Workaholics and Drop Outs in Organizations*

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February 28, 2008

Abstract

This paper reports the results of experiments designed to test the theory of the optimal composition of prizes in contests. We find that while in the aggregate the behavior of subjects is consistent with that predicted by the theory, such aggregate results mask an unexpected compositional effect on the individual level. While theory predicts that subject efforts are continuous and increasing functions of ability, the actual efforts of our laboratory subjects bifurcate. Low ability workers drop out and exert little or no effort while high ability subjects try too hard. This bifurcation, which is masked by aggregation, can be explained by assuming loss aversion on the part of the subjects.

Keywords: contests, all-pay auctions, loss aversion, experiments.

JEL classification numbers: C92, D44, J31, D72, D82.

*We thank two anonymous referess and the managing editor Patrick Bolton for helpful comments and Maher Said for valuable research assistance. Thanks are also due to seminar participants at Bonn, Copenhagen, Erfurt, Humboldt University Berlin, Rotterdam, and Tilburg. The first author acknowledges financial support from the German Science Foundation (DFG) and the Netherlands Organization for Scientific Research (NWO). Furthermore he thanks the Center for Experimental Social Science (CESS) at New York University for its hospitality.

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1 Introduction

Casual empiricism indicates that many organizations are characterized by a bifurcation of effort among workers. While one subset appears to not be able to stop itself from working (the fast track) the other exerts no effort at all (drop outs). One question that arises is why this bifurcation exists and what lessons can we learn from its existence for the proper design of economic mechanisms in general and incentive systems in particular?

In this paper we experimentally test a model proposed by Moldovanu and Sela (2001) entitled "Optimal Allocation of Prizes in Contests" (henceforth M-S) who derive the "optimal" set of prizes for an organization involved in motivating workers through an effort tournament. They investigate firms where workers are assumed to be risk neutral expected utility maximizers and have either linear, convex or concave cost-of-effort functions and where an organizational designer has a limited amount of money available for bonuses to be awarded to those workers whose outputs are highest. (Assume that output is linear in effort and non-stochastic so in essence effort is equivalent to output and both are observable). They demonstrate that for organizations where workers have linear or concave cost-of-effort functions, the optimal prize structure is one where the entire prize budget is allocated to one big prize while if costs are convex, it might be optimal to distribute the budget amongst several prizes.[1] What is interesting is that in these contests the equilibrium effort functions are continuous functions of the abilities of the workers while in the lab we observe individual effort functions which appear to be discontinuous step functions where low ability workers drop out and exert zero or low effort while high ability workers over exert themselves leading to the bifurcation of efforts described above.

The ironic aspect of our experimental results is that despite this bifurcation of effort, on average the prize structures proposed by M-S elicit approximately the correct effort levels so that with respect to the mean one could say they work. Even more interesting is the fact that when we aggregate our data across laboratory work groups, efforts appear to be continuous so that the observed bifurcation of efforts is hard to detect on the aggregate level. We suggest that the behavior of our subjects is consistent with loss aversion in the sense that we demonstrate that subjects with appropriately parameterized loss-averse utility functions exhibit behavior that is close to replicating the behavior we observe.

[1] Harbring and Irlenbusch (2003) report the effect of varying the prize structure in experimental rank order tournaments à la Lazear and Rosen (1981). They show among other things that average effort increases with a higher share of winner prizes.

One might claim that our bifurcation result is of little consequence to a risk neutral owner since, on average, the firm still gets the output it desires. There are several problems with this logic, however. First, given that subjects are behaving as if they were loss averse, there very well may exist a different incentive structure for the firm that could do even better. Remember, the M-S mechanism was only optimal under the assumption of risk neutrality. Second, if workers drop out then the best response of those who are working may be to lower their effort so that in the long run output falls.

Drop-out behavior has been observed previously in a number of experimental and field studies. In Schotter and Weigelt (1992) subjects who are disadvantaged in the competition (i.e., have higher marginal cost of effort functions) are observed to drop out of tournaments even when, in equilibrium, they are not expected to lose money. Here they are dissuaded by the low probability of winning. In that paper it takes a laboratory policy intervention, an affirmative action law, to get them to revive their effort. A similar finding occurs in Corns and Schotter (1999) where a price preference has to be given to high cost bidders in an asymmetric auction to get them to try to compete for contracts. The interesting thing there is that, by giving a price preference to the high cost bidders, the auctioneer elicits a higher effort from the low cost bidders since they now face more competition and their best response is to bid more aggressively.[2]

While in the M-S model dropping out is not part of the game's equilibrium, in other models it very well may be. For example, in Benoit (1999), members of socioeconomically disadvantaged groups and members of other groups have to decide—after learning about their ability—whether or not to invest, say, in prep courses for the SAT test. Benoit finds that if there is no affirmative action, members of the disadvantaged group might not invest, i.e. drop out. (For a different setup see Amegashie, 2003). Prendergast (1999) suggests that such drop-out behavior can be seen in sports contests.[3] Using a field experiment (running races among elementary school students), Fershtman and Gneezy (2005) demonstrate that some students simply stop running and drop out when it is clear they have no chance of winning. In legal disputes, if there are asymmetric budget constraints among the parties involved, (which can be interpreted as a contest), the party having the higher

[2]For an overview of such price preference and affirmative action programs in the US and their assessment see Holzer and Neumark (2000) as well as National Institute of Government Purchasing (1994).

[3]One interesting example of a poorly designed incentive structure in sports is discussed by Rafael Tenorio (2000). In this paper it is argued that the compensation scheme used in professional boxing according to which a boxer's payment or purse for a given fight is entirely guaranteed, provide sub-optimal incentives which may (and sometimes does) result in improper preparation for the fight and, therefore, in an increased likelihood of a poor showing.

budget can hire a better lawyer and can therefore increase its chances of winning. If this is realized by the other party, it might give up (drop out) immediately. Finally, dropping out has been noted before in studies of multiple unit all-pay auctions (see, Barut, Kovenock, and Noussair (2002)).

In this paper we will proceed as follows: In the next section we will present the M-S model and its results. In Section 3 we will describe our experimental design while in Section 4 we will present our results. In this section we demostrate that if subjects have utility functions that exhibit loss aversion, bifurcation may result. Finally, in Section 5 we will offer some conclusions and discussion.

2 Theory

2.1 Model Specification

In this section we lay out the model underlying our experiments and its predictions. In doing so we confine ourselves to the special cases relevant for our experiments. For more general results see M-S.

Assume that there exists an organization with $k \geq 3$ contestants competing in a contest in which two prizes can be awarded. The (commonly known) values of the prizes are $V_1 \geq V_2 \geq 0$ with $V_1 + V_2 = 1$. In the contest players simultaneously exert effort x_i thereby incurring cost $c_i\gamma(x_i)$. The function γ: $\mathbb{R}_+ \rightarrow \mathbb{R}_+$ is strictly increasing with $\gamma(0) = 0$ and $c_i > 0$ is an ability parameter. Notice that the lower c_i the more able is player i (i.e., the lower is his or her costs) and vice versa.

It is assumed that the ability of player i is private information to i. Abilities are independently drawn from the interval $[m, 1]$, $m > 0$, according to the (commonly known) distribution function F with $F' > 0$. The contestant with the highest effort wins the prize V_1, the contestant with the second highest effort wins prize V_2 whereas all other contestants win nothing. Accordingly, the payoff of contestant i who has ability c_i and exerts effort x_i is either $V_j - c_i\gamma(x_i)$ if i wins prize j, or $-c_i\gamma(x_i)$ if i does not win a prize. Note, then, that this contest defines an all-pay auction where bidders make effort bids and pay the cost associated with their bids whether they win or not. The contest designer determines the number of prizes and how to allocate the prize sum among the prizes in order to maximize the expected value of the sum of the efforts $\sum_{i=1}^{k} x_i$ given the contestants' equilibrium-effort functions.

All players are assumed to be risk neutral. Furthermore, assuming that all contestants other than i make an effort according to the function b and assuming that this function is strictly monotonic and differentiable, player i's maximization problem is:

$$\max_x \left[V_1(1-F(b^{-1}(x)))^{k-1} + V_2(k-1)F(b^{-1}(x))(1-F(b^{-1}(x)))^{k-2} - c\gamma(x)\right]. \qquad (1)$$

Here the factor after V_1 is the probability that x is the highest among all efforts and the factor after V_2 is the probability that x is the second highest among all efforts.

In the experiments we chose $k = 4$, $m = 0.5$ and a uniform distribution of abilities, i.e., $F(c) = 2c - 1$, $c \in [0.5, 1]$.

2.2 Predictions and Prescriptions[4]

Linear cost functions: In case all contestants have linear costs, i.e., $\gamma(x) = x$ the optimal and symmetric effort function can be shown to be

$$b(c) = V_1 A(c) + V_2 B(c) \qquad (2)$$

with

$$A(c) = -36 + 48c - 12c^2 - 24\ln c \quad \text{and} \quad B(c) = 84 - 120c + 36c^2 + 48\ln c. \qquad (3)$$

Turning to the designer's problem, let $V_2 = \alpha$ and $V_1 = 1 - \alpha$, where $0 \leq \alpha \leq 1/2$ such that the second prize is smaller than the first. A contestant's equilibrium effort is therefore given by $b(c) = (1-\alpha)A(c) + \alpha B(c) = A(c) + \alpha\,(B(c) - A(c))$. Since each contestant's average effort is given by $\int_{0.5}^{1} [A(c) + \alpha\,(B(c) - A(c))]\, F'(c)dc$, the designer's problem reads

$$\max_{0\leq\alpha\leq 1/2} 4\int_{0.5}^{1} [A(c) + \alpha\,(B(c) - A(c))]\, F'(c)dc$$

or, equivalently,

$$\max_{0\leq\alpha\leq 1/2} \alpha \int_{0.5}^{1} [B(c) - A(c)]\, F'(c)dc. \qquad (4)$$

Note that the expression in (4) is the average difference between the marginal effects of the second and the first prize. It turns out that the definite integral in (4) is negative. Hence, the solution to the designer's problem is $\alpha = 0$ such that it is optimal for the to award only one prize, i.e., $V_1 = 1$ and $V_2 = 0$.

Quadratic cost functions: In case all contestants have quadratic costs, i.e., $\gamma(x) = x^2$, the optimal and symmetric effort function can be shown to be

$$b(c) = \gamma^{-1}(V_1 A(c) + V_2 B(c)) = \sqrt{V_1 A(c) + V_2 B(c)} \qquad (5)$$

[4]See Moldovanu and Sela (2001) for a full derivation of these results.

where $A(c)$ and $B(c)$ are defined as in (3).

The designer's problem in this case reads

$$\max_{0\leq\alpha\leq 1/2} 4\int_{0.5}^{1} \gamma^{-1}\left(A(c)+\alpha\left(B(c)-A(c)\right)\right)F'(c)dc$$

and it turns out that in this case it is optimal to award two equal prizes, i.e. $V_1 = V_2 = 0.5$. As noted by M-S (p.549), "with convex cost functions, the beneficial effect of the second prize on middle- and low-ability players is amplified [vis-à-vis the linear-cost case], while the advantage of having one prize (which strongly motivates high-ability contestants) is decreased." This is why, on an intuitive level, it might be optimal to award two prizes in case of convex costs. In the special case of quadratic costs, it just turns out that awarding two equal prizes is optimal.[5]

Hence, the prescriptions of the model are clear. When costs are linear the optimal prize structure is one where all the budget available for prizes in the organization are lumped together into one grand prize while when costs are quadratic two equally valuable prizes define the optimal prize structure.

3 Experimental Design and Procedures

In the experiments we rely on a classic 2-by-2 design: We implemented contests with either linear or quadratic costs and combine them with two different compositions of prizes, one that is optimal for that cost structure and one that is not. To be more precise, in treatment LC-1 all subjects have linear costs and there is only one positive-valued prize: $V_1 = 1$, $V_2 = 0$. As we have seen above, this prize composition is optimal from the designer's perspective if contestants have linear costs. In treatment QC-2 all subjects have quadratic costs and there are two equal prizes: $V_1 = 0.5$, $V_2 = 0.5$. This prize composition is optimal from the designer's perspective if contestants have quadratic costs. In treatment LC-2 all contestants have linear costs and the composition of prizes is the one that is optimal in the quadratic case. Finally, in treatment QC-1 all contestants have quadratic costs and the composition of prizes is the one that is optimal in the linear case. A summary of our four treatments is shown in Table 1.

The computerized[6] experiments were conducted in the experimental laboratory of the Economics Department at New York University and the Center for Experimental Social Science. In each session fixed groups of four subjects were repeatedly matched to participate in a contest. Each

[5] See also M-S, p.545f.

[6] We used the software tool kit *z-Tree*, developed by Fischbacher (2007).

Treatment	Description	No. of Matching Groups	No. of Subjects	Period Endowm.	Max. Effort	No. of Periods
LC-1	linear costs	6	$6 \times 4 = 24$	0.22	1.96	50
	$V_1 = 1$, $V_2 = 0$					
LC-2	linear costs	6	$6 \times 4 = 24$	0.20	0.82	50
	$V_1 = V_2 = 0.5$					
QC-1	quadratic costs	5	$5 \times 4 = 20$	0.22	1.53	50
	$V_1 = 1$, $V_2 = 0$					
QC-2	quadratic costs	5	$5 \times 4 = 20$	0.20	0.99	50
	$V_1 = V_2 = 0.5$					
CONTROL	linear costs	6	$6 \times 8 = 48$	0.22	None	50
(Variant of LC-1)	$V_1 = 1$, $V_2 = 0$					

Table 1: Treatments.

of the experiments consisted of 50 periods. Payoffs were denoted in "points". At the beginning of each period each subject was assigned a "random number" indicating their type or ability, c_i. Each random number was an iid draw from the set of numbers {0.5, 0.51, ..., 1.00}. After subjects were informed about their individual random numbers, they simultaneously submitted "decision numbers". The set of admissible decision numbers was {0.01, 0.02, ..., *Maxeffort*} where *Maxeffort* was a number that was 20 per cent higher than the optimal effort of a contestant with ability $c = 0.5$ (the "best" ability possible) in a given treatment. In treatment LC-1, LC-2, QC-1, and QC-2 this number was respectively 1.96, 0.82, 1.53, and 0.99.[7] Subjects were informed that by choosing a decision number they would incur "decision costs." The form of the costs (depending on the treatment) was explained both verbally and in the form of a "decision cost calculator" that was accessible in each round. When fed with a trial decision number it showed the associated costs given the subject's random number in the current period. We implemented this cost calculator to help to avoid a bias due to the subjects' (possibly) limited computational capabilities.

After each member of a group had entered his or her decision number, the computer compared all of the decision numbers of the four members of a group. In one-prize contests, the player with the highest decision number received a "fixed payment" of one point whereas all other play-

[7] We expected no one would want to set a higher decision number so that this upper bound would not be binding on a subject. In fact we were almost right since there were only very few instances of subjects choosing the Maxeffort.

ers received no additional payment. In two-prize contests, the two players with the two highest decision numbers received a "fixed payment" of 0.5 points whereas all other players received no additional payment. If in the one-prize contests, two or more group members chose the highest decision number, it was randomly decided which of these "tied" members received the prize of one point. In case of ties in the two-prize contests we proceeded in a similar fashion which was explained in the instructions. It was also explained and emphasized that decision costs would be subtracted no matter whether or not a subject had won. This implies that subjects could make losses. To cover those, subjects got a lump-sum fee of \$5. (Given the exchange rate of 15 points = \$1 in each treatment, all subjects started with an amount of 75 points in their experimental accounts.) Additionally, in each period subjects received an initial per-period endowment that was equal to their expected costs in equilibrium.[8] The specific numbers are shown in Table 1.

After each period, the feedback screen first informed a subject whether or not she had won an additional payment. Furthermore, the screen reiterated a subject's random number, decision number, decision costs, the difference between the payment in the previous period and the decision costs (excluding the initial endowment per period) and individual earnings in the previous period including the initial endowment per period. A last piece of information that was given to subjects depended on the number of prizes in a treatment and on whether or not a subject had won a prize. In one-prize contests, a subject that had not won a prize was informed about the random number of the winning subject. In two-prize contests, a subject that had won a prize was informed about the random number of the other winning subject whereas a subject that had not won a prize was informed about the random numbers of the two winning subjects.

In order to avoid income effects participants were informed that after the completion of the experiment ten out of the fifty periods would be randomly selected to count towards monetary earnings. That is, subjects were paid according to the sum of their individual earnings in these ten rounds. Finally, in order to make sure subjects had a good understanding of the decision problem and the procedures, we started each experiment with three trial periods that did not count towards monetary earning.

The experiments replicated the examples of contests described in section 2. The decision number corresponds to effort, the random number to a subject's ability, the decision costs to a subject's disutility of effort, and the payment corresponds to the prize(s).

[8] In equilibrium expected costs equal $\int_{.5}^{1} c(V_1 A(c) + V_2 B(c))dc$ where V_1 and V_2 depend on the treatment and $A(C)$ and $B(c)$ are given by (3). Note that expected costs in equilibrium do not depend on the form of the cost function.

In an effort to test the robustness of our results and to show that they are not an artifact of the design features we employed, we ran a final "control" treatment which relaxed several of the features of the LC-1 treatment. First, instead of having fixed matching in groups of four subjects each, in the control treatment we employed random matching across rounds in groups of eight subjects each where, in each round, the eight subjects were randomly assigned to two groups of four subjects. We recruited 48 additional subjects, leading to six independent observations for the control treatment. Second, instead of imposing a maximal admissible bid, there was (practically) no such limit in the control treatment.[9] Third, whereas in the main treatment LC-1 losing subjects were informed about the ability parameter of the winner, this information was not provided in the control treatment. The only information given in the control treatment was whether or not one's effort choice led to winning the contest. All other design features were exactly as in the main treatment LC-1.

Some remarks regarding our experimental design are in order. First, we avoided value-laden terms in the instructions. Subjects were never called contestants or competitors. Similarly, other players were called "other group members." Also "prizes" were called "fixed payments." Second, each subject participated in only one treatment.

4 Results

In this section we will present the results of our experiments. We will do this by first presenting the aggregate results that, as we have noted in the introduction, appear to strongly support the theory. However, when this is done we will disaggregate our results and look at them more finely. Here we will demonstrate that these aggregate results mask the bifurcation phenomenon we have discussed above.

4.1 Aggregate Results

There is a sense in which an organizational designer need care only about aggregate or average results. Since he is designing the organization to maximize mean effort levels and revenues, these should be the variables he looks at. In addition, if he is risk neutral he need not worry how these means were composed.

[9] Note that the software tool kit used to program the treatments (z-Tree), forces the programmer to indicate a maximum value for any input. This maximum was set equal to 1,000,000 in the control treatment. The highest effort choice observed during the payoff relevant periods was one choice of 10.

In line with this way of thinking we first present the aggregate or mean results of our experiment and concentrate on effort behavior and revenue in the four treatments. We will present summary statistics for the first and the second half of the experiment. In our discussion of the results we will somewhat concentrate on experienced behavior as displayed in the second half of the experiment (in an effort to purge learning effects). Nevertheless we will provide test results for both halves of the experiment.

4.1.1 Effort Behavior

We will start our discussion by looking at the effort behavior of our subjects at the aggregate level. To do this consider Figure 1.

In Figure 1 we have eight graphs, two for each of our four treatments. In each graph we present the equilibrium effort function (solid line) for the parameters defining that treatment. To show the pattern of observed efforts we also present the scatter of efforts representing the mean of the actual efforts placed when that ability was realized.

There are several things to note about Figure 1. First, the average efforts made seem to track the shape of the equilibrium effort function quite well. Second, effort behavior appears to be continuous in that, on average there does not appear to be any large discontinuities in behavior. Finally, the levels of efforts appear to be consistent with the equilibrium effort function. This is particularly true for the second half of the QC-2 experiment where the equilibrium effort function appears to pass directly through the middle of the scatter of mean efforts. For the other treatments there appears to be overexertion in LC-1 and LC-2 (independent of the time horizon considered) and slight under-exertion in QC-1 (in the second half of the experiment).

This behavior manifests itself in the average revenue data as well. Table 2 presents the mean revenue generated in each of our treatments along with the revenue that would have been generated by our subjects if, given their ability realizations, they had all submitted their equilibrium efforts. (For the column labeled "Sorting" see below. The bottom row contains results of a control treatment that will be discussed later.)

The revenue data presented in Table 2 are consistent with the observed effort behavior exhibited in Figure 1. Let us concentrate on the results of the second half of the experiment. While revenue levels were above those predicted by the equilibrium theory in the LC-1 and LC-2 treatments (with average observed revenue being about 65% higher than average equilibrium revenue in the LC-1 treatment (2.391 vs. 1.452) and 25% higher in the LC-2 treatment (1.452

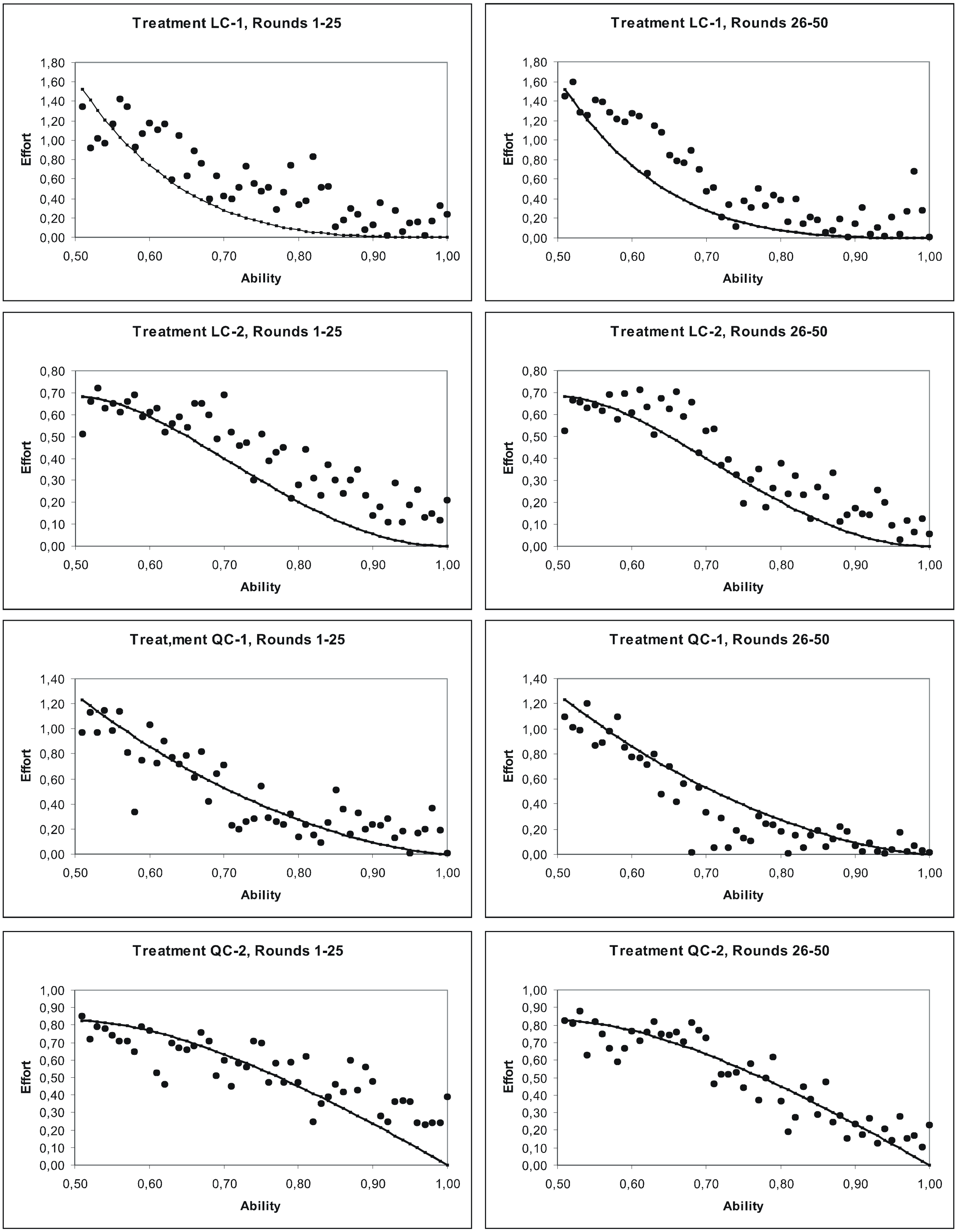

Figure 1: Average observed (•) and optimal (solid line) effort functions in the first and the second half of the experiment.

Treatment	Rounds	Average Revenue		Sorting
		optimal	observed	
LC-1	First 25	1.435	2.380	84/150
		(0.245)	(0.461)	(56.0%)
	Last 25	**1.452**	**2.391**	86/150
		(0.168)	(0.281)	(**57.3**%)
LC-2	First 25	1.307	1.752	79/150
		(0.073)	(0.126)	(52.7%)
	Last 25	**1.164**	**1.452**	70/150
		(0.061)	(0.312)	(**46.7**%)
QC-1	First 25	1.849	1.878	70/125
		(0.104)	(0.222)	(56.0%)
	Last 25	**1.859**	**1.524**	77/125
		(0.160)	(0.270)	(**61.6**%)
QC-2	First 25	1.987	2.127	56/125
		(0.145)	(0.296)	(44.8%)
	Last 25	**1.944**	**1.963**	65/125
		(0.093)	(0.364)	(**52.0**%)
CONTROL	First 25	1.431	1.706	126/300
(LC-1)		(0.143)	(0.314)	(42.0%)
	Last 25	**1.402**	**1.289**	122/300
		(0.049)	(0.379)	(**40.7%**)

Table 2: Observed revenue and sorting (Standard deviations based on group averages in parentheses)

vs. 1.164), in the QC-1 treatment they were below by about 18% (1.524 vs. 1.859). In the QC-2 treatment actual average revenues were remarkably on target (1.963 vs. 1.944). Applying a sign-test[10] to the data from the second half of the experiment we can reject the hypothesis that the median observed revenue is equal to the equilibrium level at the 1 per cent level in treatments LC-1, LC-2 and QC-1. For treatment QC-2, however, this hypothesis can not be rejected at any conventional significance level ($p = 0.858$, two-tailed).[11]

Recall that theory predicts that in a linear-cost contest revenue is maximal if only one prize is awarded while, in our quadratic-cost contest, the designer maximizes total effort by awarding two equal prizes. Both of theses predictions are confirmed by our data. According to Table 2 and concentrating on results in the second half of the experiment, we see that whereas in treatment LC-1 average observed revenue is 2.391 it is only 1.452 in treatment LC-2. Taking one matching group's average total effort as one observation, a one-tailed Mann-Whitney U-test reveals that this difference is highly significant ($p = .001$). In the quadratic-cost contests, the average total effort of 1.963 in treatment QC-2 compares to an average of 1.524 in treatment QC-1. Again this difference is statistically significant ($p = 0.028$).[12]

One might also ask, how reliable the different contests are in terms of producing the levels of average total efforts reported in Table 2. A look at standard deviations given in parentheses in Table 2 is revealing: One-prize contests are more stable than two-prize contests in the sense that standard deviations are lower in the first than in the latter (contests with linear costs: 0.281 vs. 0.312; contests with quadratic costs: 0.270 vs. 0.364; rounds 26-50).

Finally, one can ask whether our contests were efficient in sorting and promoting workers. For example, if there are one or two positions available for promotion (as in our experimental contests), the goal would be to select the worker with the highest ability or, respectively, the workers with the two highest abilities. This can be achieved with the contests studied in this paper since the equilibrium-effort functions are strictly monotonic with respect to ability. Thus if all subjects exert effort according to the equilibrium effort function, optimal sorting should occur.

[10] Consider the variable y_{jt} with $y_{jt} = 0$ in case the observed revenue in period t in session j is less than or equal to the equilibrium level and $y_{jt} = 1$ if observed revenue exceeds the equilibrium level. Then test whether or not the variable y_{jt} is binomial with 0.5 probability that $y_{jt} = 1$.

[11] For the first half of the experiment the p-values are $p < 0.001$ (LC-1 and LC-2), $p > 0.9$ (QC-1), and $p = 0.031$ (QC-2).

[12] The prediction that in a linear-cost (quadratic-cost) contest revenue is maximal if only one prize is (two prizes are) awarded is also confirmed with respect to the data in the first half of the experiment: LC-1 vs. LC-2 ($p = 0.012$) and QC-1 vs. QC-2 ($p = 0.075$).

That is, in each round and each group of four contestants we would observe that the subject with the highest ability would exert the highest effort, the subject with the second highest ability would exert the second highest effort, and so on. Clearly, in an experimental setting optimal sorting in this strict sense cannot be expected throughout the entire experiment.[13] Instead we just ask, in how many cases it was true that the contestant with the highest ability won a one-prize contest respectively in how many cases it was true that the contestants with the two highest abilities were winners in a two-prize contest. The results are displayed in the fifth column of Table 2 labeled "Sorting". The entry in each cell gives the number of cases in which sorting worked and the number of all cases along with the percentage in parentheses. Concentrating on the results in the second half of the experiment, sorting in this weaker sense occurred in respectively 57.3%, 46.7%, 61.6% and 52.0% of the cases in treatment LC-1, LC-2, QC-1 and QC-2, respectively. Put differently, in about 40% (50%) of the cases in the one-prize (two-prize) contests, contestants not having the highest abilities won the contests. However, note that for example in the majority of cases in which sorting did not work in the two one-prize contests, the winner of the contest was the subject having the second highest ability who happened to exert an effort greater than the highest-ability subject. Hence it is the rat race that is responsible for inefficiencies.[14] Note finally that, non-surprisingly, the percentage of cases in which sorting does work is higher in one-prize contests than in two-prize contests.

In summary as predicted by the theory, we find that in case of linear costs a one-prize contest raises higher revenues than a two-prize contest whereas in case of quadratic costs a two-prize contest raises higher revenues than a one-prize contest. Furthermore, contests with linear costs seem to elicit excess efforts while those with quadratic costs elicit effort levels which are either too low or approximately equal to the equilibrium efforts. Finally, we observe that in only 50-60% of the cases (depending on the treatment), the contests are won by those subjects having the highest abilities.

4.2 Disaggregated Results

As we have seen above, if one were to look only at our data aggregated within treatments, one could come away with the impression that behavior was basically continuous and, on average, not far from that predicted by the theory. In this section of the paper we will attempt to disabuse you

[13] In fact, optimal sorting in this strict sense is only observed in roughly ten per cent of all rounds in the second half of the experiment in the four different treatments.

[14] There are, however, also cases in which contestants with the second to last ability or the least ability won a contest.

of those impressions by presenting a more disaggregated analysis of our data. We will do this in several steps. First we will present a small sample of individual effort functions presented just to give you a quick first impression of what typical effort behavior looked like. While this is not an exhaustive presentation of all effort functions, the subjects we select are by no means outliers so they should give you a good idea of what we are talking about. Second, we will present a set of histograms, one for each of our four treatments, which describe the efforts subjects made. These histograms will illustrate the fact that efforts tended to be bimodal. They were either heavily concentrated around zero (for those who dropped out) or scattered across high effort levels (for those entering the rat race) with relatively few effort levels chosen in the middle effort ranges. In other words, either subjects dropped out or they entered a rat race. Finally, we perform a model-selection test by contrasting, individual by individual, the goodness of fit of the best fitting step-wise linear effort function against the best fitting continuous function of the form specified by the equilibrium theory. Here we try to convince you that subject behavior can best be described by a step function characterized by an ability cut-off level c^* such that for all abilities below c^* (low costs) effort is very high while for abilities above c^* (high costs) efforts are low (or zero).

4.2.1 Individual effort functions

Figure 2 presents individual effort functions in both halves of the experiment from four subjects one each selected from our four treatments. While not all individuals exerted effort in this manner, in this section we will attempt to convince you that these effort functions are the rules and not the exception. More precisely, we will try to convince you that rather than effort being chosen in a smooth and continuous manner, typical behavior can be characterized by a discontinuous step function with a cut off effort level of c_i^* for individual i. While c_i^* varies from individual to individual, and while some individuals violate the rule, we still consider the effort functions of these four subjects to be broadly representative of behavior.

Note how dramatic these effort functions are. For example, subject 4 in treatment LC-2 clearly exhibits a c_i^* of 0.70 (rounds 26-50) and clearly drops out for all ability levels above it while subject 5 in treatment QC-2 drops out for all $c_i^* \geq 0.80$ (rounds 26-50). Note, in addition, that when subjects exert positive effort they do so very often at levels far above those prescribed by the equilibrium effort function. These drop-out efforts and over exertions are precisely the bifurcations that were described in our introduction. Importantly, note also that the subjects' effort functions in Figure 2 display the bifurcation pattern already in the first half of the experiment.

4.2.2 Effort Histograms

Perhaps a more efficient way to demonstrate the bifurcation of individual effort in these experiments is to present Figure 3 which describes the histograms of observed individual effort levels (on the right hand side) in our four treatments along with what we would expect these histograms to look like if, given the actual ability draws of our subjects, they had all made their equilibrium effort choices (on the left hand side). Figure 3 shows results from the second half of the experiment.

To describe these histograms let us look first at those of treatment LC-2 (second from the top in Figure 3). As we see in the left panel, if subjects had all used their equilibrium effort functions to select effort levels, given the ability realizations in the sessions, we would have expected to see a more or less uniform distribution of efforts. By contrast, the right panel presents what we actually saw which is quite different. Note that there is a huge number of efforts around the 0 effort level indicating a large amount of drop-out behavior as well as a larger number of effort levels above 0.60 indicating larger than expected efforts. The same pattern exists in all of the other Figures with an even more pronounced bifurcation in treatment QC-1 and QC-2.

From these histograms it should be clear that behavior in these experiments was bimodal. Either subjects dropped out or they exerted above expected effort levels which is consistent with our bifurcation hypothesis.

4.2.3 Step-Functions

Final support for our bifurcation hypothesis comes from the following model selection exercise. If we are correct in supposing that individual behavior was bimodal and exhibits either drop-out or over-exertion behavior, then we would expect that the best fitting model of individual effort would be a step-function characterized by a cut-off ability level, c_i^*, such that if subject i's observed ability, c_i, were above c_i^* then the subject would "drop out" and exert either zero or at least very low effort, while if c_i were below c_i^*, the individual would exert positive and substantial efforts. This model can be tested against the equilibrium model which posits a continuous effort function of the form specified by (2) and (5), or the best fitting continuous effort function of that general form.

To compare these models we first fit a simple switching regression model for each subject (separately for each of the two halves of the experiment) of the form,

$$b_{it} = \alpha_0 + \alpha_1 c_{it} + \alpha_2 D_{c_i^*} + \alpha_3 D_{c_i^*} c_{it} + \varepsilon_{it} \tag{6}$$

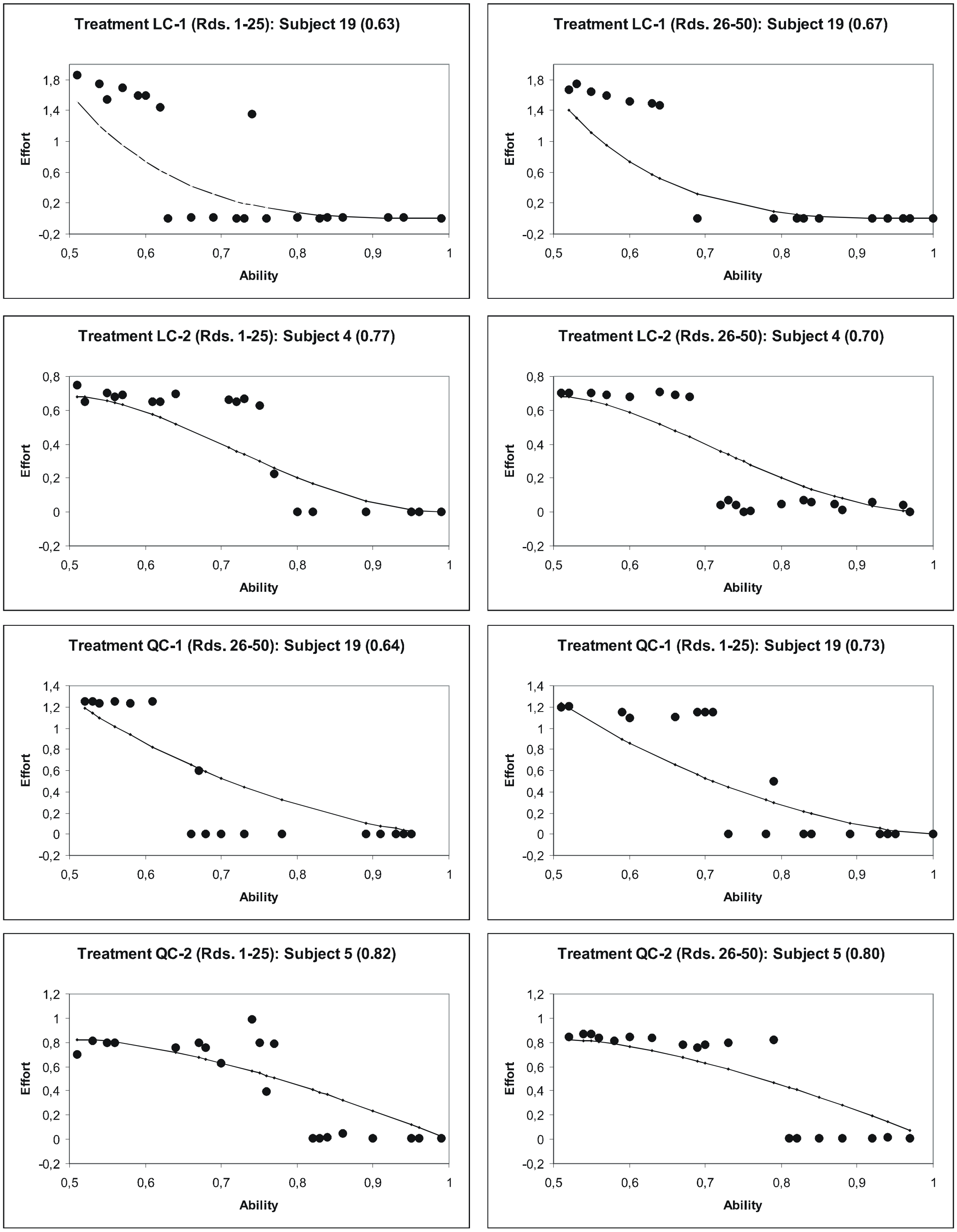

Figure 2: Examples of individual behavior (optimal solid line; observed •). Note: Cut-off levels c_i^* in parentheses (see Section 4.2.3).

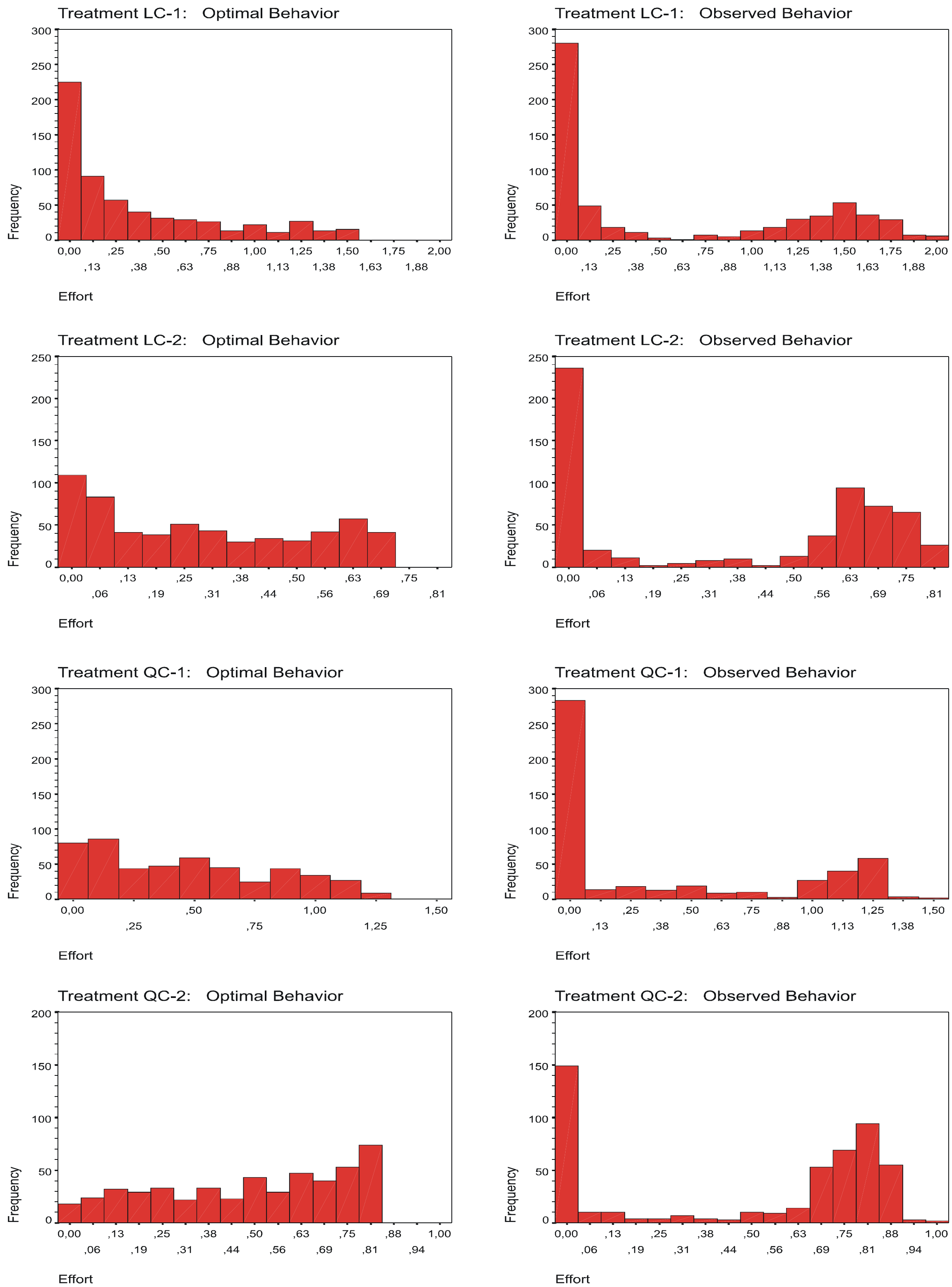

Figure 3: Histograms of individual effort choices in rounds 26-50

where b_{it} (c_{it}) is subject i's effort (ability) in period t, and $D_{c_i^*}$ is a dummy which is equal to 1 if $c_{it} > c_i^*$ and equal to 0 otherwise. The parameter $c_i^* \in \{.51, .52, ..., 1\}$ is the value of the ability at which the structural break in the subject's effort behavior occurs. Note that in case of $D_{c_i^*} = 0$ equation (6) reads $b_{it} = \alpha_0 + \alpha_1 c_{it} + \varepsilon_{it}$ whereas in case of $D_{c_i^*} = 1$ it reads $b_{it} = (\alpha_0 + \alpha_2) + (\alpha_1 + \alpha_3) c_{it} + \varepsilon_{it}$. Thus the graph of (6) consists of two line segments with intercepts α_0 before and $\alpha_0 + \alpha_2$ after the break and slopes α_1 before and $\alpha_1 + \alpha_3$ after the break, respectively. Note that in case of $-\alpha_2 \neq \alpha_3 c_i^*$ the graph in (6) has a discontinuity occurring at the point of structural break. The best-fitting breakpoint c_i^* and the respective coefficients in (6) were estimated from the data.

For this purpose, we estimated equation (6) for all possible points of structural break $c_i^* \in \{.51, .52, ..., 1\}$ and chose as the optimal breakpoint the one that maximizes the adjusted R^2. Using the corresponding estimates of the coefficients in (6), we then computed for each subject i and for each period $t \in \{1,\ 2,\ ...,\ 50\}$ the predicted effort $\left(b_i^t\right)^{pred}$and computed, subject by subject, the sum of the square deviation, SSD_i, defined as $SSD_i = \sum_{t=1}^{25} \left(\left(b_i^t\right)^{pred} - \left(b_i^t\right)^{obs} \right)^2$ where $\left(b_i^t\right)^{obs}$ is the observed effort of subject i in period t. (The SSD_i's for the second half of the experiment were computed similarly.)

We compared the resulting SSD_i's of this estimation to two others. The first was the SSD_i generated using the predictions of the equilibrium effort functions as given in (2) and (5). Second, we compared our SSD_i's to those generated by estimating the best fitting effort function for each individual of the *form* of the respective equilibrium-effort function in each of the four treatments as given in equations (2) and (5). For instance, using OLS regression we estimated for each subject in treatment LC-1 the model

$$b_{it} = \beta_0 + \beta_1 c_{it} + \beta_2 c_{it}^2 + \beta_3 \ln c_{it} + \varepsilon_{it} \qquad (7)$$

where, again, b_{it} (c_{it}) is subject i's effort (ability) in period t. (Note that equation (7) has the form of the equilibrium effort function given in (2) with the exception that the coefficients are undetermined.) Likewise for treatment LC-2. Recall that the equilibrium-effort functions for the treatments with quadratic costs, i.e. treatments QC-1 and QC-2, are the square roots of the equilibrium effort-functions in the respective linear-costs treatments (compare equations (2) and (5)). In order to be able to use OLS regression for the estimation in these treatments, too, we proceed as follows. Consider e.g. treatment QC-1. Instead of estimating (5) we estimated the model

$$(b_{it})^2 = \beta_0 + \beta_1 c_{it} + \beta_2 c_{it}^2 + \beta_3 \ln c_{it} + \varepsilon_{it}$$

	Average sum of squared deviations (SSD) based on						p-level	
	Switching Regr. Model		Equilibrium		"Equilibrium Form"		Wilcoxon test	
	Rounds		Rounds		Rounds		Rounds	
Treatment	1-25	26-50	1-25	26-50	1-25	26-50	1-25	26-50
LC-1	3.03	2.86	9.05	8.77	7.08	3.63	< 0.001	< 0.001
LC-2	0.59	0.29	1.96	1.82	1.54	0.48	< 0.001	< 0.001
QC-1	2.29	0.87	4.43	3.49	5.27	2.10	< 0.001	< 0.001
QC-2	1.02	0.59	2.66	2.08	3.31	1.05	< 0.001	< 0.001
CONTROL (LC-1)	3.51	2.39	12.05	7.87	9.92	3.06	< 0.001	< 0.001

Table 3: Overview: Sum of the square deviation (SSD)

i.e., the squared equation. In order to compute the SSD_i for these cases we then used the radical of the predicted efforts.

The results of our exercise are given in Table 3 which presents the average SSD_i value for each treatment and each half the experiment. Columns 2 and 3 present the results of our switching regression model while columns 4 and 5 (6 and 7) present the results of our equilibrium (equilibrium-form) models.

As can be seen, our simple switching regression model clearly outperforms the prediction of both the equilibrium and equilibrium-form models independent of the time horizon considered. In fact, using a Wilcoxon test to compare the individual SSD_i's based on either the switching regression model and the estimates based on the equilibrium-form regressions indicates, that the former gives a highly significantly better fit than the latter.

Table 5 shows the average cut-off levels in each of the four treatments as well as (two tailed) p-values of pairwise Mann-Whitney U-tests. Recall that the switching regime consists of two line segments with a (possible) jump between the two segments. Consider the results from rounds 26 to 50 and note that the average cut-off points in the one-prize contests are lower than the average cut-off points in the two-prize contests (0.71 in LC-1 vs. 0.78 in LC-2; 0.67 in QC-1 vs. 0.81 in QC-2). As it turns out, these differences are also statistically highly significant (Mann-Whitney U-tests). This means that subjects in the one-prize contests only start to exert serious effort when their ability parameters, the c_i's, are comparatively low. This implies that they exert low effort

Rds. 1-25	LC-1	LC-2	QC-1	QC-2	**Rds. 26-50**	LC-1	LC-2	QC-1	QC-2
	(0.72)	(0.82)	(0.71)	(0.78)		(0.71)	(0.78)	(0.67)	(0.81)
LC-1	—	—	—	—	LC-1	—	—	—	—
LC-2	0.001	—	—	—	LC-2	0.013	—	—	—
QC-1	0.786	0.002	—	—	QC-1	0.174	0.000	—	—
QC-2	0.171	0.190	0.134	—	QC-2	0.003	0.403	0.000	—

Table 4: Average cut-off levels (in parentheses) and two tailed p-values of pairwise differences in the first and the second half of the experiment

levels over a much larger interval of the domain of their effort function. Finally, note that the differences between cut-off levels in the two one-prize and the two two-prize contests are small and not significant.

Finally, having established that subjects' behavior is best described by a simple (discontinuous) step function, one might ask whether this is consistent with the fact that average bidding functions for each treatment as shown in Figures 1 and 4 do not appear to show any large discontinuities in behavior. The seeming inconsistency between individual effort functions (as shown in Figure 2) and the average effort functions (as shown in Figures 1 and 4) is resolved by the observation that different subjects have different cut-off points such that the aggregation of (discontinuous) individual effort functions leads to more or less smooth average effort function.

4.3 A control treatment

As stated in Section 3, to check whether our main result of a bifurcation effect in individual effort choices is robust to changes in the design features, we ran a control treatment. This control treatment is a variant of treatment LC-1 with the following three changes: we used random instead of fixed matching, there was no maximum admissible bid, and less feedback was offered the subjects. In particular, subjects were only informed about whether or not they had won a prize but not about the ability of the winning other subject(s). All other design features were exactly as in the main treatment LC-1.

Let us first check the effort behavior in the control treatment at the aggregate level. Figure 4 shows the equilibrium effort function for the control treatment (solid line) along with the average effort chosen conditional on each ability parameter. Concentrating on the second half of the ex-

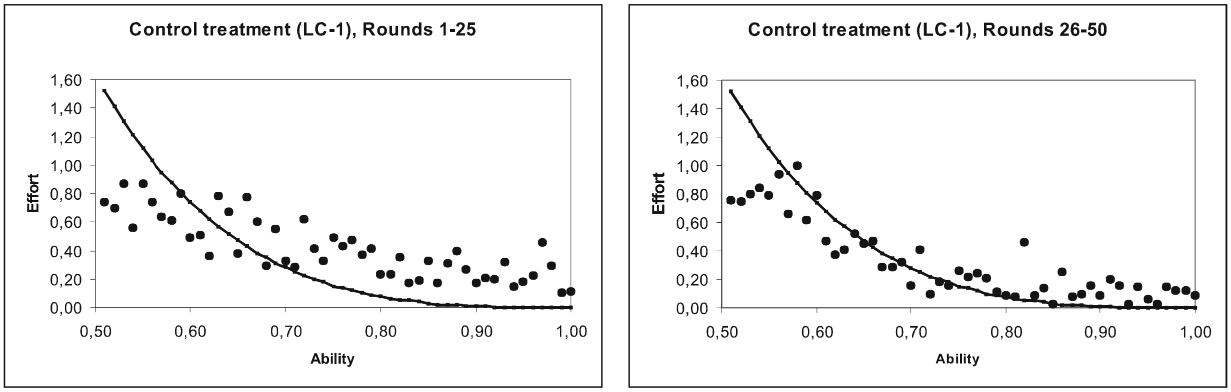

Figure 4: Average observed (•) and optimal (solid line) effort functions in the first and the second half of the control treatment.

periment, we observe that the average efforts made again track the shape of the equilibrium effort function quite well except for very low levels of the ability parameter for which average observed efforts are lower than predicted. But again, it seems fair to say that from the average effort function no clear discontinuity in behavior can be detected.

Regarding average revenue in the control treatment, refer to the bottom row of Table 2 which presents the mean revenue generated in each treatment along with the revenue according to the equilibrium efforts. Whereas average observed revenue in the control treatment is higher than average equilibrium revenue in the first half of the experiment (1.706 vs. 1.431), it is the other way around in the second half of the experiment (1.289 vs. 1.402). A sign-test reveals that we can reject the hypothesis that the median observed revenue is equal to the equilibrium level in the control treatment at the 10 per cent level ($p = 0.001$ (rounds 1-25) and $p = 0.086$ (rounds 26-50), two-tailed). Table 2 also indicates that the control treatment does worse than the original treatment LC-1 in terms of selecting the worker with the highest ability. This is true as in only 41.3% of the cases in the second half of the experiment the subject with the highest ability actually won the contest (57.3% in treatment LC-1).

Next, let us have a look at Figure 5 which describes the histograms of observed individual effort choices in the control treatment (on the right hand side) along with a histogram of choices that would result from optimal (i.e. equilibrium) behavior by subjects (on the left hand side) in the second half of the experiment.[15] Comparing the two graphs in Figure 5 we notice that there

[15] There is one effort choice of 9 not shown in the histogram of observed behavior.

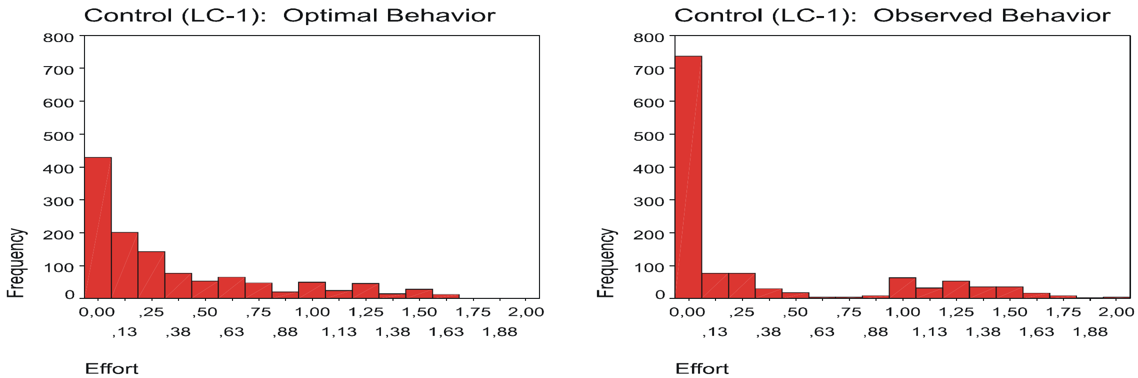

Figure 5: Histograms of individual effort choices in the Control treatment (LC-1) in rounds 26-50.

is again a huge number of actually observed effort choices close or equal to 0 implying a very high degree of drop-out behavior.[16] Furthermore, with regard to observed behavior there are virtually no choices in the interval from around 0.55 to 0.95 and a another cluster of high effort choices around 1.25. Comparing Figure 5 with the top row of Figure 3, we observe that the main new effect of the control treatment is the increase of choices around 0.[17] In any case, Figure 3 suggests that also the behavior in the control treatment is bimodal.

To check this we repeat the model selection exercise reported in section 4.2.3 for the data of the control treatment. The results are given in the bottom row of Table 3. Again, our simple switching regression model clearly outperforms the prediction of both the equilibrium and equilibrium-form models in both halves of the experiment. In fact, a Wilcoxon test reveals that the SSD_i's of the switching regression model are highly significantly lower than the ones of the equilibrium-form model. Finally, the average cut-off level for the switching regime in the control treatment is equal to 0.70 (rounds 26-50) and is thus virtually the same as the one in the main treatment LC-1 (see Table 5, rounds 26-50).

Summarizing, our main result of a bifurcation effect in individual effort choices appears to be robust to changes in the design features employed in the main treatments. The main differences in the behavior in the control treatment and the main treatment LC-1 is a reduction of average effort choices for low levels of the ability parameter (see Figure 4) and an increase of choices around

[16] There are three subjects (from three different matching groups) in the control treatment who chose an effort of 0 throughout the second half of the experiment.

[17] Note that in the control treatment we have twice as many individual decisions than in treatment LC-1 (1200 vs. 600, last 25 rounds) as there are twice as many subjects.

0 in the control treatment (see Figures 3 and 5).

4.4 A theoretical explanation for the bifurcation effect

One possible explanation for our bifurcation-of-efforts result is that subjects are loss averse. Intuitively, when a subject's cost of effort is very high, chances are that the other competitors have a lower cost of effort and thus bid high. In this case this subject might exert little or no effort for fear of loosing the cost of effort. On the other hand, if a subject's cost of effort is very low, chances are that the other competitors have a higher cost of effort and thus bid low. In this case this subject might exert very high effort for fear of not getting the prize. This argument can be made formally. For this purpose, assume the standard loss aversion function (see Kahneman and Tversky, 1979)

$$u(x) = \begin{cases} x^{\alpha} & \text{if} \quad x \geq 0 \\ -\lambda(-x)^{\alpha} & \text{if} \quad x < 0 \end{cases}$$

where $\alpha > 0$ and $\lambda > 1$ and consider for example treatment LC-1. The maximization problem of a contestant in this treatment, assuming that all contestants are loss averse, is

$$\max_{x} \left[(V_1 - cx)^{\alpha} \Pr(Win) - \lambda (cx)^{\alpha} \left(1 - \Pr(Win)\right) \right] \tag{8}$$

where $\Pr(Win) = (1 - F(b^{-1}(x)))^{k-1}$ and $V_1 = 1$ is the prize (see section 2.1). That is, with $\Pr(Win)$ a contestant wins the contest in which case his utility is $(V_1 - cx)^{\alpha}$. With the complementary probability the contestant looses the contest in which case his utility is $-\lambda(cx)^{\alpha}$. The FOC leads to a differential equation (with the boundary condition that a contestant with ability $c = 1$ exerts effort 0) that can be solved numerically.

Figure 6 shows the optimal bidding function assuming risk neutral contestants as in Moldovanu and Sela (2001) and the optimal bidding function assuming loss averse contestants (with $\alpha = 0.3$ and $\lambda = 1.25$). Inspection of Figure 6 shows that, assuming loss averse contestants, we can replicate the two main facts about observed individual bidding functions: when the cost of effort is high (low), the optimal effort of loss averse contestants is smaller (higher) than optimal effort of risk neutral contestants. Clearly, depending on parameter choices, the optimal effort of loss averse contestants can be shown to be essentially 0 when costs of effort are high and substantially higher than optimal effort of loss averse contestants when costs of effort are low. That is, assuming loss aversion we can generate the drop out and workaholic behavior we observe in our experiments.

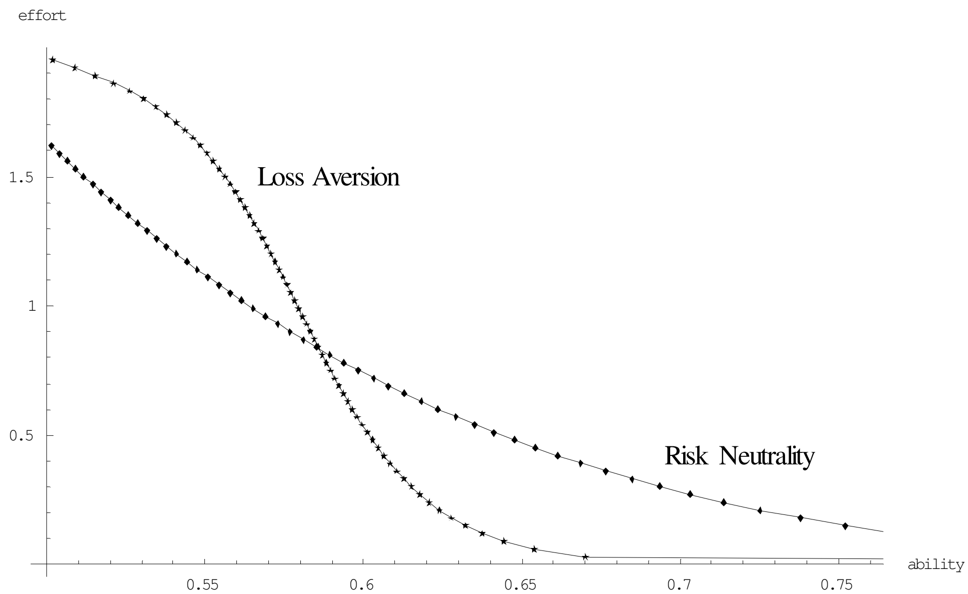

Figure 6: The equilibrium bidding function in treatment LC-1 in case of risk neutral and loss averse bidders ($\alpha = 0.3$ and $\lambda = 1.25$).

5 Conclusions and Discussion

In this paper we have investigated an incentive mechanism proposed by Moldovanu and Sela (2001) whose objective is to maximize the average effort level exerted in an organization of workers. At the equilibrium of this mechanism, workers are expected to choose effort functions which are continuous in their cost of effort. We have found that while this prediction appears to be supported in the aggregate, the underlying effort functions on the individual level are actually a set of discontinuous step functions in which low-cost high-ability workers exert higher than predicted levels of effort while those with low ability and high cost drop out and exert close to zero effort. We have attributed this result to the fact that our subjects may behave in a loss-averse manner when faced with this mechanism. This fact should be of note to those interested in mechanism design since it warns us that in order to have a successful mechanism in practice the mechanism must elicit behavior which is identical to that assumed by the designer in theory. Here, while the Moldovanu-Sela mechanism was predicated on risk neutral expected utility maximization the mechanism appears to have elicited loss averse behavior instead. Hence, given this behavior the Moldovanu-Sela mechanism may in fact not be optimal.

Finally, our results have implications for the efficiency of organizations. More precisely, if organizations hope to sort and reward workers on the basis of their ability, then we would expect that, on average, the most productive workers would receive the organizational prizes while the lesser ones would not. Since workers usually differ with respect to their abilities and since the equilibrium-effort functions in the M-S mechanism are strictly monotonic with respect to ability, the contests analyzed in this study theoretically serve the purpose of awarding promotion prizes to those workers having the highest abilities. We observe, however, that in only 50-60% of the cases our experimental contests are won by highest-ability subjects. Despite this finding we have demonstrated that when the worker with the highest ability fails to be rewarded, is it usually the second highest ability worker who is. Hence the mistakes that are made are not gross mistakes and are likely to occur when workers tremble when selecting their effort levels.

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A Instructions for treatment LC-2

This is an experiment in decision-making. If you make good decisions you can earn a substantial amount of money, which will be paid to you when you leave. The currency in this decision problem is called Points. All payoffs are denominated in this currency. At the end of the experiment your earnings in Points will be converted into real U.S. dollars at a rate indicated below.

As you read these instructions you will be in a room with a number of other subjects. Each subject has been randomly assigned an (electronic) ID number. The experiment consists of 50 decision rounds. In each decision round you will be grouped with three other subjects by a random drawing of ID numbers. These three subjects will be called your "group members." Your group members will remain the same throughout the entire experiment. The identity of your group members will not be revealed to you.

The Decision Problem

In the experiment you will perform a simple task. At the beginning of each round the computer will first independently generate a random number for every group member. The random number will be one of the 51 numbers in the set {0.50, 0.51, , 1.00}. Each of these 51 numbers has an equally likely chance of being chosen. You will then be informed about the random number that was chosen for you. You will, however, not be informed about the random numbers that were chosen for the other group members. These random numbers will be important to you since they will determine your costs in the experiment as explained below. After informing you about your random number, the computer will ask all group members to simultaneously choose a Decision Number (which will be the only decision you have to make in a round.) This Decision Number must be chosen from the set of numbers {0, 0.01, 0.02, ..., 0.82}. Associated with each Decision Number are decision costs. These decision costs depend on your random number as well as on the Decision Number you chose. More precisely, the decision costs will be equal to the product of the random number and your Decision Number. For example, say you receive a random number of 0.6 and in the experiment choose a Decisions Number of 0.7. Then your cost would be 0.42 = 0.7 x 0.6. If instead your random number was 0.9 and you chose a Decision Number of 0.7, your decision costs would be 0.63 = 0.7 x 0.9. You can consider your random number to be the per-unit cost of choosing a Decision Number so the higher the random number the higher is that per unit cost. Note that the decision costs associated with the Decision Number 0 are equal to 0.

To help you calculate what the cost of any Decision Number will be given your random number, we have provided you with a calculator that is located on the left hand side of your decision screen. To find the decision cost associated with any Decision Number simply enter a Decision Number into the box and then push the button "compute". Your cost will then be shown to you at the top left corner of your screen.

When you are ready to make your final decision, please enter your Decision Number into the box on the right hand side of your screen and push the button "OK".

Calculation of Payoffs

Your payoff in each decision round will be computed as follows. First of all, in each round each participant will receive a flat payment of 0.20 Points no matter which number he or she and the other group members have chosen. Whether or not you receive an additional fixed payment will be determined in the following way. After every member of your group has entered his or her Decision Number, the computer will compare all of the Decision Numbers of the four members of your group. If your Decision Number is one of the two highest, you will receive the fixed payment of 0.5 Points otherwise you receive no additional fixed payment. If three or more group members chose the highest Decision Number, then the computer will randomly determine which two of these "tied" members receive the additional fixed payment of 0.5 Points. Those subjects with Decision Numbers that are not the highest two will receive nothing. From your fixed payment (of either 0.5 Points or 0 Points) you will have to subtract your decision cost. Hence, while choosing a high Decision Number increases the probability that you will win a positive fixed payment it also increases the cost of doing so. In addition, if your Decision Number is not one of the two highest of the group, you will receive no additional fixed payment and have to subtract your decision costs from your initial flat payment.

Your payoff in a given round is calculated as follows: First, as mentioned above, you receive a flat payment (FP) of 0.20 Points. In addition if you chose one of the two highest Decision Numbers you will be paid a fixed payment of 0.5 Points from which you will subtract your decision cost. If you do not choose one of the two highest Decision Numbers, you will receive a fixed payment of 0 and still have to subtract your decision costs. The resulting number is multiplied by 100 to yield your final Points payoff. This is then converted into dollars at the rate of 15 Points = $1. Thus, your final payoff in Points in a given round is: Payoff = 100*(Flat payment + Fixed payment (0 or 0.5) - Decision Cost).

Note: To make life easier for you so that you do not have to enter decimal Points, you will not be asked to enter a Decision Number from the set {0, 0.01, 0.02, ..., 0.82} but from the set {0, 1, 2, ..., 82}. The computer will then automatically divide the Decision Numbers of all group members by 100 before starting to evaluate them.

Example of Payoff Calculation

Suppose the following occurs: Group member 1 gets assigned random number 0.80 and chooses Decision Number 0.21 (21). Group member 2 gets assigned random number 0.55 and chooses Decision Number 0.17 (17). Group member 3 gets assigned random number 0.91 and chooses Decision Number 0.05 (5). Group member 4 gets assigned random number 0.77 and chooses Decision Number 0.33 (33).

Since group members 4 and 1 chose the highest two Decision Numbers they receive the Payment of 0.5 Points whereas all other group members receive no payment. Therefore, group member 4's earnings in this round would be 100*(0.20 + 0.5 - 0.77*0.33) = 44.59 Points whereas group member 1's earnings in this round would be 100*(0.20 + 0.5 - 0.80*0.21) = 53.2 Points. Group members 2, and 3 each receive no additional payment. Therefore group member 2 would earn 100*(0.20 + 0 - 0.55*0.17) = 10.65 Points, and, finally, group member 3 would earn 100*(0.20 + 0 - 0.91*0.05) = 15.45 Points.

Note again that the decision cost is a function of the random number and the Decision Number. Note also that your earnings in a round depend on the following: your random number, your Decision Number and your group members' Decision Numbers. Your earnings do not depend on your group members' random numbers.

Continuing Rounds

After round 1 is over, the same procedure will be repeated for round 2, and so on for 50 rounds. That is, in each round a random number will first be generated for you, then you will choose a Decision Number which will be compared to the Decision Numbers of the other members of your group, and the computer will calculate your earnings for the round.

After each round you will be informed about which payment you receive. In case you do receive a positive payment you will be informed about the random number of the other group member who also received a payment of 0.5 Points. In case you do not receive a positive payment (because your Decision Number was not one of the two highest among the Decision Numbers of all group members or because you were not randomly selected in case you and at least two other group members chose the highest Decision Number) you will be informed about the random numbers of the group members who received the payment of 0.5 Points.

Calculation of Final Monetary Payment

At the start of the experiment you get a one-off endowment of 75 Points. (This is the $5 show-up fee you were promised, see below.)

When round 50 is completed, the computer will randomly select 10 of the 50 rounds. Your final payoff in the experiment will be the sum of your individual earnings in Points for only these 10 rounds (plus your endowment). For each 15 Points you will be paid 1 $.

Trial Periods

At the beginning of the experiment there will be three trial periods that do not count towards payment of real money.