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Measuring Rank-based Utility in Contests: The Effect of Disclosure Schemes

Abstract

This paper studies how the incentive structures and disclosing schemes of a contest affect the contestants' intrinsic motivations. Specifically, we measure the effects of these design decisions on two types of non-monetary rank-based utility: self-generated and peer-induced. We run a set of laboratory experiments involving contests under various reward spreads and disclosure schemes. We find that virtually all commonly adopted disclosure schemes generate positive peer-induced rank-based utility. However, the relative performances of alternative disclosure schemes can depend on the spread of contest rewards and the number of contestants. Second, being recognized as a winner confers positive peer-induced rank-based utility; moreover, being recognized as the sole first-place winner or as one among multiple winners does not produce significantly different peer-induced utility. Third, 'shaming' by disclosing the identity of contestants ranked at the bottom leads to negative peer-induced rank-based utility, but the effect is marginally insignificant. Finally, a smaller spread of contest rewards consistently results in higher levels of self-generated rank-based utility. These results underscore the importance of jointly choosing incentive structures and disclosure schemes.

Key words: Rank-based utility, Recognition, Sales contests, Lab experiments

INTRODUCTION

A sales contest is a competitive form of incentive compensation that firms use to motivate, recognize, and reward top performers and to better align the incentives of principals and agents (see Mantrala et al. 2010 for a review). Sales contest details can vary widely, including contest length (anywhere from one hour to one year, depending on the selling context), the metrics by which success is measured (e.g. total sales, customer meetings scheduled, sales calls completed, etc.), and the nature of the contest prizes (e.g. cash, gift cards, travel rewards, etc.). Among the important decisions for a contest designer, reward structure concerns the allocation of prizes between winners and the format of disclosure involves how the outcome of a contest is announced to the participants. The existing literature on contests focuses on the design of reward structure, e.g. winner-take-all versus multiple winners (See Krishna and Morgan 1998 and Kalra and Shi 2001 for analytical research, and Lim et al. 2009 and Orrison et al. 2004 for experimental studies), but typically does not study the effects of disclosure schemes. In practice, according to Zoltners et al. (2011), there is strong disagreement among sales leaders about the best strategy for public disclosure (or non-disclosure) of sales performance results.

This paper investigates the motivating effect of disclosure schemes on contestants. Using a set of laboratory experiments, we measure rank-based utility parameters across contests that vary in both reward structure and disclosure scheme. Rank-based utility represents non-monetary utility that a contestant derives from achieving a particular rank in a contest.[1] It is motivating if a contestant expends additional effort to increase (decrease) the chance of enjoying positive (negative) rank-based utility. We further distinguish between two types of rank-based utility: self-generated and peer-induced. Self-generated rank-based utility is generated by the knowledge

[1] Barankay (2012) refers to rank-based utility with similar terms like rank incentives and rank rewards. We use rank-based utility and rank utility interchangeably.

of one's own achievement and contest rank or status (e.g. as a winner or loser). In contrast, peer-induced rank-based utility results from public recognition of one's contest rank or status. In our model and experimental analysis, self-generated rank-based utility can be influenced by the design of the contest reward structure. On the other hand, peer-induced rank-based utility depends on the disclosure scheme, which affects the information available to a contestant's peers, in addition to varying with the reward structure. The emphasis of this paper is consistent with (but distinct from) the recent theoretical and experimental literature on non-monetary motivations in contests (e.g., Bandiera et al. 2005, Lim 2010, Yang et al. 2013).

In our experiments, 336 subjects chose their levels of effort in simulated 4- or 6-person sales contests, with rewards for the top half of finishers in each contest. A session consists of 40 or 50 independently run periods with subjects, acting as salespeople, randomly matched in each period. In each period, each subject is endowed with the same number of points, any portion of which they can choose to spend as "selling effort," keeping the rest as income. Each subject's "sales revenue" is then determined stochastically based on the effort she invests, and the top half of subjects by revenue earn rewards. The total reward value (in points) is the same for all conditions (for a given number of contestants). However, in the "high reward spread" (*HRS*) condition, the top finisher receives a much larger prize than the other winner(s), while in the "low reward spread" (*LRS*) condition, the prizes are nearly equal.

Given our focus on the effects of disclosure, we expose participants across different sessions to different forms of public disclosure of contest outcomes. These are modelled after different forms of recognition commonly used by sales organizations. We consider five disclosure schemes: a *no disclosure* scheme (*ND*), in which the outcome of the contest is never announced publicly, providing a benchmark; a *winner disclosure* scheme (*WD*), in which only the top finisher is announced (e.g. an "Employee of the Month" or "Salesperson of the Year" program); a *partial disclosure* scheme (*PD*), in which all the winners are announced, but the relative ranking between them is not disclosed (e.g. a "President's Club" program); a *winner rank disclosure* (*WRD*) scheme, in which not only are the winners announced, but their rankings are also revealed (e.g. a tiered "President's Club" with Platinum, Gold, and Silver winners); and a *full disclosure* scheme (*FD*), in which both the winners (with ranks) and the losers (without ranks) are announced (e.g. a "Wall of Fame and Shame"). Under all five schemes, each contestant is informed identically of her own outcome (e.g., 1st place, 2nd place, or non-winner in 4-player contests), so the different conditions vary only in how much one's *peers* know about her rank.

Results from the lab experiments show that, in general, some sort of public disclosure of contest outcomes increases effort choice over having no public disclosure. The efforts of the participating agents are clearly influenced by rank utility—in particular, those related to recognition among peers. Furthermore, contestants' effort levels depend on both the reward spread and the disclosure scheme of a contest. For example, when the reward spread is low, the mean effort level is (weakly) highest under *partial disclosure*. On the other hand, the mean effort level is (weakly) higher under *full disclosure* than all other disclosure schemes when the reward spread is high.

To infer rank-based utility from the selling efforts observed in the experiments, we develop a contest model that incorporates both self-generated and peer-induced rank-based utilities and derive each contestant's equilibrium selling efforts. Our estimation results show that virtually all disclosure schemes we test generate positive peer-induced rank utility. Moreover, being recognized as the sole first-place winner under the *winner disclosure* scheme generates rank utility not significantly different from being recognized as one among multiple (unranked) winners under *partial disclosure*. This result appears surprising, as one might expect higher rank-based utility from being recognized as the sole winner. But the result is indeed consistent with the common adoption of President's Club-style recognition programs in practice. Furthermore, shaming contestants by disclosing the identities of those ranked at the bottom leads to a negative net effect on peer-induced rank utility, but this effect is statistically significant only at levels slightly higher than 10%. Thus, shaming contestants to motivate them to work harder may not be very effective. Finally, a low contest reward spread results in higher levels of self-generated rank-based utility than does a high reward spread. This implies that reward structure can affect contestants' behavior not only through economic incentives, but also by generating different levels of rank-based utility.

Relation to the Literature

This paper contributes to several streams of research. First, it contributes to the sales management literature, by demonstrating not only the significance of rank-based non-monetary utilities, but also how they are affected by commonly-adopted sales management practices. The existing sales management literature mainly focuses on the design of economic incentives. For example, Basu et al. (1985) derive the optimal compensation plan and examine how the shape of such a plan depends on salespeople's characteristics (e.g., risk preference) and product-market characteristics (e.g., sales uncertainty). Extensions to this compensation plan have been investigated in consideration of sales quotas (e.g., Mantrala et al. 1994), customer satisfaction (e.g., Hauser et al. 1994), over-selling (e.g., Kalra et al. 2003), territory allocation (e.g., Caldieraro and Coughlan 2009), and haggling (Desai and Purohit 2004). By abstracting away from non-monetary utilities, these studies implicitly assume an independent relationship between economic and non-monetary utilities, allowing them to focus solely on economic incentives when comparing alternative types of incentive schemes. This paper, along with related research on non-monetary utilities in sales management (e.g., Lim 2010, Chen et al. 2011, Yang et al. 2013), suggests that future research may consider relaxing such independence assumptions.

It is worth mentioning that our disclosure manipulation differs from the manipulation of social pressure in Lim (2010) in a few important ways. Lim (2010) controls the strength of social comparisons directly, both by the selection of participant groups with varying degrees of familiarity and by the experimental procedure. By holding the proportion of winners constant at 50%, we control for the social comparison effect. Our use of varying disclosure schemes, on the other hand, is not a direct manipulation of a particular psychological variable, but rather a representation of a choice made by contest designers, as we examine how rank-based utility can be affected by contest design choices beyond prize structure. Another key difference is that there is no obvious ordinality within our disclosure conditions. It is not intuitively clear, for example, whether full disclosure should be expected to produce greater rank-based utility (and effort) than partial disclosure. Our method of measuring parameters related to rank-based utility and our experimental design allow us to contribute insights on psychological motivation in principal-agent problems.

Second, this paper conducts an empirical study of sales contests and contributes new insights to the contest literature. Existing research has investigated the optimal design of sales contests (e.g., Lazear and Rosen 1981, Nalebuff and Stiglitz 1983) and the impact of sales contests on customer value (Garrett and Gopalakrishna 2010). Our model, with rank-based utility directly incorporated, is a more general version of the privilege contest model presented in Schroyen and Treich (2013). A well-known theoretical result on the design of reward structures is that a rank-order contest should provide a smaller spread between rewards when the agents are more risk-averse (Krishna and Morgan, 1998, Kalra and Shi 2001, Lim et al. 2009). Our analysis, along with a number of others, suggests that the increase in effort choice from offering rewards that are closer to each other may not be attributable to risk aversion alone. In our model, an increase in self-generated rank-based utility may also make a contest with a smaller reward spread more effective in inducing effort from contestants. This finding can also be connected to inequity aversion, as suggested by Fehr and Schmidt (1999). There have also been a number of papers that analyze the impact of information provided to players in a contest setting. For instance, Hyndman et al. (2012) explore the impact of disclosing the winning bid on bidder regret and bidding behavior in an all pay auction. In Barankay (2012), salespeople are privately informed of their own ranking in a bonus program based on their absolute performance. In contrast, our paper focuses on varying the level of publicly available information. In a recent paper, Ashraf (2018) compares the performance of garment-factory workers in Bangladesh under two disclosure schemes that are similar to our *ND* and *FD* schemes and finds that performance is better under *ND*.

Third, this paper contributes to the research on interdependence between psychological and economic motivations, an area that has attracted growing interest in the economics and marketing literatures. Research has shown that changes in economic incentives can alter non-economic motivations. With the presence of monetary incentives, the perceived nature of a task can change. For example, the task can cease to be fun or to reflect self-image, or it can lose its association with social norms (Kreps 1997). In some cases, adding monetary incentives can even crowd out intrinsic motivations to exert effort, especially when it involves other-regarding behavior. For a survey of the literature on the impact of incentives in modifying agent behavior, see Gneezy et al. (2011). Also, see Kamenica (2012) for a detailed review of the literature on the psychology of incentives. We contribute to this literature by providing fresh evidence that contest rewards and disclosure schemes can jointly affect rank-based utility.

Finally, this paper contributes to the behavioral and experimental economics literature by proposing a modification to the agent's decision model. For example, in the marketing literature, Amaldoss and Jain (2005) study the effect of social comparisons in luxury goods markets, Cui et al. (2007) investigate the impact of fairness concerns in channel management, and Lim (2010) examines the effect of loss aversion in sales contests. In this paper, the proposed modification allows us to quantify the extent of a behavioral change due to changes in rank-based utility.

The rest of the paper proceeds as follows. We first describe the experiments. Then we explain and analyze a model consistent with the contests conducted in the experiments and propose hypotheses on rank-based utility parameters. Next, we present the results. Finally, we conclude by discussing the managerial implications.

EXPERIMENTAL DESIGN

In this section, we describe the design of a set of laboratory experiments in which contestants made effort choices in simulated sales contests. We chose the context of sales contests because of its well-established analytical framework and its practical relevance to the disclosure schemes of interest. We designed and conducted the experiments to observe and analyze how incentive structures and disclosure of contest outcomes may jointly affect contestants' effort choices.

The experiments involved contests with four and six players, in which the top half of contestants (two or three players) earned prizes and the other half did not. Both 4- and 6-player contests were played under two different reward structures. The total prize payout and the number of players receiving a prize were the same between the two structures (for a given contest size), but the difference between the prizes varied. In *high reward spread* (*HRS*) contests, the size of the first prize was ninety percent of the total payout. In *low reward spread* (*LRS*) contests, the prizes were virtually equal in size. These were chosen not only to emphasize the difference between the high and low spreads, but also to represent situations that are managerially relevant. The high spread reflects cases in which there is one "true" winner, with the runner(s)-up receiving little more than recognition. The low spread reflects cases in which multiple winners receive essentially the same reward, as is commonly the case with non-cash prizes such as President's Club trips. Lastly, to investigate the impact of different announcements of contest outcomes, we used five different disclosure schemes, as described below. While a given subject experienced both *HRS* and *LRS* reward structures, she experienced only one disclosure scheme. Contest size and disclosure scheme were held constant across all periods within a given session, but varied between sessions.

We ran 24 sessions in total—16 for 4-player contests and 8 for 6-player contests. Each 4-player contest session involved 12 subjects, while each 6-player session involved 18 subjects. Each subject participated in only one session and there were 336 subjects in total, all of whom were Canadian university students. The experiments were programmed and conducted using the software *z*-Tree, developed by Fischbacher (2007). The 4-player and 6-player contest sessions consisted of 40 and 50 contest periods, respectively. In each period, the subjects were randomly assigned into three groups consisting of 4 or 6 players (according to the specified size for the session). Thus, subjects played with a different set of competitors in each period and did not know which other subjects they were playing with when they made their effort decisions for a period. Hence, subjects had no opportunity to learn or adjust to each other's choices and each period can be considered a one-shot contest game.

To present the game in a relatable context, the subjects were asked to act as salespeople participating in a contest to generate revenue. The contest required each salesperson to choose their level of effort to sell an industrial product named "Product Beta." The subjects were ranked within their groups based on the revenue they generated, and earned rewards based on their ranks. In each period, a subject was endowed with 100 points. She could use these points as effort to generate 'sales revenue', keeping the remainder as income.[2] Suppose she used $e \in \{1,2,\ldots,99\}$ points as effort to generate sales. She would then keep $100 - e$ points as income from that period and generate $s(e) = 350 + ln(e) + \epsilon$ units of revenue, where ϵ was drawn from a logistic distribution with mean zero and variance $\pi^2/3$. For each subject, a new random term ϵ was independently drawn in each period.

In a given period, subjects chose their efforts simultaneously, without knowing the identities of the other players in their group. From their chosen effort and their draw of the random term, each subject's revenue for the period was calculated and subjects were ranked according to their generated revenue, from highest to lowest. A player who was ranked j received a reward of R_j points. In a contest with N players, we chose $R_j > 0$ with $R_j > R_{j+1}$ for $j \leq \frac{N}{2}$ and $R_j = 0$ for $j > \frac{N}{2}$.[3] A subject's income from a period in which she used e points as effort was

[2] Using points as a measure of effort makes it easy to communicate in the experiments and follows a conventional approach in the experimental economics literature, in which the effort decision is often treated as a number (or money) that is either convex in cost and linear in value (e.g. Lim 2010) or linear in cost and concave in value as in our model. The advantage of this approach is simplicity in procedure and relative homogeneity among the experiment participants, which also eliminates potential concerns such as over or under-confidence. As suggested by an anonymous reviewer, an alternative procedure in which subjects put in real physical effort on a tedious task would be closer to a real sales context and could be used in future lab experiments to represent selling efforts.

[3] Kalra and Shi (2001) show that the optimal number of winners in a sales contest should not exceed half the number of participants (unless necessary to induce participation, which is not a consideration in this experiment).

$100 - e + r$ points, where r represents her reward. As the effort cost directly enters the payoff function through a reduction in points, the effort cost could also be considered a monetary cost.[4]

There are some design differences between 4- and 6-player contests. In the rest of this section, we will describe 4-player contest design as we will present results from 4-player contests first. We will discuss the motivation for running 6-player contests and the design differences later in the paper when we present those results.

The reward scheme was varied within each session. Half of the periods were *HRS* contests and the other half were *LRS* contests. For 4-player contests, we chose R_1=360 and R_2=40 for *HRS* and R_1=204 and R_2=196 for *LRS*, with R_3 and R_4 equal to 0 for both. To control for any order effect, the *HRS* contests came first in half of the sessions under each disclosure scheme and last in the other half. In a given period within a session, all subjects faced the same reward structure.

At the beginning of each session, each subject was assigned a unique username, which remained unchanged throughout the session. This username was of the form "Salesperson *X*" where *X* represents a letter from the English alphabet or a number that identified the computer terminal where the subject was seated. Subjects were identified and known to other players by these usernames.[5]

After each period, the results of the contest were announced to the contestants according to one of five disclosure schemes. Under all disclosure schemes, each contestant learned at the

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[4] As is common in the sales contest literature, we abstract away from other factors, such as heterogeneity in productivity among salespeople and non-contest incentive compensation (such as sales commissions). This allows us to isolate and focus on the effects of contest design that are of primary interest.

[5] Subjects may not have identified with their assigned usernames very strongly and recognition itself did not provide any possible monetary benefit, even in the long run. As a result, our recognition manipulation is rather weak. Thus, if non-monetary utilities vary across disclosure schemes in our laboratory setting, it would suggest a stronger impact of public recognition in a practical setting.

end of the period which reward (if any) they won. Given our incentive schemes, the size of the reward would inform the subject of her rank if she finished in the top half, and only the fact that she was in the bottom half otherwise. Under *no disclosure*, no further information was revealed. This provides us with a benchmark, as *no disclosure* best represents a standard one-shot contest game as typically modeled. Under *winner disclosure*, contestants also learned the identity of the winner of the first prize. Under *partial disclosure*, they learned the identities of all prize winners, but not specifically who won which prize. Under *full disclosure*, they learned the identities and ranks of the reward winners and the identities (but not the ranks) of the remaining contestants who did not win rewards.[6]

Next, the subjects completed a survey in which they reported some information about themselves, including their major, year of study, and experience with laboratory experiments. They also answered some questions about their playing strategy during the session. At the end of the survey, one contest from each reward spread was randomly chosen to determine the earnings of each subject in the session. We omitted the first five periods under each reward scheme from this selection, so that subjects could use those as practice periods. Each subject was presented with a detailed instruction sheet, which included diagrams illustrating the logistic distribution and the logarithmic functions. The instructions were also verbally communicated to subjects. A sample of the relevant parts of the instructions is presented in the Appendix.

THEORETICAL MODEL

In this section, we provide a theoretical model of contests in which agents' effort choices can be affected by their rank-based non-monetary utilities, in addition to the economic incentives provided by the contest rewards. We do not focus on the intricacies of optimal contest design,

[6] We also elicited subjects' CRRA risk-preference coefficient after the sales contest using the Becker-DeGroot-Marschak (1964) mechanism. We ultimately do not use this measurement in our empirical analysis.

such as the relative efficiency of contests over other schemes (Lazear and Rosen 1981, Nalebuff and Stiglitz 1983) or the optimal prize structure (Kalra and Shi 2001). Rather, the purpose of the model is to incorporate and identify the impact (positive or negative) of rank-based utility on effort choice in a simple competitive setting. We apply this model to analyze salespeople's behavior in a sales contest based on our experimental design, incorporating the psychological effects of the contest's disclosure scheme and reward structure. Our equilibrium analysis provides a closed-form solution that links chosen effort to these effects. We start with a general model of *N*-person contests, followed by specific predictions for the different reward and disclosure schemes used in our experiments. Since this paper's main focus is on empirical investigation of the experimental data, the theoretical model and analysis only serve to facilitate the empirical analysis. The proposed model structure and equilibrium results allow us to identify rank-based utility parameters of interest. The theoretical model is an as-if model for our experimental setting, adapted from the contest model widely accepted in the literature.

General Model and Analysis

Consider a contest with N agents (denoted by $i = 1,2 \dots, N$), in which the ranking of the agents in the contest depends on the output they produce. Agent i exerts effort $e_i > 0$, which results in an output of $s(e_i) + \epsilon_i$. The production function s is commonly known, identical for all N agents, and is increasing and non-convex in e_i. Following our experiments, we assume that $s(e) = K + ln(e)$ for some positive constant K and the idiosyncratic random variable ϵ_i is drawn from a logistic distribution function with mean 0 and variance parameter 1.[7] The agents

[7] The logistic distribution is a good representative of bell-shaped distributions that is frequently used in the literature. Like the commonly-assumed normal distribution, the logistic distribution is symmetric and displays a

are compensated using a rank-order contest characterized by the reward structure $R = \{R_1, \ldots, R_N\}$ where R_j is the prize awarded to the agent producing the j^{th}-highest level of output. Suppose the principal adopts a disclosure scheme, denoted by D, which reveals the contest outcome to the contestants in a specific fashion. Thus, a contest is characterized by (R, D). For an agent who has an initial wealth level of w_i, expends effort e_i and earns a reward of r, the net utility from the contest is denoted by $U(w_i, r, e_i|R, D)$ where U is increasing in w_i and r and is decreasing in e_i. The utility function U may reflect both economic and non-economic utility from the contest.

The agent i will choose e_i to maximize her expected utility, given by:

$$\sum_{j=1}^{N} Pr_j\,(e_i, e_{-i})U\big(w_i, R_j, e_i\,\big|R, D\big) \tag{1}$$

where $Pr_j(e_i, e_{-i})$ denotes the probability that agent i attains rank j when she expends effort e_i and the efforts of the other agents are represented by the vector e_{-i}. If agent i chooses effort e_i^*, then:

$$e_i^* = \underset{e_i}{\operatorname{argmax}} \sum_{j=1}^{N} Pr_j\,(e_i, e_{-i})U\big(w_i, R_j, e_i\,\big|R, D\big). \tag{2}$$

We restrict attention to symmetric equilibria, in which each agent expends the same amount of effort ($e_k = e^*$, $\forall k$). Limiting attention to symmetric equilibria is common in the contest literature, including both experimental studies (e.g., Bull et al 1987, Lim 2010, and

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central tendency in density. The density function with mean 0 and variance parameter 1 is $f(\epsilon) = \frac{exp(-\epsilon)}{\left(1+exp(-\epsilon)\right)^2}$ with variance $\pi^2/_3$.

Orrison et al 2004) and analytical studies (e.g., Kalra and Shi 2001).[8] The first-order condition for the equilibrium effort is given by:

$$\sum_{j=1}^{N}\left(Pr_j(e_i,e_{-i}^{*})\frac{\partial U\left(w_i,R_j,e_i\,\middle|R,D\right)}{\partial e_i}+\frac{\partial Pr_j(e_i,e^{*})}{\partial e_i}U\left(w_i,R_j,e_i\,\middle|R,D\right)\right)\Bigg|_{e_i=e^{*}}=0. \qquad (3)$$

Within the bracket, the first term represents the marginal loss in utility due to an increase in effort e_i, and the second term represents the marginal increase in utility due to an increased chance of winning a reward due to that incremental effort. The second-order condition to ensure that e^* maximizes the expected utility is standard. The solution e^* represents the unique symmetric equilibrium of this contest.

Recall that, in our experiment, a subject is endowed with *w*=100 points in every period, from which she expends effort *e* in the contest. Thus, she keeps an income of *w* – *e* after expending effort. If she achieves rank *j*, earning the reward R_j, her net income from the round is $w - e + R_j$. Suppose she gains additional psychological utility from achieving rank *j* in contest (*R*, *D*). Specifically, we assume that the source of such utility can be twofold—arising from a sense of one's own achievement of a rank (denoted by o_j^R, with "*o*" indicating "own" or "self-generated") and from public disclosure of the rank (denoted by $p_j^{R,D}$, with "*p*" indicating "peer-induced"). These rank-based utility parameters can be positive or negative. For a given reward scheme *R*, rank utility derived from own achievement is independent of the disclosure scheme *D*, as a contestant's knowledge of her own performance in the contest is the same across all

[8] This paper studies symmetric contests and limits attention to symmetric equilibria. Although a continuum of asymmetric equilibria exist in a symmetric setting (Baye et al. 1996), such equilibria exist only in mixed strategies. Providing testable predictions based on asymmetric equilibria requires equilibrium selection and dramatically complicates the empirical analysis. Moreover, these equilibria will provide zero expected payoff for contestants, something we do not observe in our experiments. In a different setting, in which a contest is asymmetric because some contestants enjoy advantages, the contestants can have different rank-based utilities. For instance, the underdogs may enjoy a disproportionate thrill of winning (Chen et al. 2011, Yang et al. 2013).

disclosure schemes in our experiment. How much her peers (other contestants) know about her performance, however, varies across disclosure schemes, by design. Hence, peer-induced rank utility parameters depend on both *R* and *D*. Our model extends the existing literature on psychological values in contests, which typically limits the attention to two ranks of psychological value—winning and losing (Kräkel 2008, Yang et al 2013, Lim 2010, and Chen et al 2011). Both Kräkel (2008) and Yang et al (2013) consider a contest with two contestants and one winner. Since a player knows both her own and the other player's ranks, one cannot separate psychological utility a player receives by knowing her own rank and by knowing that other contestants know her rank in that setting. In our experiments, we offer richer informational settings to identify psychological values of a greater number ranks under different disclosure schemes.

To simplify, we assume that a contestant's utility is additively separable in monetary payoffs and non-monetary rank-based utility.[9] The overall utility specification is:

$$U\left(w, R_j, e \,\middle|\, R, D\right) = w - e + R_j + o_j^R + p_j^{R,D}. \tag{4}$$

This formulation allows us to solve for optimal effort choice. Our analytical method follows Kalra and Shi (2001). Given the assumptions on $s(e)$, the distribution of ϵ, incentive plan *R*, disclosure scheme *D*, and initial endowment *w*=100, the equilibrium effort level e^* can be determined by the following equation: $\sum_{j=1}^{N}\left(\left(100 - e^* + R_j + o_j^R + p_j^{R,D}\right)\frac{N+1-2j}{N(N+1)e^*} - \frac{1}{N}\right) = 0.$

This implies that

$$\frac{1}{N(N+1)e^*}\sum_{j=1}^{N}\left(100 - e^* + R_j + o_j^R + p_j^{R,D}\right)(N+1-2j) = 1$$

[9] This model can be thought of as a more general version of the privilege contest model in Schroyen and Treich (2013).

$$\Rightarrow N(N+1)e^* = (100 - e^*)\sum_{j=1}^{N}(N+1-2j) + \sum_{j=1}^{N}\left(R_j + o_j^R + p_j^{R,D}\right)(N+1-2j)$$

$$\Rightarrow e^* = \frac{\sum_{j=1}^{N}\left(R_j + o_j^R + p_j^{R,D}\right)(N+1-2j)}{N(N+1)}. \tag{5}$$

Further Simplification

In our experiments, only the contestants ranked in the top half received a monetary reward. Contestants in the bottom half received no reward and their relative rankings were not known to any contestants (including themselves) under any disclosure scheme. Thus, relative performance of all contestants who were ranked in the bottom half of a contest were indistinguishable from any contestant's perspective. Therefore, we assume that all players ranked in the bottom half receive the same rank-based utility. That is, $o_j^R = o_l^R$ and $p_j^{R,D} = p_l^{R,D}$ for any $j, l > \frac{N}{2}$, for any *R* and *D*.

Peer-induced rank-based utility parameters ($p_j^{R,D}$) depend on both the reward structure and the disclosure scheme. Specifically, this utility arises solely from other competitors' awareness of a player's contest outcome. Players are randomly assigned to a group in every period and contestants do not know the identities of their competitors in any given period, unless they are revealed according to the disclosure scheme. In other words, if a disclosure scheme does not disclose the identity of a particular contestant, then her competitors are not aware of her having been part of the same group. In that case, we normalize her peer-induced rank utility to zero. Thus, under the *no disclosure* scheme, $p_j^{R,ND} = 0$ for all *j*. Under the *winner disclosure* scheme, only the top-ranked contestant is publicly recognized and can derive peer-induced rank utility. Under the *partial disclosure* scheme, the identities of the reward winners (the top half of contestants) are publicly announced, creating utility from public recognition of their performance. However, their rankings are not disclosed, so the winners receive the same peer-induced rank-based utility, while non-winners (those ranked in the bottom half) receive none. Finally, under the *full disclosure* scheme, the identities of all contestants are publicly announced, clearly denoting the ranks of the reward winners and listing the non-winners (without their ranks). As a result, peer-induced utility can be non-zero for all ranks.

We summarize the above assumptions below:

Assumption 1: Rank-based utility parameters (o_j^R and $p_j^{R,D}$) have the following properties:

1) Under all reward and disclosure schemes, $o_j^R = o_l^R$ and $p_j^{R,D} = p_l^{R,D}$ for all $j, l > \frac{N}{2}$.
2) Under *no disclosure*, $p_j^{R,ND} = 0$ for all j.
3) Under *winner disclosure*, $p_j^{R,WD} = 0$ for all $j \neq 1$.
4) Under *partial disclosure*, $p_j^{R,PD} = p_l^{R,PD}$ for all $j, l \leq \frac{N}{2}$ and $p_j^{R,PD} = 0$ for all $j > \frac{N}{2}$.

Based on Assumption 1, we can simplify the optimal effort choice for some disclosure schemes. Specifically,

$$e^{R,ND} = \frac{\sum_{j=1}^{N/2}(N+1-2j)R_j+\sum_{j=1}^{N}(N+1-2j)o_j^R}{N(N+1)}, \tag{6}$$

$$e^{R,WD} = \frac{\sum_{j=1}^{N/2}(N+1-2j)R_j+(N-1)p_1^{R,WD}+\sum_{j=1}^{N}(N+1-2j)o_j^R}{N(N+1)}, \tag{7}$$

$$e^{R,PD} = \frac{\sum_{j=1}^{N/2}(N+1-2j)\left(R_j+p_1^{R,PD}\right)+\sum_{j=1}^{N}(N+1-2j)o_j^R}{N(N+1)}, \tag{8}$$

$$e^{R,FD} = \frac{\sum_{j=1}^{N/2}(N+1-2j)R_j+\sum_{j=1}^{N}(N+1-2j)\left(o_j^R+p_j^{R,FD}\right)}{N(N+1)}. \tag{9}$$

It is evident from these expressions that some of the rank-based utility parameters (o's and p's) always co-occur in the same linear combinations, making it impossible to identify them individually. However, we can identify those linear combinations, representing the net self- and peer-induced effects of interest under our various contest designs. For example, $\frac{\sum_{j=1}^{N}(N+1-2j)o_j^R}{N(N+1)}$ occurs in each of (6)-(9), and represents the net expected impact of self-generated rank-based utility on effort in a contest with N players and reward structure R. For brevity, we refer to this as "net own utility", represented by α_N^R. Thus, (6) can be re-written:

$$e^{R,ND} = \frac{\sum_{j=1}^{N/2}(N+1-2j)R_j}{N(N+1)} + \alpha_N^R \tag{10}$$

Similarly, we can identify "net peer utility" for each disclosure scheme, represented by $\beta_N^{R,WD} = \frac{(N-1)p_1^{R,WD}}{N(N+1)}$, $\beta_N^{R,PD} = \frac{\sum_{j=1}^{N/2}(N+1-2j)p_1^{R,PD}}{N(N+1)}$, and $\beta_N^{R,FD} = \frac{\sum_{j=1}^{N}(N+1-2j)p_j^{R,FD}}{N(N+1)}$, respectively. Then, (7)-(9) can be replaced by:

$$e^{R,D} = \frac{\sum_{j=1}^{N/2}(N+1-2j)R_j}{N(N+1)} + \alpha_N^R + \beta_N^{R,D} \tag{11}$$

for $D \in \{WD, PD, FD\}$.

These expressions suggest that the effects of public recognition on contestants' utility (as represented by the values of $\beta_N^{R,D}$) can be identified by observing any difference in effort between the various disclosure schemes. For example, if we observe that $e^{R,WD} > e^{R,ND}$, that would imply that $\beta_N^{R,WD} > 0$ (and thus, $p_1^{R,WD} > 0$), indicating that contestants derive positive peer-induced rank-based utility from being recognized as the winner of a contest, above and beyond the utility derived from the top prize or from their own pride, satisfaction, etc. about their victory. Furthermore, we believe that this approach makes our results (at least directionally) less sensitive to modeling assumptions such as functional forms.

Predictions

We can develop some intuitive hypotheses about the non-zero peer-induced rank-based utility parameters under different disclosure schemes. Using some sort of recognition program for high-performing salespeople is very common in practice. Specifically, recognition of the top performer (*Employee of the Month*) or an unranked set of top performers (like in a *President's Club*) is observed frequently in the real world. This suggests that being recognized as a contest winner is believed to provide a participant with positive utility. In other words, $p_1^{R,D}$ should be positive for all $D \neq ND$. From equation (11), this implies that the net peer utility ($\beta_N^{R,D}$) should be positive under *PD* and *WD*, as summarized in the following hypothesis:

Hypothesis 1 (H1): The *partial* and *winner disclosure* schemes generate positive net peer utility.

Recognition under *WD* informs the other participants that the winner finished in first place, while recognition under *PD* informs them only that she finished in the top half. As the winner's recognition under the *WD* scheme is more exclusive, one may expect $p_1^{R,WD}$ to be greater than $p_1^{R,PD}$. On the other hand, if being part of an exclusive club is more valuable than being singled out as the top performer, then this ranking would flip. While we do not have a strong prior regarding the relative ranking of $p_1^{R,WD}$ and $p_1^{R,PD}$, for expositional purposes we propose the following testable hypothesis:

Hypothesis 2 (H2)*: For a given reward structure R,* $p_1^{R,WD} > p_1^{R,PD}$.

Note that, $\beta_N^{R,WD} = \frac{(N-1)p_1^{R,WD}}{N(N+1)}$, and $\beta_N^{R,PD} = \frac{\sum_{j=1}^{N/2}(N+1-2j)p_1^{R,PD}}{N(N+1)}$ and $e^{R,D} = \frac{\sum_{j=1}^{N/2}(N+1-2j)R_j}{N(N+1)} + \alpha_N^R + \beta_N^{R,D}$. Hence, we do not have a clear prediction regarding the relative sizes of $e^{R,WD}$ and $e^{R,PD}$, even if H2 holds.

The two hypotheses above describe the predicted effects of recognition schemes on contestants' non-monetary motivations, measured by net peer utilities. The net peer utilities (β's) are linear combinations of peer-induced rank-based utilities (p's). It is important to note that some of the normalizations in Assumption 1 can affect the algebraic expressions of the β's. These normalizations may affect Hypothesis 2, but should not affect Hypothesis 1.

For a given incentive scheme, the impact of utility arising from own sense of achievement (o_j^R for any j) does not vary across disclosure schemes as knowledge of one's own performance does not vary. Given that there is evidence that multiple similar rewards can lead to higher levels of effort than a larger winner-take-all prize (Lim, 2009; Müller and Schotter 2010), which is approximated by our *HRS* prize structure, we expect that net own utility (α_N^R) will be greater under the *low reward spread* structure. Note that, while we have implicitly assumed risk-neutrality in the part of utility that comes from a contestant's monetary payoff in equation (4), α_N^R may capture some non-linearity in utility from monetary payoff, making our formulation somewhat more general.

Hypothesis 3 (H3): The net impact of self-generated rank-based utility is greater under the *LRS* than the *HRS* for a given contest size; i.e., $\alpha_N^{LRS} > \alpha_N^{HRS}$.

As the *HRS* is theoretically predicted to generate more effort than the *LRS* in the absence of any rank-based utility, H3 does not imply that the effort choice will also be higher under *LRS* for *ND*. However, if the effort choice is higher under *LRS* for *ND*, then the result implies that the hypothesis holds.

EXPERIMENTAL RESULTS: 4-PLAYER CONTEST

In this section, we present the results from our first experiment, involving contests with four players. We begin by summarizing participants' effort choices under the various contest conditions. We then use those choices to estimate the net own and peer utilities defined above. Finally, we discuss the extent to which our findings support the proposed hypotheses.

We omit the practice periods in our data analysis. Since we do not find any effect of the order of the reward structures, we pool the data from all sessions under each combination of disclosure scheme, reward structure, and contest size. Each contest period within a session is treated as independent, implying that subjects do not learn and systematically adjust their effort beyond the practice periods. The rationale for this is that subjects cannot observe or infer each other's effort choices, nor do they know which other participants they are competing with when choosing their effort in any period. To test this assumption, we run a linear regression model of effort against contest period, previous period effort, and previous period result (rank if ranked in the top half and non-winner if in the bottom half) with individual-level fixed effects. There is no significant directional effect over time (i.e. subjects do not consistently increase or decrease effort over the course of a session), and there does not appear to be any consistent or meaningful pattern across the experimental conditions in the effects of previous period results on a contestant's effort choice in the following period.

Effort Choice

Table 1 presents the mean and standard deviation of subjects' effort choices (out of 99 points) under each experimental condition. This offers some initial directional insights into participant behavior before estimating the model parameters. In the absence of any rank utility, the optimal effort level e^* equals 56 and 40.4 under the high and low reward spreads, respectively.

Comparing effort choices across disclosure schemes suggests an interesting result. Relative to *no disclosure*, other disclosure schemes appear to increase effort levels in almost all cases. This suggests that disclosing the names, and sometimes the ranks of winners and, possibly, non-winners leads to higher effort levels than not revealing outcomes publicly at all. Thus, nearly any kind of recognition seems to enhance the motivation to exert effort.

Table 1: Summary of Individual Effort Choice (4-player contests)

Mean effort	**No Disclosure**	**Winner Disclosure**	**Partial Disclosure**	**Full Disclosure**
High Reward Spread	55.0 (34.3)	60.3 (29.8)	59.2 (32.4)	58.5 (32.9)
Low Reward Spread	58.8 (33.5)	65.2 (26.3)	64.3 (28.6)	58.4 (31.0)
# of Observations	720	720	720	720

Notes: (1) Standard deviations in parentheses;
(2) Number of observations applies to <u>each</u> reward spread.

Among the disclosure schemes under which we disclose at least some information, however, the effort data does not show that any particular scheme consistently dominates the rest. Instead, the differences in effort between those schemes are generally quite small in comparison to their differences versus *no disclosure*. The absence of a dominant approach is consistent with observation from the business world. It is very common to use some kind of scheme to publicly announce the winners (and sometimes the losers) of sales contests, but there is no single type of recognition program that is overwhelmingly more common than the rest.

While there is no simple "winner" among the disclosure schemes, we do observe that the data appears to be directionally consistent with some of our hypotheses. For example, mean effort is higher under *partial* and *winner disclosures* than under *no disclosure* for each reward spread, as per Hypothesis 1. Furthermore, mean effort under *no disclosure* is somewhat higher when the reward spread is *low* than when it is *high*, which is consistent with Hypothesis 3.

The next step is to examine these differences in more detail by estimating the net own and peer utility parameters from the model described above. We can then use those estimates to better understand the drivers of the observed effort choices and to further examine the differences between contest designs.

Model Estimates

We assume that the model parameters (o_j^R and $p_j^{R,D}$, for any rank *j*, reward structure *R*, and disclosure scheme *D*) are the same across participants, with each effort choice determined by the relevant equation from (10) or (11), along with subject-level random effects (μ_i) and a zero-mean error term (ε_{it}), where i represents the subject and t represents the contest period.[10]

For example, setting *N* = 4, equation (10) gives:

$$e_{it}^{R,ND} - \frac{3R_1 + R_2}{20} = \alpha_4^R + \mu_i + \varepsilon_{it}$$

[10] Random effects are appropriate because the explanatory variables in the model are determined by random assignment to experimental conditions, so there is no reason to expect any omitted variable bias or correlation with subject-level effects. Furthermore, fixed effects would preclude the estimation of parameters related to disclosure, due to the between-subjects experimental design.

We estimate net own utility ($\alpha_4^R = \frac{3o_1^R + o_2^R - 4o_3^R}{20}$) for each reward structure with a linear, random-effects regression using the effort choices in *no disclosure* contests with that structure.

By definition, self-generated rank-based utility is unaffected by the disclosure of one's contest results to other players, so net own utility does not vary between disclosure schemes. Thus, having used the *no disclosure* results to estimate α_4^R for a reward structure, we take that estimate as given for the other disclosure schemes, allowing us to estimate the disclosure-dependent net peer utilities ($\beta_4^{R,WD}$, $\beta_4^{R,PD}$, and $\beta_4^{R,FD}$) for that reward structure in a similar way, using the following regression equation derived from equation (11):

$$e_{it}^{R,D} - \frac{3R_1 + R_2}{20} - \alpha_4^R = \beta_4^{R,D} + \mu_i + \varepsilon_{it}$$

Resulting estimates (with standard errors clustered by subject) are shown in Table 2.

Table 2: Estimated Net Own and Peer Utility Parameters (4-player contests)

	Net own utility	**Net peer utility**		
	$\boldsymbol{\alpha_4^R}$	$\boldsymbol{\beta_4^{R,WD}}$	$\boldsymbol{\beta_4^{R,PD}}$	$\boldsymbol{\beta_4^{R,FD}}$
High Reward Spread	-1.0 (3.4)	5.3* (3.0)	4.2* (2.4)	3.4 (3.4)
Low Reward Spread	18.4*** (3.5)	6.4** (2.6)	5.5** (2.7)	-0.4 (3.5)

N

otes:

(1) Robust standard errors clustered by subject shown in parentheses

(2) $***$, $**$, and $*$ represent statistical significance at 1%, 5%, and 10%, respectively

The last three columns of Table 2 show that public recognition of performance often, although not always, has a significant impact on contest participants' utility, above and beyond the impact of the contest prize values and the participants' own knowledge of their achievements (captured by net own utility). The importance of recognition in sales contests is intuitive, and is reflected in the common practices of sales organizations, but has not been quantified and shown previously in the literature. Most critically for contest design, these results allow us to further examine how different disclosure schemes, along with different reward structures, affect participants' effort choices. We begin by re-visiting our hypotheses:

Hypothesis 1 (H1) is based on the expectation that a contest participant derives positive utility from being recognized publicly as a winner (i.e. $p_1^{R,WD} > 0$ and $p_1^{R,PD} > 0$). From Table 2, H1 holds under *low reward spread* at 5% significance and *high reward spread* at 10% significance.

Table 3: Parameter Differences for Hypothesis Testing (4-player contests)

	(H2) $\boldsymbol{p_1^{R,WD} - p_1^{R,PD}}$	**(H3)** $\boldsymbol{\alpha_4^{LRS} - \alpha_4^{HRS}}$
High Reward Spread	14.1 (23.5)	19.4^{***} (2.6)
Low Reward Spread	15.2 (21.9)	

Notes:

(1) Robust standard errors clustered by subject in parentheses

(2) $***$, $**$, and $*$ represent statistical significance at 1%, 5%, and 10%, respectively

Table 3 shows parameter comparisons that are relevant to the remaining hypotheses. (As shown above, $\beta_4^{R,WD}$ and $\beta_4^{R,PD}$ are simple multiples of $p_1^{R,WD}$ and $p_1^{R,PD}$, respectively, so the latter values and the difference between them can be determined quite easily for each reward spread.)

Hypothesis 2 (H2) implies that contest participants derive greater value from being recognized for finishing in 1st place than for finishing among multiple prize-winners. While the results are directionally consistent with this hypothesis ($p_1^{R,WD} > p_1^{R,PD}$), the difference is not statistically significant under either reward structure, with both *p*-values around 0.5. In other words, we find no evidence that participants differentiate between recognition as the winner of a contest and recognition as a winner.

Lastly, Hypothesis 3 (H3) relates to the psychological utility generated by participants' own knowledge of their contest performance, independent of public disclosure. Our findings are consistent with previous findings in the literature, that such utility is larger when the reward spread is *low* than when it is *high*.

Beyond our initial hypotheses, two other observations from Table 2 warrant some discussion. Firstly, net own utility (α_4^R) is significantly positive under *low reward spread*, but is insignificant under *high reward spread*. To understand why this may be the case, consider the definition of net own utility from above: $\alpha_4^R = \frac{3o_1^R + o_2^R - 4o_3^R}{20}$. In other words, net own utility in a four-player contest includes multiples of the self-generated utility derived from winning, from being the runner-up, and from being a non-winner. It seems intuitive that winning would provide non-negative self-generated utility. Similarly, we expect non-winners to receive non-positive utility. The valence of own utility from the runner-up position is less obvious. For example, Medvec et al (1995) find evidence of counterintuitive emotional responses by runners-up in competitions. In particular, they conclude that finishing in second place is a "mixed blessing", with satisfaction from a relatively strong performance mitigated by disappointment with having come close but fallen short of first place. Furthermore, in our experiment, the two reward spreads send very different signals to participants, particularly about the value of second place – *low* *spread* indicates that it is nearly as valuable as first place, while *high spread* suggests that it is much closer to losing than to winning. Thus, one explanation for this result is that the negative effect on self-generated rank-based utility of being ranked in the bottom half is not particularly strong, but that the effect of finishing as a runner-up either adds to the effect of winning or acts as a counter-balance to it, depending on what is implied by the reward spread. If this is indeed the case, then we might expect to see a similar (or even more pronounced) effect in larger contests, if the high reward spread similarly rewards all runners up with minimal prizes.

Next, we see from Table 2 that net peer utility under *full disclosure* $\left(\beta_4^{R,D}\right)$ is not significant under either reward spread (in contrast with *winner* and *partial* disclosures). *Full disclosure* represents a *Wall of Fame and Shame* approach, under which not only are top employees' identities and ranks disclosed, but bottom-ranked employees are identified as well. We intuitively expect public recognition to result in negative peer-induced utility for non-winners, motivating contestants to exert more effort to avoid such "shaming." In the language of our model, this would be represented by a negative value of $p_3^{R,FD}$, which increases net peer utility ($\beta_4^{R,FD} = \frac{3p_1^{R,FD}+p_2^{R,FD}-4p_3^{R,FD}}{20}$). However, we do not see evidence of this in our results. One possible explanation is similar to the one above (for net own utility under *HRS*), with public recognition as a runner-up resulting in negative peer-generated utility ($p_2^{R,FD} < 0$). An alternative explanation is that participants may derive positive utility from recognition *regardless of position*. If true, this would reverse the intended shaming effect and effectively cancel out the benefits of recognizing high performers. As our manipulation of identity and recognition is relatively weak, it is a valid question whether a clearer association between a subject's identity and assigned username would still lead to such a weak effect of faming and shaming.

To address this concern, and to further test and explore some of the ideas discussed above, we make a few minor adaptations to our experimental design and run it with a new set of participants. First, each sales contest in the revised experiment involves six players, instead of four. For the 6-player contests, we choose R_1=540, R_2=40, and R_3=20 for *HRS* and R_1=205, R_2=200, and R_3=195 for *LRS*, with R_4, R_5, and R_6 equal to 0 for both. This functions as something of a robustness check of our test of Hypotheses 1-3 from the initial experiment, but also allows us to test the conjecture above that increasing the number of runners-up in *high reward spread* contests will further decrease net own utility. Second, while subjects were identified as "Salesperson *X*" during the experiment just like in the first experiment, we make subjects' assigned identities more salient to themselves and each other by announcing each individual's full name and their assigned username and having them identify themselves (similar to a roll call) at the beginning of each experimental session. We expect this to strengthen the effects of recognition, particularly the shaming effect of being recognized as a non-winner under *full disclosure*. Lastly, we replace *winner disclosure* with *winner rank disclosure*, which is similar to *full disclosure* in that the winners of a contest are recognized by rank (as opposed to collectively, as in *partial disclosure*), but differs in that the non-winners are not identified. Therefore, consistent with Assumption 1, $p_j^{WRD} = 0$ for all $j > \frac{N}{2}$. Moreover, equation (11) characterizes the optimal effort choice from this disclosure scheme where $\beta_N^{R,WRD} = \frac{\sum_j^{N/2}(N=1-2j)p_j^{R,WRD}}{N(N+1)}$. Comparison of *winner rank disclosure* and *full disclosure* allows us to isolate and measure the shaming effect of publicly recognizing the contestants in the bottom half. Based on the expectation that being recognized as a non-winner does, in fact, result in negative peer-induced utility (i.e. shame), we propose an additional hypothesis.

Hypothesis 4 (H4): *Full disclosure* will generate higher net peer utility than *winner rank disclosure*.

EXPERIMENTAL RESULTS: 6-PLAYER CONTEST

In this section, we present the results from the second experiment, involving contests with six players. Again, we begin by summarizing participants' effort choices under the various contest conditions. We then use those choices to estimate the net own and peer utilities and discuss the extent to which our findings support our hypotheses. It should be noted that, due to the differences in experimental design, the results and estimates from the six-player contests cannot be compared directly to those above from the four-player contests.

Effort Choice

The optimal level of effort choice in the absence of any rank-based utility equals 67.6 and 43.2 under high and low reward spreads, respectively. Table 4 presents the mean and standard deviation of subjects' effort choices under each experimental condition. As in the four-player results, we see that all forms of disclosure are more effective than *no disclosure.* We also see again that no single scheme clearly and consistently outperforms all others, although *full disclosure* now appears to be weakly dominant (with *partial disclosure* performing roughly equally under *LRS*) with the new experimental design.

Model Estimates

Next, we estimate net own (α_6^R) and net peer utilities ($\beta_6^{R,PD}, \beta_6^{R,WRD}, \beta_6^{R,FD}$), using the same approach as above, with the regression equations adapted for six players as follows:

$$e_{it}^{R,ND} - \frac{5R_1 + 3R_2 + R_3}{42} = \alpha_6^R + \mu_i + \varepsilon_{it}$$

$$e_{it}^{R,D} - \frac{5R_1 + 3R_2 + R_3}{42} - \alpha_6^R = \beta_6^{R,D} + \mu_i + \varepsilon_{it}$$

Table 4: Summary of Individual Effort Choice (6-player contests)

Mean effort	**No Disclosure**	**Partial Disclosure**	**Winner Rank Disclosure**	**Full Disclosure**
High Reward Spread	48.0 (31.7)	52.4 (36.6)	52.1 (34.5)	59.2 (31.9)
Low Reward Spread	53.1 (31.2)	63.8 (29.0)	57.0 (33.2)	65.1 (27.8)
# of Observations	720	720	720	720

Notes: (1) Standard deviations in parentheses;

(2) Number of observations applies to each reward spread.

Re-visiting our hypotheses, we see that there is mixed evidence for H1, with *partial disclosure* resulting in significant positive net peer utility under *low reward spread*, but not under *high reward spread*. The remainder of H1 and H2 pertain to *winner disclosure*, which is not tested here.

Table 5: Estimated Net Own and Peer Utility Parameters (6-player contests)

	Net own utility	**Net peer utility**		
	$\boldsymbol{\alpha_6^R}$	$\boldsymbol{\beta_6^{R,PD}}$	$\boldsymbol{\beta_6^{R,WRD}}$	$\boldsymbol{\beta_6^{R,FD}}$
High Reward Spread	-19.6^{***} (3.8)	4.4 (4.8)	4.1 (4.2)	11.2^{***} (3.8)
Low Reward Spread	9.8^{**} (4.1)	10.7^{***} (3.9)	3.9 (3.9)	12.0^{***} (3.2)

Notes: (1). Robust standard errors clustered by subject shown in parentheses

(2). $***$, $**$, and $*$ represent statistical significance at 1%, 5%, and 10%, respectively

As in the four-player contests, we find strong evidence for H3, with net own utility significantly higher when the reward spread is *low* than when it is *high*. Furthermore, we find that net own utility is significantly negative under *high reward spread*, which is consistent with our speculation that finishing as a runner-up can result in negative self-induced rank-based utility when prize values for second place and below are minimal.

Table 6: Parameter Differences for Hypothesis Testing (6-player contests)

	(H3) $\boldsymbol{\alpha_6^{LRS} - \alpha_6^{HRS}}$	**(H4)** $\boldsymbol{\beta_6^{R,FD} - \beta_6^{R,WRD}}$
High Reward Spread	29.4*** (4.5)	7.1 (5.6)
Low Reward Spread		8.0 (5.0)

Notes:

(1) Robust standard errors clustered by subject in parentheses

(2) ∗∗∗, ∗∗, and ∗ represent statistical significance at 1%, 5%, and 10%, respectively

Lastly, H4 implies that *full disclosure* results in negative peer-generated utility for non-winners, by publicly disclosing their status as such. The desire to avoid this "shaming" is expected to motivate participants to exert greater effort under *full disclosure* than under *winner rank disclosure*, which recognizes winners in the same way without identifying the non-winners. The experimental results are directionally consistent with this hypothesis, but are not significant (although bordering on marginal significance under *low reward spread, with* p = 0.108). Taken in combination with the H1 results, there is evidence that both positive and negative recognition affect participants' utility and effort choices when the reward spread is *low*, but that these effects are mitigated when it is *high*.

Finally, Table 5 demonstrates that net peer utility under *winner rank disclosure* is not significant under either reward spread. This is particularly interesting in light of the findings about *partial* and *winner disclosures* from Hypotheses 1 and 2 for the four-player contests. For example, the absence of evidence for H2 indicates that all prize-winners effectively benefit from *partial disclosure* as though they are being recognized as 1st-place finishers. Under *winner rank disclosure*, on the other hand, runners-up (prize-winners below 1st place) are clearly identified as such, diminishing the value of their recognition in comparison with *partial disclosure*. This could explain why $\beta_6^{R,PD}$ can be significantly positive (under *low reward spread*) while $\beta_6^{R,WRD}$ is not. Furthermore, we can contrast the non-significance of net peer utility under *WRD* with the four-player result from H1 that $p_1^{R,WD}$ is significantly positive. Although observed under different experimental conditions, this offers some evidence that public recognition as a runner-up may, in fact, generate negative utility rather than the intended positive effect. This would imply that recognition provides positive peer-induced utility only when it indicates a 1st-place finish (i.e. a clear winner), or the possibility thereof (as under *partial disclosure*). This result may also be consistent with the "silver-medal syndrome" found by Medvec et al. (1995).

CONCLUSION AND DISCUSSION

This paper demonstrates that reward structures and disclosure schemes in sales contests can affect the participating agents' rank-based utility, and hence their effort decisions. We decompose rank-based utility into two components—self-generated and peer-induced. Our results show that, first, such rank-based non-monetary utilities do contribute to effort decisions.

Under virtually all experimental conditions, including the *no disclosure* condition that is closest to the theoretical benchmark, some rank-based utility parameter that we estimate is statistically and, economically, significant.

Second, we show that the choice of disclosure scheme can affect contest participants' effort levels. Among many results regarding disclosure schemes, we find that, overall, recognizing one or more winners can generate positive peer-induced rank utility and increase effort (as compared to having no public recognition). These results provide strong support for the wide acceptance of recognition programs in industry. Moreover, rank utility parameters from being recognized as the sole winner and as one among multiple winners are not significantly different. This result is consistent with the advice of industry experts (e.g., Zoltners et al. 2011) and may help to explain why President's Club-style recognition programs are very popular in practice.

Third, we find limited evidence that shaming by disclosing the identities of low-ranked contestants is motivating. Such disclosure can generate negative peer-induced rank utility for low ranks, which may motivate contestants to expend additional efforts to avoid being shamed. While the results are directionally consistent with this idea, the significance is marginal at best. Nonetheless, the effect may be stronger in a setting in which contest participants have strong social and/or professional ties. This, combined with potential negative consequences of shaming that are not captured in our model or experiment (such as increased turnover or low morale), may explain why shaming is not a very common practice.

Finally, we find that the incentive structure can affect the values of both self-generated and peer-induced rank utilities. For example, when the reward spread is low, the net own utility (denoting an index of self-generated rank-based utility parameters) tends to be higher. Thus, a low reward spread could lead to higher effort through enhanced self-generated rank utility. Similarly, peer-induced rank utility under some recognition programs, such as *partial disclosure*, is significantly positive when the reward spread is low, but may not be so when the spread is high.

This paper provides a number of implications for sales management. Most generally, the significant effect of rank-based utility on effort decisions indicates that managers must account for them in order to design truly optimal sales contests and other motivation programs. Specifically, consideration should be given to the non-monetary impacts of both the distribution of prizes and the public announcement of outcomes. In considering whether, and to what extent, contest results should be announced publicly, managers should be aware that public recognition of contest winners appears to have a positive effect on participants' effort levels. Moreover, while announcing the identities of non-winners (shaming) might also be motivating, its effect is uncertain.

In determining the optimal prize distribution for a contest, sales managers should watch for the possibility of the prize distribution affecting rank-based non-monetary utilities. Managers should also be mindful that the effects of public recognition and prize distribution can be intertwined. Thus, sales managers should treat the decisions about contest prize distribution and mode of public announcement as joint rather than separate decisions. For example, a manager designing a sales contest can maximize rank-based utility by distributing rewards among multiple winners and publicly recognizing all of them. Taking full advantage of the salespeople's non-economic motivations allows her to induce greater effort with the same financial resources, or the same effort with less.

Future research may extend the current paper in a number of directions. One direction is to examine the impact of effort type. For instance, some tasks can be more difficult or more tedious than others. Testing this will require an experimental procedure involving cognitive tasks, rather than direct effort choice. Another direction is to investigate the impact of socialization on rank-based utilities (e.g. Lim 2010). Future research may also study the issue in asymmetric contests, providing some contestants with advantages (or disadvantages) as in Yang et al. (2013). Finally, our empirical study is based on lab experiments. Future research should further examine this issue using field data.

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Appendix: Experimental Instructions (as provided to subjects in 4-player contests)

General Rules

This session is part of an experiment about sales force decision making. If you follow the instructions carefully and make good decisions, you can earn points during the session. Based on your points earning, you will be paid in cash at the end of the session.

There are twelve people (including yourself) in this laboratory who are participating in this session as subjects. They have all been recruited in the same way as you and are reading the same instructions as you are for the first time. It is important that you do not communicate to any of the other participants in any manner until the session is over.

The session will consist of 40 contest periods in each of which you can earn points. There will also be a 3-period long risk-attitude elicitation round where, in each period, you have to report your willingness-to-pay for a lottery. At the end of the experiment, two contest periods and one out lottery period will be randomly chosen to determine the earnings of all players. One of the two periods will be chosen from periods 6 to 20 and the other will be chosen from periods 26 to 40. You will be paid a show-up fee of $5 plus an amount based on your point earnings from the three chosen periods. For payments, 15 points are worth $1. Thus, if you earn *y* points in total from these randomly chosen periods, then your total income will be $5 + *y*/15. The more points you earn, the more cash you will receive.

Identification

At the beginning of the session, you will be assigned an identifying username as a sales person. This username will be of the form "Sales Person *X*" where *X* is a letter from the English alphabet. This username will be your identity for the entire session and you will be known to other players by this username.

Description of a Period

For this experiment, assume that you are employed as a sales person. Your job is to sell Product Beta which is an industrial product. In this task, you will have to make decisions on how much effort you expend in selling the product. At the beginning of each period, you will be randomly matched with exactly three other subjects. You and these three other subjects will participate in a 4-player sales contest. The winners of the contests will be determined by the amount of revenue each player brings. In each period, you will receive 100 points, up to 99 points of which you can use as effort to generate revenue. The remainder will be counted as part of your income (in points) from that period. Here using 1 point for effort represents expending very little effort in selling Product Beta and using 99 points represents expending the maximum possible level of effort. You can save the amount of points that you do not use as effort as your income. Suppose you use *e* points as effort to generate sales. Then, you will keep 100 – *e* points as your income from that period and you will generate $s(e) = 350 + ln(e) + \epsilon$ units of revenue. Here ϵ is distributed according to a logistic distribution with mean of zero and variance of $\pi^2/3$. Specifically, the probability distribution function (pdf) is $(x) = \frac{exp(-x)}{(1+exp(-x))^2}$. The attached figures graphically present the function 350 + *ln*(*e*) and the pdf *f*(*x*).

Your revenue will be used in determining the reward you receive from the sales contest in a given period. All four players (including yourself) will choose their efforts (*e*) simultaneously. On the computer screen, you will choose how many points you want to use as effort. Your effort has to be an integer between 1 and 99 (inclusive). You have one minute to make this decision. If you do not make your decision within one minute, you will be forced to make an immediate choice. Once all 4 players choose their effort levels, the computer will independently generate a random ε for each player and the revenue amount of each player will be calculated. Then, the player who generated the highest revenue will receive a reward of *A* points and the player who generated the second highest revenue will receive a reward of *B* points. The remaining two players will not win any reward. Thus, your income from a period in which you use *e* points as effort will equal 100 – *e* + *R* points where *R* is the reward you win. At the end of a period, you will learn how much revenue you generated and the amount of reward (if any) you received in that period.

Additionally, the following sentences were appended at the end of the above paragraph in the *partial*, *winner*, and *full disclosure* treatments.

Partial Disclosure: You will also learn the identities of the two players who received the rewards but not their ranking.

Winner Disclosure: You will also learn the identity of the winner of the contest.

Full Disclosure: You will also learn the identities of the winner and the runner-up of the contest and the two players who did not win any reward.

Differences between Periods

Recall that there will be 40 periods in this experiment and you will be randomly assigned to three other players in each period. You will participate in the above-mentioned 4-player sales contest in every period. However, the reward scheme will not be the same in every period. In periods 1 to 20, the rewards *A* and *B* will equal 360 and 40 points, respectively. In periods 21 to 40, they will equal 204 and 196 points, respectively. You will be reminded of the reward scheme before period 1 and before period 21 and it will also be listed on the effort choice screen. All twelve players in the session will face the same reward scheme in a given period.

Ending the Session

At the end of the risk-attitude elicitation round, you will see a screen displaying your earnings from each period. You will receive $5 for participating in this experiment. On top of that, you will earn an amount based on your point earnings from two randomly chosen periods from the sales contest periods and one randomly chosen period from the 3 lotteries in the risk-attitude elicitation round. Recall that, if you earn y points from these three periods, your total income from the experiment will be $5 + y/15. You will be paid this amount in cash.