WORKAHOLICS AND DROPOUTS IN ORGANIZATIONS

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Abstract
This paper reports the results of experiments designed to test the theory of the optimal composition of prizes in contests. In the aggregate the behavior of subjects is consistent with that predicted by the theory, but we find that such aggregate results mask an unexpected compositional effect on the individual level. Whereas 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, and high-ability workers try too hard. This bifurcation, which is masked by aggregation, can be explained by assuming loss aversion on the part of the subjects. (JEL: C92, D44, D72, D82, J31)

1. Introduction

Casual empiricism indicates that many organizations are characterized by a bifurcation of effort among workers. Whereas one subset appears unable to stop itself from working (workaholics), the other subset exerts no effort at all (dropouts). This bifurcation raises several questions: Why does it exist? What lessons can we learn from its existence for the proper design of economic mechanisms in general and for incentive systems in particular?

In this paper we experimentally test a model proposed by Moldovanu and Sela (2001; 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 to have either linear, convex, or concave cost-of-effort functions and where

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an organizational designer has a limited amount of money available to award as bonuses for workers whose outputs are highest. (Assume that output is non-stochastic and linear in effort; so in essence, effort is equivalent to output and both are observable.) The authors demonstrate that, for organizations whose 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, whereas if costs are convex, it might be optimal to distribute the budget among several prizes.[1] In this model, the equilibrium effort functions are continuous functions of the abilities of the workers. In the lab, however, individual effort functions appear to be discontinuous step functions, with low-ability workers dropping out by exerting little or no effort and high-ability workers overexerting themselves; this leads to the bifurcation of efforts described previously.

One interesting aspect of our experimental results is that, despite this bifurcation of effort, on average the prize structures proposed by M-S do elicit approximately the correct effort levels, and so, with respect to the mean, one could say that they work. Even more interesting is that, when we aggregate our data across laboratory work groups, efforts appear to be continuous; hence 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 this sense: We demonstrate that subjects with appropriately parameterized loss-averse utility functions exhibit behavior that nearly replicates the behavior we observe.

One might claim that our bifurcation result is of little consequence to a risk-neutral owner because, 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 may well exist a different incentive structure for the firm that could yield even better performance. Remember, the M-S mechanism is optimal only 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; in this case the long-run output falls.

Dropout 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. These subjects are dissuaded by the low probability of winning. In that paper, reviving their efforts takes the laboratory policy intervention of an affirmative action law. A similar finding is in Corns and Schotter (1999), where a price preference must be given to high-cost bidders in an asymmetric auction to induce them to compete for contracts. It is interesting that, by

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.

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 so their best response is to bid more aggressively.[2]

Dropping out is not part of the game's equilibrium in the M-S model, but in other models it may be. For example, in Benoit (1999), members of socioeconomically disadvantaged groups and members of other groups must 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, then members of the disadvantaged group might drop out by not investing (for a different setup see Amegashie 2004 and Amegashie, Cadsby, and Song 2007). Prendergast (1999) suggests that such dropout behavior can be seen in sports contests.[3] Using a field experiment (running races among elementary school students), Fershtman and Gneezy (in press) demonstrate that some students simply stop running and drop out when it is clear they have no chance of winning. In legal disputes (which can be interpreted as contests), if there are asymmetric budget constraints among the parties involved, then the party with the higher budget can hire a better lawyer and thereby increase its chances of winning. Realizing this, the other party might give up (drop out) immediately. Finally, dropping out has been observed in studies of multiple unit all-pay auctions (see Barut, Kovenock, and Noussair 2002).

In this paper we proceed as follows. In Section 2 we present the M-S model and its results and in Section 3 we describe our experimental design. Our results are presented in Section 4, where we demonstrate that bifurcation may result if subjects have utility functions that exhibit loss aversion. Finally, in Section 5 we 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 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

2. For an overview of such price preference and affirmative action programs in the United States 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 Tenorio (2000). He argues that the compensation scheme used in professional boxing—whereby a boxer's payment or purse for a given fight is entirely guaranteed—provides suboptimal incentives that may (and sometimes do) result in improper preparation for the fight and hence an increased likelihood of a poor showing.

prizes are $V_1 \geq V_2 \geq 0$ with $V_1 + V_2 = 1$. In the contest, players simultaneously exert effort x_i and so incur cost $c_i\gamma(x_i)$. The function $\gamma : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ 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 are i's 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 $[m, 1]$, where $m > 0$, 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, and 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 those bids whether or not they win. 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 problem is to maximize

$$V_1(1 - F(b^{-1}(x)))^{k-1} + V_2(k-1)F(b^{-1}(x))(1 - F(b^{-1}(x)))^{k-2} - c\gamma(x). \tag{1}$$

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., $F(c) = 2c - 1$ with $c \in [0.5, 1]$).

2.2. Predictions and Prescriptions

See M-S for a full derivation of the results in this section.

2.2.1. Linear cost functions. If all contestants have linear costs (i.e., if $\gamma(x) = x$), then one can show the optimal and symmetric effort function to be

$$b(c) = V_1 A(c) + V_2 B(c), \tag{2}$$

where

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

Turning to the designer's problem, let $V_2 = \alpha$ and $V_1 = 1 - \alpha$, where $0 \le \alpha \le 1/2$ such that the second prize is smaller than the first. A contestant's equilibrium effort is then given by

$$b(c) = (1 - \alpha)A(c) + \alpha B(c) = A(c) + \alpha(B(c) - A(c)).$$

Because each contestant's average effort is $\int_{0.5}^{1}(A(c)+\alpha(B(c)-A(c)))F'(c)\,dc$, the designer's problem reads

$$\max_{0\le\alpha\le 1/2} \quad 4\int_{0.5}^{1} \big(A(c) + \alpha\big(B(c) - A(c)\big)\big)F'(c)dc$$

or, equivalently,

$$\max_{0\le\alpha\le 1/2} \quad \alpha\int_{0.5}^{1} (B(c) - A(c))F'(c)\,dc. \tag{4}$$

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

2.2.2. Quadratic cost functions. If all contestants have quadratic costs (i.e., if $\gamma(x) = x^2$), then one can show that the optimal and symmetric effort function is

$$b(c) = \gamma^{-1}(V_1A(c) + V_2B(c)) = \sqrt{V_1A(c) + V_2B(c)}, \tag{5}$$

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

The designer's problem in this case reads

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

and it turns out that in this case it is optimal to award two equal prizes: $V_1 = V_2 = 0.5$. 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 when costs are convex. In the special case of quadratic costs, it simply turns out that awarding two equal prizes is optimal (see also M-S, p. 545f).

Hence, the prescriptions of the model are clear. When costs are linear, the optimal prize structure is one where the organization's entire prize budget goes to a single grand prize. When costs are quadratic, two equally valuable prizes define the optimal prize structure.

TABLE 1. Treatments.

Treatment	Description	No. of matching groups	No. of subjects	Period endowm.	Max. effort	No. of periods
LC-1	linear costs $V_1 = 1$, $V_2 = 0$	6	$6 \times 4 = 24$	0.22	1.96	50
LC-2	linear costs $V_1 = V_2 = 0.5$	6	$6 \times 4 = 24$	0.20	0.82	50
QC-1	quadratic costs $V_1 = 1$, $V_2 = 0$	5	$5 \times 4 = 20$	0.22	1.53	50
QC-2	quadratic costs $V_1 = V_2 = 0.5$	5	$5 \times 4 = 20$	0.20	0.99	50
CONTROL (variant of LC-1)	linear costs $V_1 = 1$, $V_2 = 0$	6	$6 \times 8 = 48$	0.22	None	50

3. Experimental Design and Procedures

In the experiments we rely on a classic 2×2 design. We implement contests with either linear or quadratic costs and combine them with two different compositions of prizes, one that is theoretically 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 ($V_1 = 1$ and $V_2 = 0$). As we have seen, 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 ($V_1 = 0.5$ and $V_2 = 0.5$). This prize composition is optimal from the designer's perspective if contestants have quadratic costs. In treatment LC-2, all contestants have linear costs yet the composition of prizes is the one that is optimal for the quadratic case. Finally, in treatment QC-1, all contestants have quadratic costs yet the composition of prizes is the one that is optimal for the linear case. A summary of our four treatments is given in Table 1.

The computerized experiments were conducted in the experimental laboratory of the Economics Department at New York University and the Center for Experimental Social Science.[4] In each session, fixed groups of four subjects were repeatedly matched to participate in a contest. Each of the experiments consisted of 50 periods. Payoffs were denominated 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 i.i.d. draw from the set of numbers $\{0.50, 0.51, \ldots, 1.00\}$. After subjects were informed about their individual random numbers, they simultaneously submitted "decision numbers." The set of admissible decision numbers was $\{0.01, 0.02, \ldots, \text{Maxeffort}\}$ where Maxeffort was a number 20% higher than the optimal effort of a contestant with ability

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

$c = 0.5$ (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.[5] 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 given a trial decision number, this calculator showed the costs associated with the subject's random number in the current period. We implemented the cost calculator to help avoid any 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 and all other players 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 and all other players received no additional payment. If two or more group members in a one-prize contest chose the highest decision number, then it was randomly decided which of these "tied" members received the prize of one point. For ties in a two-prize contest we proceeded in a similar fashion, which was explained in the instructions. It was also explained and emphasized that decision costs would be subtracted whether or not a subject had won. This implies that subjects could incur losses. To cover these, subjects received a lump-sum fee of $5. (Given the exchange rate of 15 points = $1 in each treatment, all subjects started with 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.[6] 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 who had not won a prize was informed about the random number of the winning subject. In two-prize contests, a subject who won a prize was informed about the random number of

5. We expected that no one would want to set a higher decision number and so assumed that this upper bound would not be binding on a subject. In fact, we were almost right because there were very few instances of subjects choosing the Maxeffort.

6. In equilibrium, expected costs equal $\int_{0.5}^{1} c(V_1 A(c) + V_2 B(c))\, dc$, where V_1 and V_2 depend on the treatment and $A(c)$ and $B(c)$ are given by equation (3). Note that expected costs in equilibrium do not depend on the form of the cost function.

the other winning subject, and subjects who did not win a prize were 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 10 of the 50 periods would be randomly selected to count toward monetary earnings. That is, subjects were paid according to the sum of their individual earnings in those ten random periods. Finally, in order to ensure that subjects had a good understanding of the decision problem and the procedures, we started each experiment with three trial periods that did not count toward monetary earnings.

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).

In an effort to test the robustness of our results and to show that they are not an artifact of the design features employed, we ran a final "control" treatment that 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.[7] Third, whereas losing subjects in the main LC-1 treatment were informed about the ability parameter of the winner, this information was not provided in the control treatment where the only information given 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." Finally, each subject participated in only one treatment.

4. Results

We first present the aggregate results, which (as noted in the Introduction) appear to strongly support the theory. We then disaggregate our results and examine them more closely. We shall demonstrate that the aggregate results mask the bifurcation phenomenon discussed previously.

7. 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.

4.1. Aggregate Results

There is a sense in which an organizational designer need care only about aggregate or average results. Because 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 then he need not worry about how these means are achieved.

In line with this way of thinking, we begin with the aggregate or mean results of our experiment, concentrating on effort behavior and revenue in the four treatments. We will present summary statistics for the first and second halves of the experiment. In our discussion of the results we will focus a bit more 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.

We will start our discussion by looking at the effort behavior of subjects at the aggregate level. Toward this end, consider Figure 1. The figure consists of 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 a scatter plot representing the mean of the actual efforts put forth for a given ability parameter.

There are several things to note about Figure 1. First, the average efforts seem to track the shape of the equilibrium effort function quite well. Second, effort behavior appears to be continuous in that, on average, there seem to be no 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 plot of mean efforts. For the other treatments there seems to be overexertion in LC-1 and LC-2 (independent of the time horizon considered) and slight underexertion in QC-1 (in the second half of the experiment).

This behavior manifests itself also in the average revenue data. 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 given their equilibrium efforts. (The column labeled "Sorting" is explained at the end of this section, and the table's bottom row contains results of the control treatment to be discussed in Section 4.3.)

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. Although 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

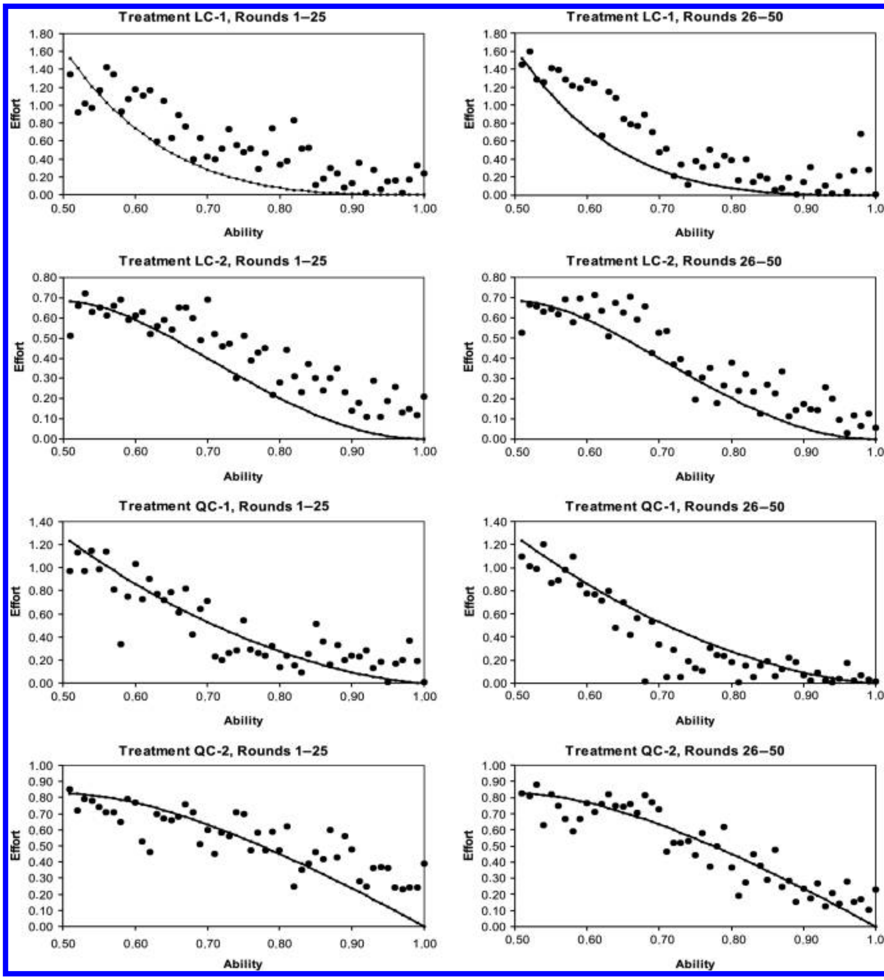

FIGURE 1. Average observed (•) and optimal (solid line) effort functions in the first and the second half of the experiment.

(1.452 vs. 1.164), in the QC-1 treatment they were below predictions 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[8] 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% level in treatments

8. Consider the variable y_{jt} where $y_{jt} = 0$ if 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 probability 0.5 that $y_{jt} = 1$.

TABLE 2. Observed revenue and sorting (standard deviations, based on group averages, in parentheses).

Treatment	Rounds	Average revenue: Optimal	Average revenue: Observed	Sorting
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**%)

LC-1, LC-2, and QC-1. For treatment QC-2, however, this hypothesis cannot be rejected at any conventional significance level ($p = 0.858$, two-tailed).[9]

Recall that theory predicts that in a linear-cost contest revenue is maximal if only one prize is awarded, whereas in our quadratic-cost contest, the designer maximizes total effort by awarding two equal prizes. Both of theses predictions are confirmed by our data. Concentrating on results in the second half of the experiment, we see in Table 2 that, whereas in treatment LC-1 the average observed revenue is 2.391, it is only 1.452 in treatment LC-2. Taking one matching group's average total effort as a single observation, a one-tailed Mann–Whitney U-test reveals that this difference is highly significant ($p = 0.001$). 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 ($p = 0.028$).[10]

9. 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).

10. The prediction that revenue in a linear-cost (respectively, quadratic-cost) contest is maximal if only one prize is (respectively, 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 ($p = 0.075$).

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 former 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), then 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 because 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. That is, in each round and each group of four contestants, we would observe that the subject with the highest ability exerts the highest effort, the subject with the second-highest ability exerts the second-highest effort, and so on. It is clear that, in an experimental setting, optimal sorting in this strict sense cannot be expected throughout the entire experiment. [11] Instead we simply ask: In how many cases did the contestant with the highest ability win a one-prize contest; and in how many cases were the contestants with the two highest abilities the winners in a two-prize contest? The results are displayed in the fifth column of Table 2 under "Sorting." The entry in each cell gives the number of cases in which sorting worked, the number of all cases, and the percentage (in parentheses). Looking at the results in the second half of the experiment, sorting in this weaker sense occurred in 57.3%, 46.7%, 61.6%, and 52.0% of the cases in treatment LC-1, LC-2, QC-1, and QC-2, respectively. Stated differently: In about 40% (50%) of the cases in the one-prize (two-prize) contests, contestants not having the highest abilities won the contests. Note, however, that in the majority of one-prize contests that did not exhibit strict sorting, the winner was the subject with the second-highest ability yet who exerted more effort than the highest-ability subject. Hence it is the "rat race" that is responsible for inefficiencies.[12] Note finally that, not surprisingly, the proportion of contests that do exhibit sorting is higher in one-prize contests than in two-prize contests.

In summary, we find (as predicted by the theory) that with linear costs a one-prize contest raises higher revenues than a two-prize contest and vice versa with quadratic costs. Furthermore, contests with linear costs seem to elicit excess efforts whereas those with quadratic costs elicit effort levels that are either too

11. In fact, optimal sorting in this strict sense is observed in only about 10% of all rounds in the second half of the experiment in the four different treatments.

12. There are, however, also cases in which contestants with the least or second-to-least ability won a contest.

low or approximately equal to the equilibrium efforts. Finally, we observe that in only 50%–60% of the cases (depending on the treatment) are the contests won by the subjects with the highest abilities.

4.2. Disaggregated Results

Looking at our data only as aggregated within treatments, as we have done so far, could give one the impression that the observed behavior was basically continuous and, on average, not far from that predicted by the theory. In this section we dispel any such impressions by presenting a more disaggregated analysis of the data. We will do this in several steps. First we present a small sample of individual effort functions to give a quick first impression of what typical effort behavior looks like. Although this is not an exhaustive presentation of all effort functions, the selected subjects are by no means outliers and so should give a good idea of what we are talking about. Second, we present a set of histograms—one for each of the four treatments—that portray the subjects' efforts. These histograms illustrate 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 ranges. In other words, subjects either dropped out or became workaholics. Finally, we perform a model-selection test by contrasting, individual by individual, the goodness of fit of the best-fitting stepwise linear effort function against the best-fitting continuous function of the form specified by the equilibrium theory. We argue that subject behavior can best be described by a step function characterized by an ability cutoff 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 the four treatments. Of course, not all individuals exerted effort in this manner, but in this section we claim that these effort functions are typical. We show, more precisely, that rather than being chosen in a smooth and continuous manner, effort is typically characterized by a discontinuous step function with a cutoff effort level of c_i^* for individual i. Although c_i^* varies among individuals and 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) by dropping out for all ability levels above it, and subject 5 in treatment QC-2 drops out for all $c_i^* \geq 0.80$ (rounds 26–50). Observe also that, when subjects exert positive effort, they often do so at levels far above those prescribed by the equilibrium effort function. These

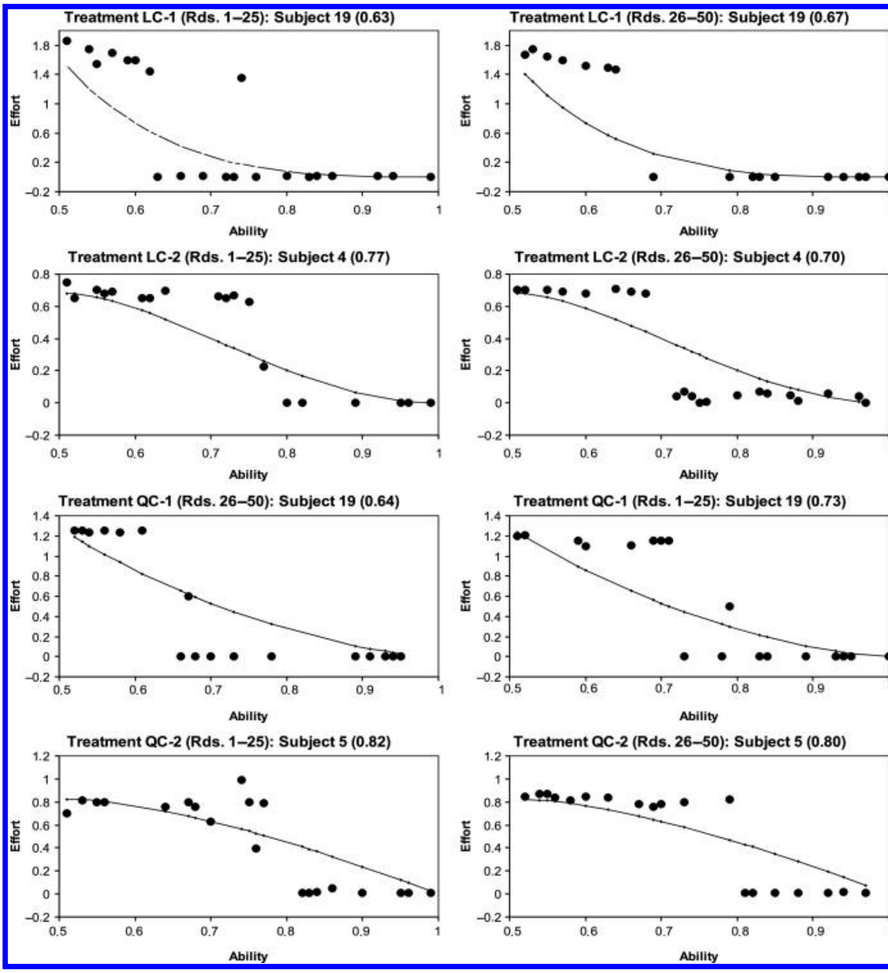

FIGURE 2. Examples of individual behavior (optimal, solid line; observed, •); cut-off levels c_i^* in parentheses (see Section 4.2.3).

under- and overexertions are precisely the bifurcations described in the Introduction. It is important to note 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 shows histograms of observed individual effort levels (right-hand side) in the 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

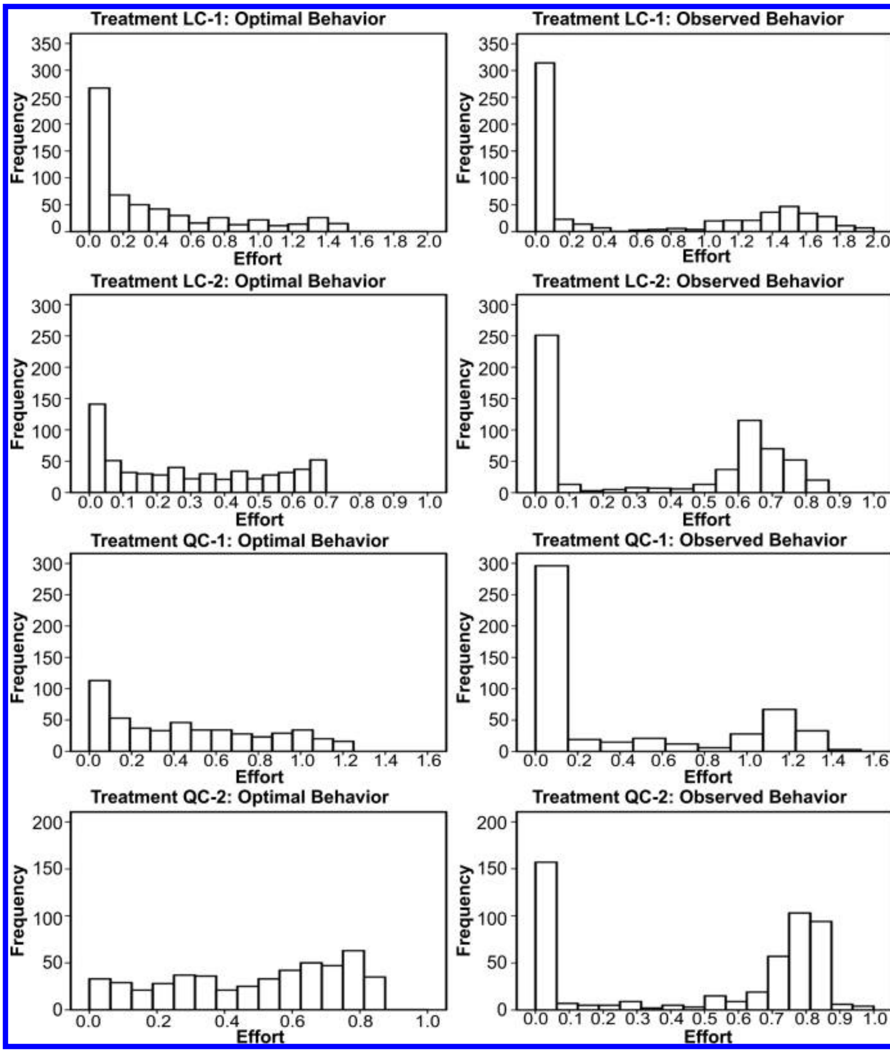

FIGURE 3. Histograms of individual effort choices in rounds 26–50.

choices (left-hand side). The results in Figure 3 are 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 shown in the left panel, if subjects had all used their equilibrium effort functions to select effort levels (given the ability realizations in the sessions), then we would expect to see a more or less uniform distribution of efforts. The right panel presents the actual observations, which are quite different. There is a clustering of efforts around the zero effort level, indicating a large amount of dropout behavior, and a large number of effort levels above 0.60, indicating efforts that were greater than expected. The same pattern exists in all of the other figures, with a more pronounced bifurcation in treatment QC-1 and QC-2.

From these histograms it should be clear that behavior in the 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 dropout or overexertion behavior, then we would expect that the best-fitting model of individual effort would be a step function characterized by a cutoff ability level, c_i^*, such that if a subject i's observed ability, c_i, were above c_i^* then the subject would drop out, exerting little or no effort; and if c_i were below c_i^* then the individual would exert positive and substantial effort. This model can be tested against the equilibrium model, which posits a continuous effort function of the form specified by equations (2) and (5), or against 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

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

where b_{it} (respectively, c_{it}) is subject i's effort (respectively, ability) in period t and where $D_{c_i^*}$ is a dummy equal to 1 if $c_{it} > c_i^*$ and equal to 0 otherwise. The parameter $c_i^* \in \{0.51, 0.52, \ldots, 1.00\}$ is the value of the ability at which the structural break in the subject's effort behavior occurs. Note that if $D_{c_i^*} = 0$ then equation (6) reads

$$b_{it} = \alpha_0 + \alpha_1 c_{it} + \varepsilon_{it},$$

but if $D_{c_i^*} = 1$ it reads

$$b_{it} = (\alpha_0 + \alpha_2) + (\alpha_1 + \alpha_3) c_{it} + \varepsilon_{it}.$$

Thus the graph of equation (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. If $-\alpha_2 \neq \alpha_3 c_i^*$ then the graph of equation (6) has a discontinuity at the point of structural break. The best-fitting breakpoint c_i^* and the respective coefficients in equation (6) were estimated from the data.

For this purpose, we estimated equation (6) for all possible points of structural break $c_i^* \in \{0.51, 0.52, \ldots, 1.00\}$ and each subject separately, and chose as the optimal breakpoint the one that maximizes the adjusted R^2. Using the corresponding estimates of the coefficients in equation (6) we then computed, for each subject i and for each period $t \in \{1, 2, \ldots, 50\}$, the predicted effort $(b_i^t)^{\text{pred}}$; we also computed, subject by subject, the sum of the squared deviation SSD_i, defined as

$$\text{SSD}_i = \sum_{t=1}^{25} \left((b_i^t)^{\text{pred}} - (b_i^t)^{\text{obs}}\right)^2,$$

where $(b_i^t)^{\text{obs}}$ is the observed effort of subject i in period t. (The SSD_i for the second half of the experiment were computed similarly.)

We compared the resulting SSD_i values of this estimation to two others. The first was the SSD_i generated using the predictions of the equilibrium effort functions as given in equations (2) and (5). Second, we compared our SSD_i 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, we used ordinary least squares (OLS) regression to estimate, for each subject in treatment LC-1, the model

$$b_{it} = \beta_0 + \beta_1 c_{it} + \beta_2 c_{it}^2 + \beta_3 \ln c_{it} + \varepsilon_{it}; \tag{7}$$

here, 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 equation (2) except that the coefficients are undetermined.) We did 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 use OLS regression for the estimation in these treatments, too, we proceed as follows. Consider for example treatment QC-1. Instead of estimating equation (5), we estimated the model

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

that is, the squared equation. 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 of the experiment. Columns (2) and (3) present the results of our switching regression model; columns (4) and (5) [(6) and (7)] present the results of our equilibrium (equilibrium-form) models.

Our simple switching regression model clearly outperforms the prediction of both the equilibrium and equilibrium-form models, regardless of the time horizon considered. In fact, using a Wilcoxon test to compare the individual SSD_i

TABLE 3. Overview of the sum of the square deviation (SSD).

	Average sum of squared deviations (SSD) based on						p-level	
	Switching regr. model rounds		Equilibrium rounds		"Equilibrium form" rounds		Wilcoxon test rounds	
Treatment (1)	1-25 (2)	26-50 (3)	1-25 (4)	26-50 (5)	1-25 (6)	26-50 (7)	1-25 (8)	26-50 (9)
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

values based on the switching regression model versus the "equilibrium form" regressions indicates that the former yields a much better fit than does the latter.

Table 4 shows the average cutoff 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 26–50 and note that the average cutoff points in the one-prize contests are lower than those 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 highly significant statistically (Mann–Whitney U-tests). This means that subjects in the one-prize contests exert serious effort only when their ability parameters, the c_i, are comparatively low. This implies that they exert low effort levels over a much larger interval of the domain of their effort function. Finally, note that the differences between cutoff levels within the two one-prize and the two two-prize contests are small and not significant.

Finally, having established that each subjects' behavior is best described by a simple (discontinuous) step function, one might ask whether this is consistent with the absence of behavior discontinuities in the average bidding functions for each treatment, as shown in Figure 1. The seeming inconsistency between individual effort functions (as shown in Figure 2) and the average effort functions

TABLE 4. Average cutoff levels (in parentheses) and two-tailed p-values of pairwise differences in the first and the second half of the experiment.

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

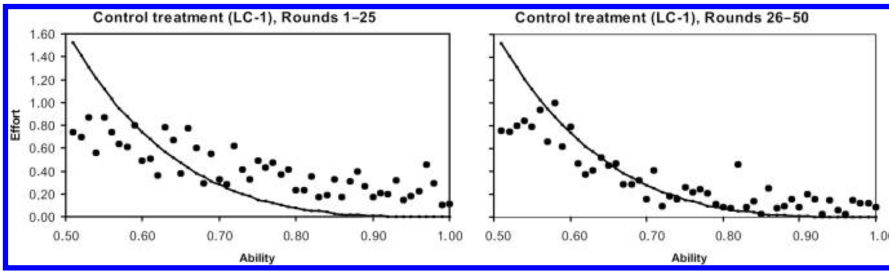

FIGURE 4. Average observed (•) and optimal (solid line) effort functions in the first and the second half of the control treatment.

(as shown in Figures 1 and 4) is resolved by the observation that, even though different subjects have different cutoff points, the aggregation of (discontinuous) individual effort functions leads to a 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 treatment is a variant of 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 only were informed about whether they had won a prize, 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. In the second half of the experiment (right panel) we observe that the average efforts again track the shape of the equilibrium effort function quite well except for very low levels of the ability parameter, where average observed efforts are lower than predicted. But again it seems fair to say that no clear discontinuity in behavior can be discerned in the average effort function.

The bottom row of Table 2 gives the mean revenue generated in each treatment along with the revenue associated with 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), the reverse holds in the second half (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% level ($p = 0.001$, rounds 1–25; $p = 0.086$, rounds 26–50; two-tailed). Table 2 also indicates that the control treatment does

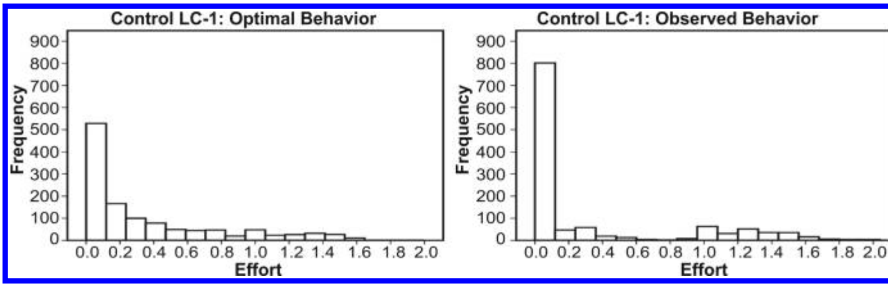

FIGURE 5. Histograms of individual effort choices in the control treatment (variant of LC-1) in rounds 26–50.

worse than the original treatment LC-1 in terms of selecting the worker with the highest ability: In only 41.3% of the cases (in the second half of the experiment) does the subject with the highest ability actually win the contest (vs. 57.3% in treatment LC-1).

Next, we review Figure 5, which depicts histograms of observed individual effort choices in the control treatment (right panel) along with a histogram of choices that would result from equilibrium behavior by subjects (left panel) in the second half of the experiment.[13] We see that there is again a large number of observed effort choices close or equal to 0, implying a high degree of dropout behavior.[14] Furthermore, with regard to observed behavior there are virtually no choices in the interval from 0.55 to 0.95, and yet there is a 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.[15] In any case, Figure 3 suggests that also the behavior in the control treatment is bimodal.

In order 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 values of the switching regression model are significantly lower than those of the equilibrium-form model. Finally, the average cutoff level for the switching regime in the control treatment is 0.70 (rounds 26–50) and is thus virtually the same as the level in the main treatment LC-1 (see Table 5, rounds 26–50).

13. There is one effort choice of 9 that is not shown in the histogram of observed behavior.

14. 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.

15. There are twice as many individual decisions in the control than in the LC-1 treatment (1,200 vs. 600, last 25 rounds) because there are twice as many subjects.

In summary, 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 between behavior in the control treatment and in 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 0 in the control treatment (see Figures 3 and 5).

4.4. A Theoretical Explanation for the Bifurcation Effect

One possible explanation for these bifurcation results is that subjects are loss averse. Intuitively, when a subject's cost of effort is high, chances are that the other competitors have a lower cost of effort and thus bid high. Then this subject might exert little or no effort for fear of losing the cost of effort. Conversely, if a subject's cost of effort is low then chances are that the other competitors have a higher cost of effort and thus bid low. Then this subject might exert very high effort for fear of not winning the prize.

The argument can be made formally. For this purpose, assume the standard loss-aversion function (see Kahneman and Tversky 1979):

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

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

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

where $\Pr(\text{Win}) = (1 - F(b^{-1}(x)))^{k-1}$ and $V_1 = 1$ is the prize (see Section 2.1). That is, with $\Pr(\text{Win})$ a contestant wins the contest, in which case his utility is $(V_1 - cx)^{\alpha}$. With the complementary probability the contestant loses the contest, in which case his utility is $-\lambda(cx)^{\alpha}$. The first-order condition 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 M-S) versus 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 (respectively, low), the optimal effort of loss-averse contestants is smaller (respectively, higher) than the optimal effort of risk-neutral contestants. Clearly, depending on parameter choices, we can show that the optimal effort of loss-averse contestants is essentially 0 when costs of effort are high

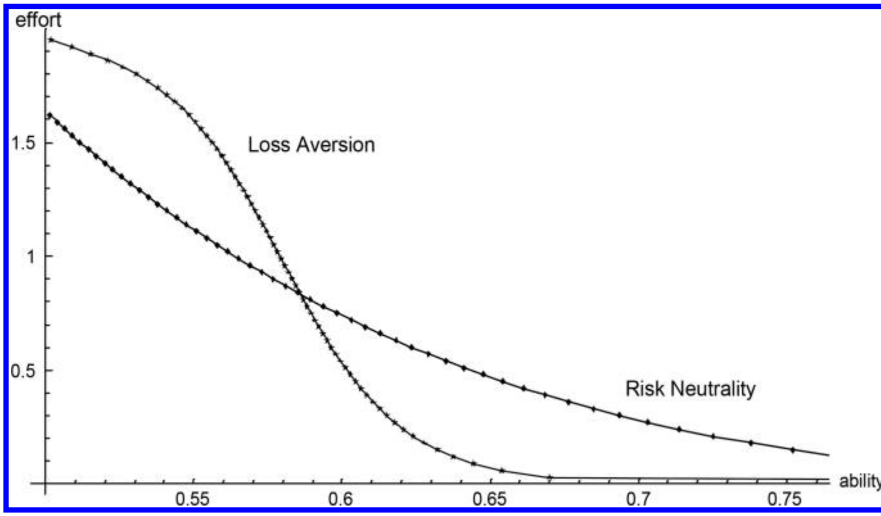

FIGURE 6. The equilibrium bidding function in treatment LC-1 for risk-neutral and loss-averse bidders ($\alpha = 0.3$, $\lambda = 1.25$).

and that this effort is much greater when costs of effort are low. That is, by assuming loss aversion we can generate the dropout and workaholic behavior we observe in our experiments.

5. Conclusions and Discussion

In this paper we have reported on 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 that are continuous in their cost of effort. Although this prediction appears to be supported in the aggregate, we have found that the underlying effort functions on the individual level are actually a set of discontinuous step functions whereby low-cost, high-ability workers exert higher than predicted levels of effort and workers with low-ability and high-cost drop out, exerting close to zero effort. We have attributed this result to the possibility that subjects behave in a loss-averse manner when faced with this mechanism. This should be of note for those interested in mechanism design, because it warns us that a successful mechanism must elicit behavior identical to that assumed by the designer in theory. The M-S mechanism was predicated on risk-neutral expected utility maximization, but it appears to have elicited loss-averse behavior instead. Hence, in the light of this observed behavior, the M-S mechanism may actually be not optimal.

Finally, our results have implications for the efficiency of organizations. More precisely, organizations that hope to sort and reward workers on the basis of their ability will likely expect that, on average, the most productive workers receive the organizational prizes and the lesser ones do not. Because workers usually differ with respect to their abilities and because 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 with the highest abilities. We observe, however, that only 50–60% of the cases in our experimental contests are won by highest-ability subjects. Despite this fact, if the worker with the highest ability fails to be rewarded then the one with the second-highest ability usually is. Hence the lack of strict ordering is not a gross mistake and is likely to occur when workers "tremble" when selecting their effort levels.

Appendix: 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 member." 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 $\{0.50, 0.51, \ldots, 1.00\}$. 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 $\{0.00, 0.01, 0.02, \ldots, 0.82\}$. 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 $0.42 = 0.7 \times 0.6$. If instead your random number was 0.9 and you chose a Decision Number of 0.7, your decision costs would be $0.63 = 0.7 \times 0.9$. 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 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:

$$\text{Payoff} = 100 \times (\text{Flat payment} + \text{Fixed payment}(0 \text{ or } 0.5) - \text{Decision Cost}).$$

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 $\{0.00, 0.01, 0.02, \ldots, 0.82\}$ but from the set $\{0, 1, 2, \ldots, 82\}$. 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).

Because 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 $100 \times (0.20 + 0.5 - 0.77 \times 0.33) = 44.59$ Points whereas group member 1's earnings in this round would be $100 \times (0.20 + 0.5 - 0.80 \times 0.21) = 53.2$ Points. Group members 2 and 3 each receive no additional payment. Therefore group member 2 would earn $100 \times (0.20 + 0 - 0.55 \times 0.17) = 10.65$ Points, and, finally, group member 3 would earn $100 \times (0.20 + 0 - 0.91 \times 0.05) = 15.45$ 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.

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