have been caused by the small size of our sample: Only seven problems in the experiment involved multi-period payments (problems 1–4, 8, 11–12 only deal with single-period lotteries). Note also that, in our sample, the lotteries with more than one payment period are typically more complicated than the single-payment lotteries. It therefore might be the case that the complexity effects also shows up in the low discount factor δ. Indeed, when we have run the winning model constraining δ to 0.85, the complexity coefficient β^C has decreased from −0.086 (in the unconstrained model) to −0.128 (in the constrained model). The corresponding t-statistic has decreased from −1.89 to −2.84. Moreover, when we have run the proportional model constraining both (direct) complexity effects to zero (ie assuming $\beta^C = 0$ and $\sigma^2 = k^2$), the discount factor δ has further decreased to 0.247 ($t = 3.47$).

The value coefficient β^V is (as expected) positive and highly significant. The complexity coefficient β^C is (as expected) negative and significant at $p < 0.05$. (The significance of β^C is considerably improved when estimating the random-

[23] The coefficient β^V receives high values in the proportional model (relatively to the values it obtains in the differential model) since the values $[V(B_j) - V(A_j)]/V(A_j)$ are relatively low in our sample.

effects model, see Section 8.2.) Table A3 in the Appendix presents the predictions of the winning model versus the actual results for the 14 problems.

The fact that the model with noise of the form (2) has outperformed the model (1) with fixed variance $\sigma_j^2 = k^2$ (in terms of lower AIC scores) suggests that complexity also increases the noise in the choice process, so that, as hypothesised at the introduction, complexity affects choice in two ways:

1 Subjects penalise lotteries for (relative) complexity; ie the coefficient β^C is significantly different from zero.
2 Complexity increases the noise in the choice process in the sense that the variance of the noise ϵ_i^* increases with the complexity of the underlying alternatives.

8.2. *Results – Random Effects*

When trying to estimate general versions of the model (with direct estimation of α and δ), the NLMIXED procedure did not converge. We thus decided to use the value function obtained in estimating the best fixed-effects model –

$$V(L) = \sum_{i=1}^{m} p_i [\sum_{t=1}^{T} \delta^{t-1} (x_{i,t})^{\alpha}]$$

with α and δ as in Table 7, for the estimation of the random-effects model.

While estimating the random-effects model for the six different specifications of the basic model (as described in Section 8.1), we have realised that $\sigma(C)^2$, the random effect for the complexity coefficient, is not statistically significant. We have thus run the six basic models again assuming a random effect on the value parameter β^V and a fixed β^C. The lowest AIC score (1,721) was obtained for the proportional model (Section 7.2) with the heteroscedastic variance form (3). The parameters of the winning model are also given in Table 7. Note that the significance of the complexity-parameter β^C increases in this estimation to a level of 0.003 which is much stronger than the one obtained when estimating the fixed-effect models. Finally, note that the AIC scores of the other basic models – eg the proportional model with the heteroscedastic variance form (2) – were very similar to the one of the winning model, eg 1,728.8 for the proportional model with the variance form (2). The results of the estimations (highly significant β^V, β^C, and $\sigma(V)^2$) were also quite close.

8.3. *Robustness of Results*

We now briefly outline the results of estimating some generalisations of the fixed-effects models described in Section 8.1.

Table 7

Parameters

Parameter	Estimate	Standard Error	Significance
Lowest AIC Model[24]			
α	0.588	0.103	0.00
δ	0.316	0.082	0.00
β^V	84.85	16.21	0.00
β^C	−0.087	0.046	0.03
Lowest AIC Random–Model			
β^V	53.44	6.23	0.00
$\sigma(V)^2$	1,048	347.09	0.00
β^C	−0.173	0.045	0.00

- *Quasi-hyperbolic discounting*
  We have also estimated a two-piece quasi-hyperbolic discounting scheme where the discount factor for period $t \geq 1$ is $\psi\delta^t$, as in Laibson (1997), O'Donoghue and Rabin (1999) and others. However, the attempt to estimate four different parameters concurrently $(\psi, \delta, \alpha, \beta^V)$ that measure the value-effect on subjects' choice patterns (from only 14 observations) did not succeed. The estimators for ψ, δ and β^V were all statistically insignificant.[25]
- *Rank Dependent Utility*
  To test the robustness of the conclusions to the specification of the value function as outlined above we have also run the six models for the case where the value of each (single-period) lottery is calculated using the rank dependent utility model (Quiggin, 1982) with the probability weighting function

  $$w(p) = \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{-\gamma}}$$

  as used in Camerer and Ho (1994). The results were quite similar to the ones presented in Table 7 but we could not reject the hypothesis that the coefficient $\gamma = 1$. In estimating the proportional model with the heteroscedastic noise from (2) – the best model with no γ – for instance, we obtained $\gamma = 1.139$ with a standard error of 0.14.[26]
- *Neilson's Model*
  We have also directly estimated a special case of Neilson's (1992) model where the utility function applied in the evaluation of a (single-period) lottery with n prizes takes the form $a^n U(x)$ where a is a free parameter of the model. The estimated a, however, was 0.999 and not significantly different from 1.

[24] Note, however, (see Table 5) that the AIC (lower is better) scores of all other five models were not very different from the score of the winning model. This might have been caused by our small sample size (only 14 observations).
[25] Recall also that only seven problems in the experiment actually involved multi-period payments.
[26] The AIC score of the corresponding (5-parameters) model was 1,695.

9. Discussion

Since complicated lotteries are more difficult to evaluate, it seems interesting to check the impact of disclosing the expected value and the standard deviation of each payment on the observed decision patterns. For this purpose, we have presented a modified version of Problems 5–7 and Problems 11–13 to a different class of 154 undergraduate students. The modified problems were identical to the originals except for the disclosure of expected values and standard deviations of each payment.[27] The results for Problems 5–7 were not significantly different from the originals (see Table 8). In Problems 11–13, however, the proportion of subjects choosing the efficient Alternative *B* has increased significantly.

Note that the complexity effects still show up (in the modified design) in the move from Problem 5 to 6 and in the move from Problem 11 to 12. The increased proportion of choosing *B* in Problems 11–13 is intuitively reasonable and might be explained by the fact that Alternative *B* dominates *A* in these problems in the sense that it has a similar expected pay-off and lower standard deviation. The modified design helps the subjects to observe this domination.

The difference in results (across the designs) is most significant in the case of the most complicated problem (13) where 40% of the subjects choose the efficient alternative in the original design while 77% choose the efficient alternative in the modified design. This suggests that in 'very complicated' choice problems decision makers might put stronger emphasise on representing statistics of the underlying alternatives. A serious examination of this hypothesis is left for future research.

Altogether, our results suggest that complexity considerations should be taken into account explicitly in modelling (intertemporal) choice with uncertainty. One approach in this direction was suggested by Neilson (1992); see the discussion in Section 1. Alternatively, one may follow Becker and Sarin's (1987) 'lottery dependent expected utility' framework and assume that the value assigned to the lottery $L = (\mathbf{p}, \mathbf{X})$ is $\sum_{i=1}^{n} p_i u(x_i, c_L)$ where c_L is a real number, dependent on the characteristics of the lottery L. Following this approach, one may define a complexity-based discounted expected utility model where the value assigned to L is

$$\sum_{i=1}^{n} p_i \sum_{t=1}^{T} \delta(t) u[x_{it}, COMP(L)]$$

Table 8

Proportion of B in Modified vs Original Experiment (%)

Problem	5	6	7	11	12	13
Statistics enclosed	63	51	56	80	67	77
No statistics enclosed	57	49	50	69	53	40

[27] The statistics were presented in small letters after each alternative. In the modified instructions, subjects were told that 'for your convenience we will disclose the expected value and the standard deviation of each payment, for each alternative'. The problems were presented to the subjects in two separate session: Problems 5, 7, and 12 in one session; Problems 6, 11, 13 at the second.

and the utility function $u(x, y)$ increases in the pay-off element x and decreases in the complexity measure y. Note, however, that this approach implicitly assumes that the discount factor $\delta(t)$ is independent of the underlying lottery. A more general framework would suggest that the discount factor might also be changing with the complexity of the lottery.[28]

Alternatively, one may think of a generalised framework where there exists some basic collection $\mathcal{A}$ of *Evaluation Procedures*, a collection $\mathcal{L}$ of *Sub-lotteries* of lottery L,[29] and a probability distribution $q(\cdot)$ on $\mathcal{A} \times \mathcal{L}$ with $q(a, \tilde{L})$ denoting the probability (or density) that DM would apply procedure $a \in \mathcal{A}$ to the sub-lottery $\tilde{L} \in \mathcal{L}$ when evaluating the lottery L. The basic underlying idea is that DM restricts attention to some sub-lottery $\tilde{L} \in \mathcal{L}$ and applies some evaluation procedure $a \in \mathcal{A}$ (eg expected pay-off) to the sub–lottery $\tilde{L}$, so as to evaluate the basic lottery L. Note that this framework generates a probabilistic evaluation model where the value of lottery L, is a random variable, $V(L)$. The model can be extended in the obvious way to a probabilistic choice model. Since the number of sub-lotteries increases with the complexity of the basic lottery L, it should be straightforward to use this framework to formally argue that the standard deviation of $V(L)$ increases with L's complexity; which is our second complexity effect. We believe that this general framework can also be used to lay formal foundations to the first complexity effect; ie present sufficient conditions under which the expected value of $V(L)$ decreases with L's complexity, but we have not derived any formal results yet.

Note that the proposed framework might be considered a generalisation of the specific models estimated in Section 8. One may try to estimate the generalised model by imposing specific structure on the collection $\mathcal{A}$ (eg assume that it contains some collection of perturbations on the expected value model) and demonstrate the significance of the two complexity effects in the generalised framework. The current data set, however, is not rich enough for such an estimation.[30]

Further experimental investigation of the specific ways in which complexity affects multi-period lotteries' evaluation (eg issues like the possible interaction between increased complexity and stronger discounting) is left for future research. Some hints on possible findings, however, might come from Prelec and Loewenstein (1991) attempts to characterise choice anomalies by some general principles. In particular, Prelec and Loewenstein show that:

1 the value of an attribute (in a choice problem) decreases when we add a constant amount to that attribute in each one of the alternatives under consideration

[28] Benzion *et al.* (1989) demonstrate that the intensity of discounting might indeed depend on the characteristics of the underlying pay-off.

[29] The term Sub-Lottery is defined in the obvious way; eg 30, 40 with probability 0.5 each is a sub-lottery of the lottery 20, 30, 40, 50 with probability 0.25 each.

[30] Note also that, by measuring the response times in computerised experiments, as in Wilcox (1993), one may estimate the amount of computation performed in each task. These observations, in turn, can be used in estimating or calibrating the model, eg by checking the correlation between the response times and the 'noise' predicted by the model.

2 the value of an attribute (in a choice problem) increases when we multiply that attribute (in each one of the alternatives) by a positive constant (bigger than one).[31]

In the current context, the first principle implies that the complexity effect should be marginally decreasing (eg an increase in complexity from 100 to 150 should have a more serious impact than an increase in complexity from 500 to 550). The second principle may suggest that the complexity effect should be stronger, for instance, in a choice problem where $COMP(A) = 2k$ and $COMP(B) = 6k$ then it will be in a choice problem where $COMP(A) = k$ and $COMP(B) = 3k$. (This second conjecture indeed holds when the noise in the choice process is of the form $\sigma_j^2 = k^2[COMP(A_j) + COMP(B_j)]$ as suggested in Section 8.1.)

Note also that, in most of the problems analysed in this paper, subjects were requested to choose between a simple lottery and a complicated one. It is interesting, however, to check what happens when subjects are asked to choose between two complicated lotteries; eg Lottery 3(B) and Lottery 4(B). If, for instance, most subjects would see the dominance relation and prefer 4(B), this might provide strong evidence against the multiplicative heteroscedastic variance form (3). This issue is also left for future research.[32]

The complexity effect might have interesting practical implications. We have demonstrated that the effect might explain inefficient portfolio selection. If subjective uncertainty makes the distribution of future pay-offs more complicated and increased complexity indeed induces stronger discounting then increased uncertainty might increase decision makers' myopic inclinations. Similarly, 'Strategic Uncertainty' (Sonsino, 1997) may induce myopic behaviour in repeated games.

Technion, Israel Institute of Technology, Haifa

Date of receipt of first submission: September 1999
Date of receipt of final typescript: September 2001

Appendix

Figure A1 presents the instructions as given to subjects (translates). Table A1 describes the experimental sessions; Table A2 presents the lotteries' data; and Table A3 given the actual vs predicted proportion of choosing Alternative B (see Section 8.1.).

An Experiment in Choosing between Lotteries

General Instructions

In the course of the experiment, you will be asked to choose among lotteries that pay given amounts of money in given dates. Examine, for example, the following lottery:

[31] As an example of the first attribute, Prelec and Loewenstein give the immediacy effect. As an example of the second, they give the certainty effect.

[32] We thank an (anonymous) referee for suggesting this direction.

Probability	Payment 1: 1/5/1999	Payment 2: 1/11/1999	Payment 3: 1/5/2000
60%	80	100	90
15%	90	90	45
35%	80	120	70

Participation in the above lottery will give you a stream of pay-offs as follows:

- With probability 60%, you will receive: 80 NIS at 1/5/1999, 100 NIS at 1/11/1999, and 90 NIS at 1/5/2000.
- With probability 15%, you will receive: 90 NIS at 1/5/1999, 90 NIS at 1/11/1999, and 45 NIS at 1/5/2000.
- With probability 25%, you will receive: 80 NIS at 1/5/1999, 120 NIS at 1/11/1999, and 70 NIS at 1/5/2000.

In the course of the experiment, you will be asked to choose between lotteries of this type. Here is an example for a typical question in the experiment: (See Fig. 1).

In the course of the experiment, you will be asked to answer XX choice problems of this type.

At the end of the experiment, we will conduct the lotteries that you have chosen for you. We will pay each one of the participants three (deferred) cheques where the amount of each cheque depends on the average amount that you have earned for the corresponding periods.

Thus, each one of you will receive three deferred cheques from us: one for 1/5/99; a second for 1/11/1999; and a third for 1/5/2000. The amount that you will receive for each period increases with the total amount that you have earned for that period. At any rate, we promise to pay you at least 30 NIS.

We ask you to take the experiment seriously and think about your answers.

Fig. A1. *Instruction to Subjects*

Table A1
*Experimental Sessions**

Session no.	No. of subjects	Problems	Results for control
Class I: Session 1	75	2,5,9,11	33%
Class I: Session 2	75	1,4,7,8,12	(33%)
Class I: Session 3	75	3,6,10,13,14	(33%)
Class II: Session 1	22	1,4,6,10,13	27%
Class II: Session 2	22	2,5,9,12	(27%)
Class II: Section 3	22	3,7,8,11,14	(27%)
Class III: Session 1	23	11,12,13	26%

*Class I was an undergraduate class in 'Corporate Finance'. Class II was a graduate class in 'Microeconomic Theory 1' with students from the joint graduate programme in Economics of Haifa University and the Technion. Class III was recruited by advertising the experiments at the Faculty of Industrial Engineering and Management at the Technion. It contained a mix of graduate (30%) and undergraduate (70%) students. The proportion of subjects choosing alternative *A* (or alternative *B*) in each problem were similar across classes; all differences were statistically insignificant. The results for Problem 11 are presented at the right column of the table (we chose this problem as a control because of its simplicity).

As mentioned in the text above, the problems were divided across sessions so that 'similar' problems will not be presented to the subjects at the same session. In particular, note that each of the Problems 2, 3 and 4 were presented to the subjects at different sessions. Similarly, each of the Problems 5, 6 and 7 were presented at different sessions. Finally, Problems 8, 9 and 10 were also presented at separate sessions.

Table A2

Lotteries' Data[33]

Lottery	Payment 1	Payment 2	Payment 3	COMP
1(*A*)	95	–	–	2
1(*B*)	101	–	–	2
2(*A*)	95	–	–	2
2(*B*)	102	–	–	2
3(*A*)	95	–	–	2
3(*B*)	99.54	–	–	6
4(*A*)	95	–	–	2
4(*B*)	100.08	–	–	9
5(*A*)	160	–	–	1
5(*B*)	118	60	–	4
6(*A*)	160	–	–	1
6(*B*)	118.9	60.9	–	8
7(*A*)	160	–	–	1
7(*B*)	119.4	61.4	–	16
8(*A*)	95	–	–	2
8(*B*)	99.9	–	–	6
9(*A*)	55	95	–	4
9(*B*)	55	99.9	–	12
10(*A*)	50	61.5	95	6
10(*B*)	50	61.5	99.9	18
11(*A*)	107	–	–	3
11(*B*)	107	–	–	1
12(*A*)	107	–	–	3
12(*B*)	107	–	–	6
13(*A*)	84	105	–	8
13(*B*)	84	105	–	18
14(*A*)	100	107	–	5
14(*B*)	100.45	107.4	–	12

Table A3

Actual vs Predicted Proportion of Choosing B

Problem	Actual	Predicted
1	0.94	0.95
2	0.93	0.94
3	0.80	0.77
4	0.70	0.74
5	0.57	0.54
6	0.49	0.54
7	0.50	0.49
8	0.80	0.78
9	0.69	0.55
10	0.41	0.50
11	0.69	0.65
12	0.53	0.54
13	0.40	0.50
14	0.66	0.51

[33] The table presents the expected pay-off (EP) from each lottery for each period and the COMP of each lottery.

References

Ainslie, G. and Haslam, N. (1992). 'Hyperbolic discounting', in (G. Loewenstein and J. Elster, eds.) *Choice over Time*, New York: Russel Sage Foundations.

Akaike, H. (1974). 'A new look at statistical model information', *Automatic Control*, vol. 19, pp. 716–23.

Becker, J. and Sarin, R. (1987). 'Lottery dependent utility', *Management Science*, vol. 33, pp. 1367–82.

Benzion, U., Rapoport A. and Yagil J. (1989). 'Discount rates inferred from decisions: an experimental study', *Management Science*, vol. 35, pp. 270–84.

Bruce, A. C. and Johnson, J. E. (1996). 'Decision making under risk: effect of complexity on performance', *Psychological Report*, vol. 79, pp. 67–76.

Camerer, C. F. (1995). 'Individual decision making', in (J. L. Kagel, and E. R. Roth, eds.) *Handbook of Experimental Economics*, Princeton: Princeton University Press.

Camerer, C. F. and Ho, T. H. (1994). 'Violations of the betweenness axiom and nonlinearity in probability', *Journal of Risk and Uncertainty*, vol. 8, pp. 167–96.

Fishburn, P. C. (1982). 'Nontransitive measurable utility', *Journal of Mathematical Psychology*, vol. 26, pp. 31–67.

Fishburn, P. C. (1983*a*). 'Transitive measurable utility', *Journal of Economic Theory*, vol. 31, pp. 293–317.

Fishburn, P. C. (1983*b*). 'Utility functions on ordered convex sets', *Journal of Mathematical Economics*, vol. 12, pp. 221–32.

Fishburn, P. C., and Rubinstein, A. (1982). 'Time preferences', *International Economic Review*, vol. 23, pp. 677–94.

Gilboa, I (1994). 'Philosophical applications of kolmogrov's complexity measure', in (D. Prawitz, and D. Westerstahl, eds.) *Logic and Philosophy of Science in Uppsala*, Dordrecht: Kluwer Academic Publishers.

Hey, J. D. and Carbone, E. (1995). 'Stochastic choice with deterministic preferences: an experimental investigation', *Economic Letters*, vol. 47, pp. 161–7.

Hucks, S. and Weizsacker, G. (1999). 'Risk, complexity and deviations from EV maximization – results of a lottery choice experiment', *Journal of Economic Psychology*, vol. 20, pp. 699–715.

Humphrey, S. J. (1995). 'Regret aversion or event-splitting effects – more evidence under risk and uncertainty', *Journal of Risk and Uncertainty*, vol. 6, pp. 263–74.

Humphrey, S. J. (1998). 'More mixed results on boundary effects', *Economic Letters*, vol. 61, pp. 79–84.

Humphrey, S. J. (2000). 'The common consequence effect: testing a unified explanation of recent mixed evidence', *Journal of Economic Behavior and Organization*, vol. 41. pp. 239–62.

Johnson, J. E. V. and Bruce, A. C. (1997*a*). 'A profit model for estimating the effect of complexity on risk taking', *Psychological Reports*, vol. 80, pp. 763–72.

Johnson, J. E. V. and Bruce, A. C. (1997*b*). 'An empirical study of the impact of complexity on participation in horse race betting', *Journal of Gambling Studies*, vol. 13(2), pp. 159–72.

Johnson, J. E. V. and Bruce, A. C. (1998). 'Risk–strategy under task complexity: a multivariate analysis of behavior in a naturalistic setting', *Journal of Behavioral Decision Making*, vol. 11(1), p. 17.

Kahneman, D. and Tversky, A. (1979). 'Prospect theory: an analysis of decision under risk', *Econometrica*, vol. 47, pp. 363–91.

Keren, G. and Roelofsma, P. (1995). 'Immediacy and certainty in intertemporal choice', *Organizational Behavior and Human Decision Processes*, vol. 63, pp. 287–97.

Koopmans, T. C. (1960). 'Stationary ordinal utility and impatience', *Econometrica*, vol. 28, pp. 287–309.

Kroll, Y., Levy, H. and Rapoport, A. (1988*a*). 'Experimental tests of the separation theorem and the capital asset pricing model', *American Economic Review*, vol. 78, pp. 500–19.

Kroll, Y., Levy, H. and Rapoport, A. (1988*b*). 'Experimental tests of the mean-variance model for portfolio selection', *Organizational Behavior and Human Decision Processes*, vol. 42, pp. 388–441.

Laibson, D. (1997). 'Golden eggs and hyperbolic discounting', *Quarterly Journal of Economics*, vol. 112, pp. 443–77.

Loewenstein, G. and Prelec D. (1991). 'Negative time preference', *American Economic Review*, vol. 80, pp. 347–52.

Loewenstein, G. and Prelec D. (1992). 'Anomalies in intertemporal choice: evidence and an interpretation', *Quarterly Journal of Economics*, vol. 107, pp. 573–97.

Loewenstein, G. and Prelec D. (1993). 'Preferences for sequences of outcomes', *Psychological Review*, vol. 100, pp. 91–108.

Neilson, S. W. (1992). 'Some mixed results on boundary effects', *Economic Letters*, vol. 39, pp. 275–78.

O'Donoghue, D. and Rabin, M. (1999). 'Doing it now or later', *American Economic Review*, vol. 89, pp. 103–24.

Payne, J. W., Bettman, J. R. and Johnson, E. J. (1993). *Adaptive Decision Maker*, Cambridge: Cambridge University Press.

Prelec, D. and Loewenstein, G. (1991). 'Decision making over time and under uncertainty: a common approach', *Management Science*, vol. 37, pp. 770–86.

Quiggin, J. (1982). 'A theory of anticipated utility', *Journal of Economic Behavior and Organization*, vol. 3, pp. 323–43.
Segal, U. (1990). 'Two–stage lotteries without the reduction axiom', *Econometrica*, vol. 58, pp. 359–73.
Sonsino, D. (1997). 'Learning to learn, pattern recognition, and Nash equilibrium', *Games and Economic Behavior*, vol. 18, pp. 286–331.
Starmer, C. (1999). 'Cycling with rules of thumb: an experimental test for a new form of non–transitive behavior', *Theory and Decision*, vol. 46, pp. 141–58.
Starmer, C. and Sugden, R. (1993). 'Testing for juxtaposition and event-splitting effects', *Journal of Risk and Uncertainty*, vol. 6, pp. 235–54.
Thaler, D. (1981). 'Some empirical evidence on dynamic inconsistency', *Economic Letters*, vol. 8, pp. 201–7.
Tversky, A. and Kahneman, D. (1986). 'Rational choice and the framing of decisions', *Journal of Business*, vol. 59, pp. s251–78.
Wilcox, N. T. (1993). 'Lottery choice: incentives, complexity and decision time', Economic Journal, vol. 103, pp. 1397–417.