UNIVERSITY *of York*

Discussion Papers in Economics

No. 15/13

Do People Disinvest Optimally?

John D Hey and Konstantina Mari

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

Do People Disinvest Optimally?

Abstract

The disinvestment decision is of importance in many contexts: if funds are tied up for too long in a poorly-performing project, then opportunities for re-investment may be missed. Optimal disinvestment theory is a component of real options theory, but is relatively ignored by experimentalists. Two recent papers conclude that decision-makers stay in projects longer than that prescribed by the optimal behaviour of a risk-neutral agent. This departure is explained through risk-aversion, but without a formal hypothesis under test. We report here on an experiment which explains the behaviour of the subjects through an estimation of risk-aversion. We also explore an alternative hypothesis – that subjects are myopic. Our results show that few subjects appear to be risk-neutral, many seem to be risk-averse but few are myopic.

Authors

John D Hey, Department of Economics and Related Studies, University of York, Heslington, York YO10 5DD, UK; e-mail: john.hey@york.ac.uk; phone: 0044 1904 323786; mobile: 0044 779 256 4905; fax: 0044 1904 323759.

Konstantina Mari, Department of Economics and Related Studies, University of York, Heslington, York YO10 5DD, UK; e-mail: km824@york.ac.uk; mobile: 0044 777 426 4789 fax: 0044 1904 323759.

Running Head

Do People Disinvest Optimally?

Keywords

disinvestment, experiments, myopia, real options, risk-aversion, rolling horizon.

1. Introduction

This paper reports on an experimental study of the disinvestment problem. In this, the decision-maker (DM) holds an asset which yields stochastic cash flows until its disposal. There is a deadline for the disposal of the asset. The decision problem consists of deciding when to dispose of the asset; the optimal disposal point is dependent on both the time period and the cash flow at that time[1].

Clearly this problem is a special case of the class of dynamic decision problems, and, more particularly, of the class of real options problems. It is in some ways the converse of the optimal investment problem, but we single out its investigation because of its importance in many fields of economics, affecting the performance of many firms and individuals. Moreover, although theorists may regard it as the converse of an investment problem, it remains to be seen whether actual decision-makers regard it as such.

Our inspiration for this study are the papers by Sandri *et al* (2010) and by Musshoff *et al* (2013), who experimentally explore a disinvestment problem. Their main experimental finding is implicit in the title of their articles, and is that many subjects hold on to the asset for longer than that prescribed by the theory appropriate for a risk-neutral DM. They conjecture from this that risk-aversion may have a role to play. The way that they model this is not to assume that the objective function of the DM is a concave function of the payoff(s), but by using "risk-adjusted discount rates". Their analysis concludes with their Proposition P3: "The larger an individual's risk aversion, the earlier the disinvestment occurs" in the first paper and the similar Hypothesis H4: "Risk-averse farmers disinvest earlier" in the second. These propositions seem to go against the conclusions of the theoretical paper by Henderson and Hobson (2013), in which they report that risk-aversion *may* delay the disinvestment decision: it depends upon the objective function.

Sandri *et al* and Musshoff *et al* elicited risk-attitudes independently of the disinvestment problem, using a Holt-Laury (2002) price list, and used these elicited risk-attitudes to explain observed behaviour. In contrast, in this paper, we fit to the data two models of risk-averse DMs, and find the

[1] And perhaps other things – depending upon the objective function – as we shall show later.

risk-attitude and the model which best explains the behaviour of our subjects. So our risk indices are not elicited independently of the disinvestment problem, but estimated from the disinvestment behaviour. The reason for this is that it would not be clear what one could infer from the results if the independent elicitation differed from that implied by behaviour – other than that the elicitation method influenced the elicitation result (which has been found elsewhere).

We also explore an alternative hypothesis in an attempt to explain behaviour. This hypothesis embodies the idea that DMs are unable to solve the backward induction solution to the dynamic problem, and instead use a shorter horizon, which they roll forward period-by-period as the problem unfolds. We call this the Rolling Strategy; we give details later.

The paper is structured as follows. In the next section we describe the decision problem and find its optimal solution for two different objective functions (both embodying risk-aversion); we also find its solution for a DM who follows the Rolling Strategy. In section 3 we describe the experimental implementation, and in section 4 we present our findings. Section 5 concludes.

2. Theory

We start from the set-up of Sandri *et al*. We operate in a discrete world. The DM owns some asset which must be disposed of by some final period, denoted by T. Until the asset is disposed of, the DM receives cash flows every period. These cash flows follow a binomial random walk: if we denote the cash flow in period t by x_t, then the cash flow in period $t+1$ is either x_t+h or x_t-h with respective probabilities p and $1-p$. The parameters h and p are constant. The theory usually embodies a discount rate applied to future incomes, but, because of the impossibility of having real discounting in an experiment lasting around one hour, we introduce interest on the disposal value of the asset, L, from the time when disposal occurs until T. So if the asset is disposed of in period t the value of the disposal is Lr^{T-t} where r is the rate of return (one plus the rate of interest). Interest is not received on the cash flows. After disposal takes place no further cash flows are received. The DM receives the value of the asset plus interest and the sum of the cash flows experienced until disposal. We have the usual trade-off: the later disposal takes place the more cash flows are received but the lower the disposal value of the asset.

The solution is found in the normal way, using backward induction. We start with a risk-neutral DM and later generalise to a risk-averse DM. Let us denote by $V_t(x_t)$ the expected payoff to the DM as viewed from period t when the cash flow in that period is x_t. In the final period T the DM must dispose of the asset if he or she has not done so earlier. It follows that

$$V_T(x_T) = L + x_T \tag{1}$$

Let us proceed to the general backward induction on V. In any period t, the DM disposes of the asset if the payoff from so doing exceed the expected payoff from continuing to hold the asset. So we have

$$V_t(x_t) = \max[x_t + Lr^{T-t}, pV_{t+1}(x_t+h)+(1-p)V_{t+1}(x_t-h)] \tag{2}$$

the first term in this expression being the payoff from disposing of it now and the second term the expected payoff from continuing to hold the asset. The decision in t is implicit in this expression: if the first term is the maximum it is best to dispose of it now; if the second term is the maximum it is best to continue holding it. Notice that previous cash flows do not enter into this equation as they cancel out on both sides. This provides the optimal strategy for a risk-neutral DM.

Now we turn to a non-risk-neutral DM, that is, one with a non-linear function $u(.)$ over payoffs. In many dynamic decision problems, with the monetary payoff in period t denoted by y_t, the objective function is normally assumed to be the maximisation of the expectation of the expression

$$u(y_1) + u(y_2) +\ldots+ u(y_T) \tag{3}$$

Taking this to be the objective function, which we are going to call Objective Function 1 (OF1), equations (1) and (2) above become

$$V_T(x_T) = u(L + x_T) \tag{1'}$$

and

$$V_t(x_t) = \max[u(x_t + Lr^{T-t}), pV_{t+1}(x_t+h)+(1-p)V_{t+1}(x_t-h)] \tag{2'}$$

As before the sum of the utilities of previous cash flows cancel out from both sides of (2').

This provides the optimal strategy for a DM with OF1, which is given by equation (3). Obviously the solution depends upon the form of the utility function *u(.)*. In what follows we consider both the Constant Relative Risk Aversion (CRRA) form and the Constant Absolute Risk Aversion (CARA) form.

However, in the context of an experiment OF1 may seem a bit odd. The subject walks out of the laboratory with some money; presumably therefore it is the expected value of the utility of that money which concerns him or her. If that is so, then the objective is the maximisation of the expectation of the expression

$$u(y_1 + y_2 + \ldots + y_T) \tag{4}$$

This we call Objective Function 2 (OF2) – the maximisation of the expected value of the utility of the sum of the payoffs – in contrast to OF1 – the maximisation of the expected value of the sum of the utilities of the payoffs.

It may appear that OF2 is more reasonable from a behavioural point of view – though it is only by looking at behaviour can we be sure; in the analysis section we shall see which fits behaviour best. For the moment we note a complication with computing the optimal strategy. With OF2 past cash flows no longer cancel out of the two sides of equation (2'). This means that the decision in any period with any given cash flow in that period depends *also* on the accumulated cash flows to that point. Equation (2') is no longer valid. We present the solution in Appendix 1 which can be found at EXEC, the Centre for Experimental Economics at the University of York.

Finally, we describe in more detail the Rolling Strategy. This embodies the notion that the DM is myopic and looks ahead every period only *S* periods; the DM has a short horizon that is rolled forward every period. If $S=T-1$ then the DM behaves as above, but if $S<T-1$ then until period $T-S+1$ the DM acts as if he or she thinks that he or she has to dispose of the asset in period $t+S$. So if $S=3$ and $T=6$, then in period 1 the DM acts as if he or she thinks that he or she has to dispose of the asset in period 4, in period 2 the DM acts as if he or she thinks that he or she has to dispose of the asset in period 5, while in periods 3, 4, 5 and 6 the DM correctly acts as if he or she thinks that he or she has

to dispose of the asset in period 6. Obviously it is not optimal, but it is not clear in general how much the DM loses by using it.

We assume that a DM who uses the Rolling Strategy is risk-neutral[2]. The implied decision rules can be immediately found from those above, though some new notation is required. Let us denote by $D(t,x_t,T)$ the optimal decision (either 1 for continue or 0 for disposal) of a risk-neutral DM (implied by equation (2)) in time period t with cash flow x_t when the true horizon is T, and denote by $d(t,x_t,S,T)$ the decisions of someone with a rolling horizon of S in the same position but with a true horizon of T. We have that

if $t \geq T\text{-}S$ then $d(t,x_t,S,T) = D(t,x_t,T)$ because the true horizon is within the correct horizon

if $t < T\text{-}S$ then $d(t,x_t,S,T) = D(t,x_t,t+S)$ because the DM is optimising under the (wrong) assumption that he/she *has* to liquidate in period $t+S$.

Full details are given in Appendix 1, to be found on the EXEC website.

3. Experimental Implementation

The experiment was carried out in the EXEC laboratory. Subjects started by reading the written Instructions; they could ask questions for clarification. The experiment was computerised, with the code written in Visual Studio. The core of the experiment was a binomial tree – a screen shot is in Figure 1. Subjects were presented with a series of 15 different problems (chosen after extensive simulation by us[3]). All problems had a final disposal period of T=15. At the start of each problem they were told: the initial cash flow, x_1; the disposal value, L; the rate of interest on the disposal value, r; the jump size, h; and the probability of an upward jump, p. They then had to decide each period (until they disposed of the asset) whether to dispose of it or not. If they chose not to dispose of it, Nature moved randomly (according to the specified probability) and the appropriate part of the tree

[2] Alternatively we could have assumed risk-aversion, so that all the models considered are nested within this model.

[3] The problems were chosen in such a way that different degrees of risk aversion, or different rolling horizons, would imply different optimal strategies – so that we could distinguish between subjects. See the simulation code.

eliminated. Figure 1 shows the situation in a problem with initial cash flow 20, liquidation value 280, interest rate 5%, jump size 5 and probability of jumping up 0.9, where the DM has decided not to dispose of the asset in the first period, Nature has moved Up and it is now the time for the DM to decide what to do in the second period. In order to encourage the subjects to think about the problem the 'Continue' and 'Stop' buttons did not appear until 20 seconds had elapsed, but they were restricted to a total time of 40 seconds in any one period[4]. The 'Confirm' button did not appear until they had clicked on either 'Continue' or 'Stop'.

In the tree, each vertically-aligned pair of small boxes represents a node that the DM might reach (depending on their decisions and Nature's moves) – with the top number indicating the cash flow at that node and the bottom number indicating the probability of getting to that node (if the DM had not disposed of the asset earlier). So, in the example in Figure 1, where the DM is in period 2, the possible nodes reachable in period 3 imply cash flows of 30, if Nature moves Up, or 20, if Nature moves Down (with respective probabilities 0.9 and 0.1). At the left-hand side of the screen (not shown in Figure 1) was a summary of the Instructions, and, as will be seen from the figure, information is provided about the move that Nature has just made, the cash flow of that period, and the disposal value of the asset if disposed of in that period (the disposal value plus interest to the end of the problem). Written Instructions were also provided, with a number of examples. Subjects read the Instructions before the experiment started. Any questions were answered by the experimenters.

Subjects were paid the sum of the show up fee (£2.50) and their total payoff in one of the 15 problems chosen randomly, using the exchange rate of 100 tokens equalling £1. There was a total of 74 subjects; the average payment was £10.67.

We note that the 15 problems were chosen after extensive simulations using Matlab following a small pilot study. A key requirement for the problem set was that we could infer from the data the level of risk-aversion of the subjects, and/or the length of their rolling horizon (if they were following

[4] If they had not taken a decision by the time that these 40 seconds had elapsed, the software assumed that the subject wished *not* to dispose of the asset.

the rolling strategy). This meant that we needed problems where different levels of risk-aversion, or different lengths of the rolling horizon, implied different decisions. We should briefly explore what this means and how we took it into account.

The decisions that we observe are binary decisions: either Stop (coded 0) or Continue (coded 1). So a strategy is defined by a set of 0's or 1's at each of the nodes in the tree. Let us confine the discussion to OF1[5]. The nodes in a tree of length T consist of 1 in the first period, 2 in the second period, … , t in the t'th period, … , up to $T-1$ in the $(T-1)$'th period: a total of $(T-1)T/2$ nodes[6]. At each of these nodes a strategy implies a decision D which is either 0 or 1. If we add together these 0's and 1's we get a total (call it N) which indicates the number of continuation nodes in the tree. We want different values of N for different levels of risk aversion (or of the rolling horizon). So we looked for problems where the variance of N over a reasonable set of risk aversion levels (or over different horizons) was as large as possible. We also wanted problems where a risk-neutral person behaving optimally would expect to earn around £10 (the conversion rate between experimental tokens and money was 1 token = 1p). To decide on our problem set we carried out pre-experimental simulations. The problem set is given in Table 1.

An alternative experimental task, possibly for future work, would have been to ask subjects to specify a *strategy* – a statement of what they would do at each possible decision node that they might reach. Given the number of such decision nodes this would have been time-consuming and complicated. We could simplify the task of specifying a strategy by asking them to impose a *threshold* in each time period – above which they would liquidate – but this would suggest to them the nature of the optimal strategy, and we would be pushing them towards the 'correct' solution.

4. Results and analysis

[5] With OF2 we need to define nodes not just by the period and the vertical positioning in the tree at that point but also by the accumulated cash flow at that point.

[6] We ignore the final period as the compulsory decision is to dispose of the asset.

The data that we have on each subject and in each problem are the decisions of the subject at each node that the subject reached – for each problem, the data are a string of 0's followed by a '1'. Because of the nature of the data, we proceed as follows. We would like to know, for each of OF1 and OF2, for each utility function (CRRA and CARA), which level of risk-aversion, and for the Rolling strategy which horizon, best explains the behaviour of each subject, and how much of that behaviour it explains. Suppose a subject takes a total of *N* decisions throughout the course of the experiment (this number varies from subject to subject), then, for each Objective Function, for each utility function (CRRA and CARA), and for each level of risk-aversion, and for the Rolling strategy for each horizon, we can calculate how many of the decisions of the subject are consistent with that specification. We can then calculate the percentage of the decisions taken by the subject that are consistent with that specification. Call this *pc*. It depends in general on the specification. This variable definitely is not smooth; if we graph it against, for example, the risk aversion, or against the rolling horizon, it is a step function. Finding its maximum (which would give us the best-fitting risk-aversion or the best-fitting horizon) using Maximum Likelihood techniques would not work due to the fact that it is not smoothly concave. But we need to find where it reaches its maximum and find its value at the maximum. We show this graphically; Figure 2 illustrates – this is for subject 66. On the vertical axis is the variable *pc*. On the horizontal axis is the rolling horizon *S* for the rolling strategy. The horizontal axis also indicates the level of risk-aversion, with risk-aversion *decreasing* from left to right, going from very risk-averse at the left to risk-neutrality at the right when *x=14*. There are five 'curves' in the picture, with – indicating OF1 CRRA and so on. It will be seen that all the five curves finish (at *x=14*) at the same vertical point. This is because when the horizon is the correct horizon (14) and the DM is risk-neutral, all five strategies lead to the same decisions. So for this subject, assuming he or she is risk-neutral, or working with the correct horizon, explains just 70% of the subject's decisions. It will be noticed that all the curves are indeed step-functions: the horizontal line shows that for OF2 CARA changing the level of risk-aversion has no effect on decisions; this is an implication of the CRRA utility function in the context of OF2. The greatest percentage correct is with OF1 CRRA – with 91% correct; the second highest is with OF1 CARA – with 79% correct. We might ask whether 91% is significantly larger than 79%. This, of course, depends upon the number of decisions, which, for this subject, was 43. Carrying out the standard test as to whether one proportion is greater than another shows that 91% is significantly greater than 70% at 10% but not at 5%. However the hypothesis that the subject is risk-averse explains significantly more than the hypothesis that the subject is risk-neutral. The CRRA utility function is $u(x)=x^r$ and the best-fitting value of *r* for this subject is between[7] 0.70 and 0.73 – a moderately risk-averse person.

Table 2 lists the best-fitting specifications and the best-fitting risk-aversion index or best-fitting rolling horizon subject by subject. For some subjects there are clear unique winners – as Table 3 shows. If Risk-Neutrality is the best, then, since all the other specifications have risk-neutrality nested within them, we do not list them for the other specifications. So a subject whose behaviour is listed in the category OF1 CRRA is *strictly* risk-averse, and so on. We note that OF2 CRRA only appears the best for the risk-neutral subjects; in fact, as a glance at Figure 2 will show, the optimal decisions for someone with an OF2 CRRA preference functional are *not* dependent on the level of risk-aversion[8], and are therefore the same as for a risk-neutral subject.

It is clear from Table 3 that the Rolling Strategy does not do well – only coming joint winner with OF1 CRRA for two subjects. The best-performing specification is OF1 CRRA coming first on its own for 38 subjects, and joint first with OF1 CARA 10 times.

It is of interest to see whether the winning specification is *significantly* better than the others, and, in particular, significantly better than risk-neutrality. Table 4 gives the details of standard t-tests of the difference between two proportions. It will be seen that with the exception of the 5 risk-neutral subjects, for 43 out of our 74 subjects the winning specification fits significantly better than risk-neutrality at 1%, for 6 subjects at 5%, and for 1 subject at 10%.

---

[7] We only get a range estimate because the *pc* function is horizontal at its peak – again a consequence of the the data that we have.

[8] This is a consequence of the CRRA utility function.

5. Conclusions

It is clear from these results that Sandri *et al* and Musshoff *et al* were right – risk-aversion is needed to rationalise the behaviour of the subjects; our Rolling Strategy does not do very well. It is also clear from our results that risk-aversion varies considerably across the subjects. Taking into account the risk-aversion significantly improves the results – as Table 4 shows. Looking at Figure 3 it seems that we can explain much of the behaviour with one or other of our specifications for many of our subjects.

However, Figure 3 also shows that for some subjects we can only rationalise a rather small percentage of their decisions (as low as 62% for one subject). This suggests that there may be some other decision rule that these subjects were following. One possibility is that subjects thought that Nature may have had a memory (though this was not true). If so, earlier sequences of moves by Nature may have affected their future decisions. Investigating this possibility may be of interest for future work. After all backward induction is a complicated and computationally complex procedure. It would not be surprising if subjects developed simple heuristics for tackling the problem.

References

Henderson V and Hobson D (2014), "Risk aversion, indivisible timing options, and gambling", *Operations Research,* 61, 126-137.

Holt C A and Laury S K (2002), "Risk aversion and incentive effects", American *Economic Review*, 92, 1644–1655.

Musshoff O, Odening M, Schade C, Maart-Noelck S C and Sandri S (2013), "Inertia in disinvestment decisions: experimental evidence", *European Review of Agricultural Economics* , 40, 463-485.

Sandri S, Schade C, Mußhoff O and Odening M (2010), "Holding on for too long? An experimental study on inertia in entrepreneurs' and non-entrepreneurs' disinvestment choices", *Journal of Economic Behavior and Organization,* 76, 30-44.

Table 1: The Problem Set

Number	p	h	L	r	x_1
1	0.6	1	40	1.25	10
2	0.1	1	75	1.2	20
3	0.3	1	40	1.25	20
4	0.8	1	150	1.15	15
5	0.5	1	75	1.2	20
6	0.2	2	80	1.2	20
7	0.3	2	135	1.15	35
8	0.9	5	280	1.05	20
9	0.7	1	80	1.2	5
10	0.4	2	140	1.15	30
11	0.8	1	45	1.25	0
12	0.1	2	40	1.25	25
13	0.6	1	70	1.2	20
14	0.3	1	45	1.25	10
15	0.4	5	260	1.1	5

p: probability of jumping Up
h: jump size
L: disposal value
r: rate of return on disposal
x_1: initial cash flow

Table 2: The 'Winning' hypotheses subject by subject (Note: ranges are given when the best-fitting value is not unique)

SUBJECT	OF1 CRRA	OF1 CARA	OF2 CRRA	OF2 CARA	ROLLING	RN
1	0.11-0.41	0.024-0.0445				
2	0.83-1	0-0.001	0.11-1	0-0.018	7-14	Y
3	0.11-0.5	0.0095-0.0445				
4	0.66 , 0.7					
5				0.0185		
6	0.68-0.69					
7	0.58-0.59					
8	0.11-0.5	0.03-0.0445				
9	0.58					
10				0.029		
11	0.11-0.5 , 0.54-0.58	0.0065 , 0.0075-0.0445				
12	0.68-0.69					
13	0.11-0.5	0.007-0.008 , 0.031-0.0445				
14	0.59					
15				0.0185		
16				0.031 , 0.0355		
17	0.7-0.72					
18	0.58-0.59 , 0.62-0.63 , 0.69					
19	0.67-0.68					
20				0.0185		
21	0.81-0.82				5	
22	0.67					
23				0.0355 , 0.0365		
24				0.029		
25	0.67					
26	0.7					
27	0.67 , 0.7-0.71					
28	0.58-.059					
29	0.58					
30		0.005				
31	0.67-0.69					
32	0.67 , 0.7					
33	0.71-0.74					
34	0.6-0.63					
35	0.75 , 0.79-0.82 , 0.84-1	0-0.002	0.11-1	0-0.018	7-14	Y
36	0.81-0.82					
37	0.59					
38	0.66					
39	0.6-0.63					
40	0.11-0.46	0.011-0.0445				
41				0.0395		

42				0.039		
43	0.59					
44				0.0285-0.029 , 0.0355 , 0.0365 , 0.0385		
45	0.83-1	0-0.001	0.11-1	0-0.018	7-14	Y
46	0.73-0.75					
47				0.019		
48	0.73-0.75					
49	0.11-0.5 , 0.54-0.59	0.0075-0.0445				
50	0.66				2 , 3	
51	0.77-0.8	0.0015-0.002				
52	0.11-0.5 , 0.54-0.55 , 0.58-0.59	0.006-0.0065 , 0.0075-0.008 , 0.031-0.0445				
53	0.11-0.5	0.005 , 0.007-0.0445				
54		0.013-0.0305				
55				0.019, 0.0205		
56	0.6-0.63 , 0.67					
57	0.59 , 0.67					
58	0.67					
59				0.019		
60	0.67-0.69					
61	0.58-0.59 , 0.62-0.63 , 0.65 , 0.67-0.69 , 0.71	0.004		0.0445		
62	0.67 , 0.7-0.71					
63	0.58-0.59 , 0.62-0.63 , 0.68					
64				0.019		
65				0.0185		
66	0.7-0.73					
67				0.0185		
68	0.83-1	0-0.001	0.11-1	0-0.018	7-14	Y
69	0.83-1	0-0.001	0.11-1	0-0.018	7-14	Y
70	0.11-0.5	0.0085-0.0445				
71	0.59					
72				0.0365 , 0.0385		
73	0.68 , 0.7-0.72 , 0.76					
74	0.6-0.63					

Table 3: A Classification of the Winners

specification(s)	*n*
RN	5
OF1 CRRA	38
OF1 CARA	2
OF2 CARA	16
OF1 CRRA *and* OF1 CARA	10
OF1 CRRA *and* Rolling	2
OF1 CRRA, OF1 CARA *and* OF2 CARA	1
Total	74

n = the number of subjects for which this/these are the best

Table 4: Tests of Significance

subject	Number decisions	*p*	Risk-Neutral?	t-stat 1st vs 2nd	t-stat 1st vs 3rd	t-stat 1st vs 4th	t-stat 1st vs RN
1	129	88	N	0,00	3,04***	6,16***	11,42***
2	29	100	Y	-	-	-	-
3	68	78	N	0,00	1,19	3,73***	4,51***
4	44	77	N	0,95	0,95	1,14	1,14
5	21	90	N	0,40	0,40	0,40	0,40
6	50	84	N	0,76	0,76	2,86***	2,86***
7	73	82	N	0,16	2,20**	3,05***	5,43***
8	77	83	N	0,00	3,76***	5,14***	7,46***
9	52	79	N	0,25	0,48	0,94	2,50***
10	65	80	N	0,42	0,42	2,26**	4,44***
11	65	80	N	0,00	0,28	2,49***	3,80***
12	50	90	N	1,40*	1,64**	2,90***	3,65***
13	44	68	N	0,00	0,69	1,90**	2,73***
14	51	78	N	0,36	1,24	1,45*	2,26**
15	22	73	N	0,36	0,36	0,36	0,36
16	51	75	N	0,23	0,45	1,92**	4,06***
17	31	77	N	1,04	1,36*	2,06**	2,36***
18	61	80	N	0,14	1,39*	1,97**	3,89***
19	88	90	N	0,82	2,17**	2,76***	7,19***
20	37	81	N	0,32	0,32	0,32	0,32
21	29	72	N	0,00	0,25	0,25	0,49
22	56	82	N	0,40	0,40	0,66	3,38***
23	43	77	N	0,32	0,74	1,03	1,03
24	35	69	N	0,53	0,53	0,79	1,70**
25	53	83	N	1,13	2,01**	2,22**	3,12***
26	39	79	N	0,21	0,52	0,52	0,52
27	52	85	N	1,04	1,04	1,94**	2,85***
28	83	89	N	0,20	3,80***	3,92***	6,48***
29	50	74	N	0,23	1,49*	3,24***	4,40***
30	68	82	N	0,15	0,44	0,44	7,00***
31	45	73	N	0,21	0,21	0,62	0,92
32	51	82	N	0,50	0,86	2,15**	2,35***
33	50	86	N	0,55	1,04	2,93***	2,93***
34	62	81	N	0,28	0,55	2,01**	3,94***
35	38	76	Y	0,00	0,00	0,00	0,00
36	48	90	N	0,31	1,49*	2,14**	3,39***
37	65	82	N	0,29	1,10	1,10	4,38***
38	50	78	N	0,47	0,47	1,54*	2,14**
39	58	83	N	0,55	1,18	2,85***	3,56***
40	98	86	N	0,00	2,41***	2,99***	7,94***
41	75	84	N	0,16	0,48	2,79***	5,66***
42	49	76	N	0,56	0,56	1,19	2,57***
43	74	84	N	0,32	1,49*	2,77***	5,63***
44	38	68	N	0,46	0,46	1,60*	1,85**
45	35	83	Y	-	-	-	-
46	24	67	N	0,64	0,64	0,64	0,64
47	25	72	N	0,31	0,31	0,31	0,61
48	26	65	N	0,52	0,81	1,09	1,09
49	83	86	N	0,00	1,64**	3,27***	6,49***
50	31	71	N	0,00	0,26	1,54*	1,84**
51	39	85	N	0,00	0,69	0,90	1,20
52	60	80	N	0,00	1,50*	2,92***	3,65***
53	71	82	N	0,00	1,02	2,30**	5,68***
54	146	95	N	0,37	4,43***	5,46***	12,51***
55	22	68	N	0,28	0,28	0,28	0,28
56	55	76	N	0,36	1,26	1,26	4,94***
57	54	78	N	0,49	1,28*	1,71**	2,63***
58	58	81	N	0,40	1,72**	3,00***	4,52***
59	39	79	N	0,52	0,52	0,52	0,52
60	46	78	N	0,66	0,66	2,61***	2,61***
61	54	80	N	0,00	0,00	0,74	2,87***
62	45	82	N	0,47	0,70	0,70	1,02
63	46	72	N	0,21	1,50*	1,79**	1,79**
64	25	68	N	0,59	0,59	0,59	0,59
65	32	69	N	0,26	0,26	0,26	0,26
66	43	91	N	1.56 *	2.07 **	2.46 ***	2.46 ***
67	24	79	N	0,33	0,33	0,33	0,33
68	35	83	Y	-	-	-	-
69	18	78	Y	-	-	-	-
70	84	87	N	0,00	2,68***	5,75***	6,68***
71	59	81	N	0,40	1,51*	1,85**	2,71***
72	45	78	N	0,97	0,97	1,17	1,46*
73	29	62	N	0,23	0,23	1,07	1,07
74	50	76	N	0,46	1,31*	1,51*	4,22***

p: the percentage of decisions consistent with the best-fitting specification.
First entry is the test statistic, the asterisks indicate significance:
 * at 10% (1,28), ** at 5% (1,64), *** at 1% (2,32)

Figure 1: An Example of a Binomial Tree

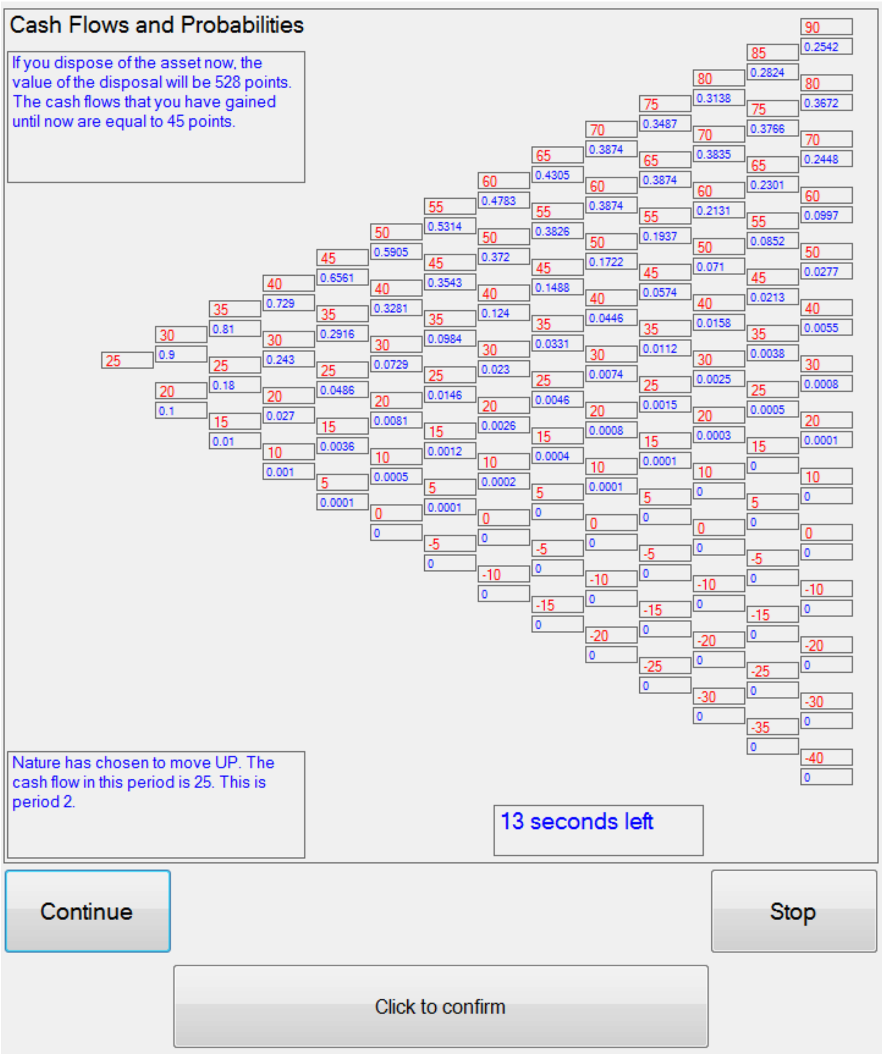
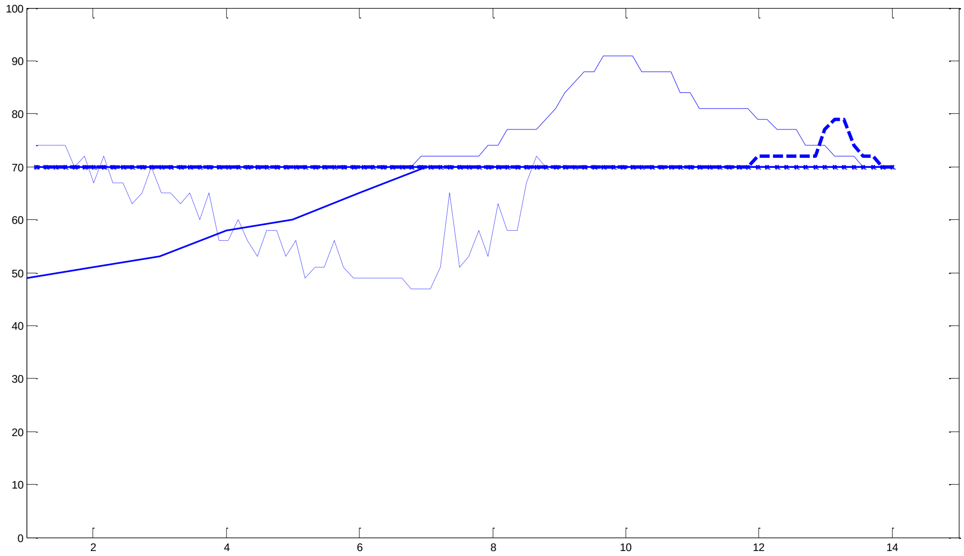


Figure 2: Subject 66



OF1 CRRA —

OF1 CARA --

OF2 CRRA x

OF2 CARA – .

RH ▬

At some points the ‘curves’ overlap.

Figure 3: Histogram of Maximum Percentage Consistent Over All 74 Subjects