Managing Psychological Motivations in Contests

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Abstract

This paper studies how a firm can manage an agent’s psychological motivations in a contest through the design of incentive structures and disclosure schemes—how the contest outcomes are publicly announced. We run a set of laboratory experiments involving contests among salespeople and use the data to examine the levels of psychological motivations. We develop two new methods to separate the effect of psychological motivations from the effects of economic incentives and risk aversion. We find that recognizing multiple top performers without revealing the ranking among them and recognizing the single best performer both generate positive and significant psychological motivations. However, the relative performances of alternative disclosure schemes often depend on the spread of contest rewards. A smaller spread of contest rewards may induce higher levels of psychological motivations. Overall, this paper demonstrates the significant impact of an agent’s psychological motivations on her effort choice and underscores the importance to managers of jointly choosing incentive structures and disclosure schemes.

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1. Introduction

Employee motivation has long been considered a major research area in both economics and marketing, particularly as it relates to sales management. The existing literature has overwhelmingly focused on economic incentives, investigating how well alternative compensation plans can align the incentives of principals and agents (see Mantrala et al. 2010 for a review). However, the literature has paid far less attention to the effects of psychological motivations, although their importance has long been recognized in motivation theory (e.g., Maslow 1943, Bandura 1986, Malone and Lepper 1987). Psychological motivations can result from, for example, fun nature of work (e.g., playing video games), satisfaction from reaching goals (e.g., making a quota), or social recognition from achievement (e.g., winning “Employee of the Month” award).

In this paper, we study the impact of psychological motivations on agents’ effort choices and how those motivations may depend on the design of incentive structures and disclosure schemes. We investigate this research issue in the context of sales contests in which agents are rewarded and recognized solely based on their relative performances. Ranking employees by performance is a common practice among many reputable companies, including GE, Microsoft, and Cisco (Grote 2005). Among the contests commonly observed in practice, incentive structures often differ by the spreads between rewards assigned to different ranks. Contests can also differ by the format of disclosure, i.e., how the outcome of a contest is announced to the participants (see Zoltners et al. 2011 for a discussion on disclosure schemes in sales management).

In this paper, we consider four types of disclosure schemes: a no disclosure scheme, in which the outcome of the contest is never announced publicly; a winner disclosure scheme, in which only the top finisher is announced (e.g. an “Employee of the Month” or a “Salesperson of the Year” program); a partial disclosure scheme, in which all the winners are recognized, but the relative ranking between them is not disclosed (e.g. a “President’s Club” program); and a full disclosure scheme, in which the rankings of the winners and the identities of the losers are announced (e.g. a “Wall of Fame and Shame”). No disclosure provides a benchmark, consistent with the standard contest game typically represented in the literature, while the others represent the contest designs most commonly observed in practice. From a contestant’s point of view, these disclosure schemes vary in terms of how much other contestants know about her performance but all four provide the same information about her own performance. Thus, any variation in the
resulting level of psychological motivation comes from the effect on a contestant’s sense of achievement based on how peers regard her, not on how she regards herself.

Our empirical study examines data collected from laboratory experiments in which 192 subjects chose their levels of effort in simulated four-person sales contests, with rewards for the top two finishers in each contest. Each subject participated in 40 contest iterations under one of the four disclosure schemes described above (full, winner, partial, or no disclosure), with 20 iterations each under two different reward spreads (high and low). In a single contest iteration, each of the four subjects was endowed with an equal sum of points, of which they could choose to spend any number as “selling effort,” keeping the rest as income. Each participant’s sales revenue was then determined stochastically as a function of the effort she invested, and the two salespeople with the highest revenues had rewards added to their income. Finally, the results of the contest were revealed (or not), according to the disclosure scheme being employed. We also elicited each subject’s certainty equivalents for a series of lotteries, to calculate a risk-aversion parameter.

Results from the lab experiments show that contestants’ effort levels depend on both the reward spread and the disclosure scheme of a contest. While the mean effort levels under partial and winner disclosures are higher than that under no disclosure for each reward structure, they are higher than that under full disclosure only for the low reward spread. In general, some sort of public disclosure of the contest outcomes increases effort choice over having no public disclosure. Clearly, the efforts of the participating agents were influenced by their psychological motivations, which in turn depend on the disclosure scheme and reward spread.

In order to infer levels of psychological motivations from the selling efforts observed in the experiments, we develop a contest model that includes psychological motivations and derive each contestant’s equilibrium selling efforts. For our empirical analysis, we have considered two alternative approaches. First, we take a direct approach to modeling an agent’s psychological values from winning rewards and/or earning recognition. We also distinguish the sources of psychological values as “own” (induced by knowledge of one’s own achievement) versus “peer-generated” (induced by public recognition). Under this direct approach, we find that agents obtain positive and significant peer-generated psychological value from being recognized as one of the top performers under partial disclosure or as the single top performer under winner disclosure.

Second, we develop an indirect approach to estimate a unique psychological motivation parameter for each combination of incentive and disclosure schemes. The direct approach
described above suffers from a plethora of psychological value parameters, not all of which can be individually identified. This drawback is further exacerbated as the number of contestants and ranks increases. The indirect approach takes advantage of the property that the equilibrium effort is determined by equating agents’ marginal gains and the marginal cost of their incremental efforts. When inferring psychological motivations from observed efforts, modeling the marginal increase (decrease) in direct utilities is equivalent to modeling the marginal decrease (increase) in effort costs. In essence, the effects of multiple psychological values on selling efforts can be captured by a single parameter reflecting the change in the marginal cost of effort. In this indirect approach, we develop a parsimonious and robust way of capturing the aggregate effect of multiple psychological values at work. We estimate the psychological motivation parameter among the contestants in our experiment, beginning with an assumption of risk neutrality and then relaxing that assumption using the risk-aversion parameter estimated from the lottery part of the experiment. Under the assumption that the subjects are risk neutral, the medians of the psychological motivation parameter by treatment are mostly positive, suggesting that the sales contests generate positive psychological motivations. Furthermore, those estimates remain significant after accounting for risk aversion. In particular, the level of psychological motivation to work becomes higher when a partial disclosure or a winner disclosure scheme is employed, and is higher under the low reward spread than under the high reward spread.

The rest of this paper is structured as follows: The following subsection discusses the contribution of the paper in light of the existing literature. Section 2 explains the design of the laboratory experiments. In Section 3, we describe the experimental results regarding subjects’ effort choices. Section 4 provides an extended model of sales contests, directly incorporating into an agent’s utility function the psychological values of winning rewards and recognitions. Our theoretical analysis leads to an equilibrium prediction for the level of effort under each treatment. We also use the data to make empirical inferences about the psychological values. In Section 5, we present a new method to indirectly quantify the value of psychological motivations and to estimate the resulting parameters using lab data. Finally, we conclude by discussing the implications of our results and some directions of future research to extend this paper.
**Literature Review**

This paper contributes to several streams of research. First, it contributes to the sales management literature, by demonstrating not only the significance of psychological motivations, but also how they are affected by commonly-adopted sales management practices. The existing sales literature mainly focuses on the design of economic incentives. For example, Basu et al. (1985) derives the optimal compensation plan and examines how the shape of such a compensation plan should depend on salespeople’s characteristics (e.g., risk attitude) and product-market characteristics (e.g., sales uncertainty). Extensions to the compensation plan suggested by Basu et al. (1985) 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). The existing studies of optimal compensation plans, by abstracting away from psychological motivations, implicitly assume an independent relationship between economic and psychological motivations. Under such an implicit assumption, when comparing alternative types of incentive schemes, researchers can assume that psychological motivations remain the same and, hence, focus solely on economic incentives. This paper, along with related research on psychological motivations 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. To the best of our knowledge, this is also the first study on the effects of recognition programs on the performance of salespeople.

Second, this paper conducts an empirical study in sales contests and thus 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 psychological motivation 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, as well as 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 the psychological motivation to exert effort 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 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 regret by bidders and on their bidding behavior in an all pay auction. In a field experiment by Barankay (2012), salespeople are informed of their own ranking in a bonus program based on the absolute performance of the salespeople. In contrast, our paper focuses on the change in the level of a contestant’s psychological motivation coming from changes in how much information her peers have about her achievement.

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 psychological motivation levels. 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 psychological motivations. A number of papers, including Frey and Oberholzer-Gee (1997) and Gneezy and Rustichini (2000), find evidence that economic incentives can crowd out psychological motivations. 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. To the best of our knowledge, the empirical work in this area remains qualitative, typically demonstrating the interdependence of the two types of motivation, but not identifying and quantifying the levels of psychological motivations. This paper offers an analytical model and experimental procedure to empirically investigate the magnitude of psychological motivations arising from public recognition of agent performance. This methodology can be readily adapted to future studies in other contexts.

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) studies the effect of social comparisons in luxury goods markets, Cui et al. (2007) investigates 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 bias due to psychological motivations. Following
our method, one can augment theoretical models to estimate the extent of other types of deviations from observed or experimental data.

2. Experimental Design

In this section, we describe the design of a set of laboratory experiments in which contestants make effort choices in sales contests. We choose 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.

Our experiments involved four-player contests in which the top two contestants earned prizes and the remaining two did not. The total prize payout was the same in all contests, but we varied the difference between the prizes of the top two contestants. In high reward spread (HRS) contests, the first prize was nine times larger than the second prize, while in low reward spread (LRS) contests, the first and second prizes were virtually equal. 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 a runner-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. For each reward spread, we applied four disclosure schemes, which are described below. Thus, we implemented a 2×4 experimental design with eight treatments in total.

We ran 16 sessions with 12 subjects in each session. Each subject participated in only one session, so there were 192 subjects in total. The sessions were run between March 2012 and February 2013 at McMaster University in Canada, with all subjects being students of the university. The experiments were programmed and conducted using the software z-Tree, developed by Fischbacher (2007). Each session consisted of 40 contest periods. In each period, the 12 subjects were randomly assigned into three 4-player groups.

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 4-player 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 some or all of
these points as effort to generate revenue, keeping the remainder as income. Suppose she used $e \in \{1,2,...,100\}$ 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 $\epsilon$ was drawn from a logistic distribution with mean zero and variance $\pi^2/3$. For each subject, a new random term $\epsilon$ was independently drawn in each 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. The player who generated the highest revenue received a reward of $R_1$ points and the player who generated the second-highest revenue received a reward of $R_2$ points. The remaining two players did not receive any reward.¹ A subject’s income from a period in which she used $e$ points as effort was $100 - e + r$ points, where $r \in \{R_1, R_2, 0\}$ represents her reward. As the effort cost directly enters the payoff function through a reduction in points, the effort cost can be considered a monetary cost.²

The reward scheme was varied within each session. In half of the periods, subjects participated in high reward spread contests, in which $R_1$ equaled 360 and $R_2$ equaled 40. The other half were low reward spread contests, in which $R_1$ and $R_2$ equaled 204 and 196, respectively. To control for any order effects, 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 players faced the same reward structure.

At the beginning of every 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. A subject was identified and known to other players by this username. After each period, the results of the contest were announced to the contestants according to one of four disclosure schemes, each of which was employed in four experimental sessions. Under all of the regimes, each contestant learned their own reward (indicating whether they finished first, second, or in the bottom two). Under no disclosure, no further information was revealed. This provides us with a benchmark, as no disclosure best

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¹ Kalra and Shi (2001) shows 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).

² 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.
represents a standard one-shot contest game. Under *winner disclosure*, contestants also learned the identity of the winner of the first prize. Under *partial disclosure*, they learned the identities of the first and second prize winners, but not specifically who won which prize. Under *full disclosure*, they learned the specific identities of the first prize winner and the second prize winner and also learned the identities (but not the ranks) of the two remaining contestants who did not win a reward. A subject did not know the identities of the three other players she was participating with in a given period when choosing her effort. Moreover, a given subject experienced both reward-spread treatments, but only under a single disclosure scheme. As the usernames were somewhat mechanical-sounding and were chosen by us, subjects may not have identified with their usernames very strongly. Furthermore, recognition itself did not provide any possible monetary benefit, even in the long run. As a result, our recognition manipulation is potentially rather weak. Thus, any evidence of our disclosure schemes affecting subject behavior would suggest quite a strong impact of public recognition in a real workplace, in which people are closely attached to their identities and recognition may bring future benefits and opportunities.

After the 40 sales contest periods, each subject participated individually in a risk-attitude elicitation round with three periods. In each period, we elicited the subject’s certainty equivalent for a lottery. We asked the subject to report her willingness-to-pay (WTP) for a lottery that took a value of 0 with probability $1-p$ and a value of 20 points with probability $p$. The values of $p$ in the three periods were 30%, 50%, and 80%, with the order varying across subjects to control for order effects. The subject reported an integer between 1 and 19 as her WTP and her earnings for the period were determined by the Becker-DeGroot-Marschak (1964) mechanism. An integer between 1 and 19 (inclusive) was chosen randomly with equal probability, independent of the subject’s reported WTP. If this integer was above the reported WTP, the subject received that many points as her earnings from the period. If it was below her reported WTP, the subject’s earnings were determined by the lottery. Thus, the subject’s unique weakly-dominant strategy was to truthfully report her certainty equivalent of the given lottery as her willingness to pay. We chose to use three different lotteries so that our measurements of subjects’ risk preferences are not specific to one particular lottery.

After the subjects participated in the contests and the lotteries, they 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 and one lottery period were randomly chosen to determine the earnings of each subject in the session. Contest periods 1 to 5 and 21 to 25 were omitted from this selection, so that subjects could use those as practice periods for the two reward spreads. Total point earnings from the three selected periods—two contests and one lottery—were translated into Canadian dollars using an exchange rate of $1 per 15 points. Moreover, each subject earned $5 as a show-up fee. The subjects spent less than an hour and a half in the laboratory, including the reading of instructions, payment and debriefing. The average payment made to a subject was $25.71, paid in cash. 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 using a recorded reading of the instruction sheet, with subjects listening on headphones. A sample of the instructions is presented in the Appendix.

3. Theoretical Model

In this section, we provide a theoretical model of contests in which agents have psychological motivations to exert effort, in addition to the economic motivation provided by the contest rewards. We do not focus on intricacies of optimal contest design, 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 psychological motivations 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 disclosure scheme and the reward structure of the contest. Our equilibrium analysis provides a closed-form solution that links chosen effort to this psychological effect.

General Model and Analysis

Consider a contest with four agents (denoted by $i = 1, \ldots, 4$), in which the ranking of the agents in the contest depends on the output they produce. The analysis can be extended easily to arbitrary $N$ contestants. Agent $i$ exerts effort $e_i > 0$, which results in an output of $s(e_i) + \varepsilon_i$. The production function $s$ is commonly known, identical for all four 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 $\epsilon_i$ is drawn from a logistic distribution function with mean 0 and variance parameter 1.\footnote{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 central tendency in density. The density function with mean 0 and variance parameter 1 is $f(\epsilon) = \frac{\exp(-\epsilon)}{1+\exp(-\epsilon)}$ with variance $\pi^2/3$.} The agents are compensated using a rank-order contest characterized by the reward structure $R = \{R_1, \ldots, R_4\}$ 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. 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 $U(w_i, r, e_i \mid R, D)$ where $U$ is increasing in $w_i$ and $r$ and is decreasing in $e_i$. The utility function $U$ may include both economic and psychological payoffs from the contest.

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

$$
\sum_{j=1}^{4} P_r_j (e_i, e_{-i}) U(w_i, R_j, e_i \mid R, D)
$$

where $P_r_j(e_i, e_{-i})$ 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 $e_{-i}$. Thus, if agent $i$ chooses effort $e_i^*$, then

$$
e_i^* = \arg\max_{e_i} \sum_{j=1}^{4} P_r_j (e_i, e_{-i}) U(w_i, R_j, e_i \mid R, D)
$$

We restrict attention to symmetric equilibria, in which each agent expends the same amount of effort ($e_k = e^*, \forall k$). The first-order condition is given by:

$$
\sum_{j=1}^{4} \left( P_r_j(e_i, e_{-i}^*) \frac{\partial U(w_i, R_j, e_i \mid R, D)}{\partial e_i} + \frac{\partial P_r_j(e_i, e_{-i}^*)}{\partial e_i} U(w_i, R_j, e_i \mid R, D) \right) \bigg|_{e_i = e^*} = 0
$$

The second-order condition to ensure that $e^*$ maximizes the expected utility is also standard.

Recall that, in our experiment, a subject was endowed with 100 points in every period, from which she expended effort $e$ in the contest. Thus, her earnings from the contest equaled $100 - e + R_j$ if she won a reward of $R_j$. This provided economic utility of $u(100 - e + R_j)$ for some utility function $u$ that is increasing and weakly concave. Moreover, $u$ is at least twice differentiable and the values of the derivatives depend on the total monetary holding, $w + r - e$. 


Next, we model an agent’s psychological value from the contest, which potentially depends on both the reward structure and the disclosure scheme. We assume that the monetary and psychological payoffs are additively separable and propose the following utility specification:

\[ U(w, R_j, e | R, D) = u(w - e + R_j) + o_j^R + p_j^{R,D}. \]  (4)

Equation (4) indicates that the source of the psychological values can be twofold—arising from a sense of one’s own achievement of a rank (denoted by \( o_j^R \), “o” indicating “own”) and from public disclosure of the rank (denoted by \( p_j^{R,D} \), “p” indicating “peer-generated”). These psychological values can be positive or negative. The \( o_j^R \) and \( p_j^{R,D} \) parameters can be thought of as the net effects of a (potentially complex) combination of psychological factors. While we can speculate on what those factors might be, we will restrict our focus to the net effects, which are sufficient for providing managerial direction on contest design.

Under all eight treatments in our experiment, a subject learns whether she was ranked first, second, or among the bottom two contestants. Hence, we assume that the value from knowing one’s own rank (\( o_j^R \)) does not depend on the disclosure scheme, but it may depend on the reward structure. Furthermore, since the ranking of the bottom two contestants is not known to any of the contestants and \( R_3 = R_4 \), we assume that \( o_3^R = o_4^R \) for any \( R \).

On the other hand, the peer-generated psychological value (\( p_j^{R,D} \)) depends on both the reward structure and the disclosure scheme. We assume that if the identity of an agent is not publicly disclosed, then she does not receive any peer-generated psychological value. Thus, under the no disclosure scheme, \( p_j^{R,ND} = 0 \) for all \( j \). Under the winner disclosure scheme, only the identity of the top contestant is publicly recognized. Thus, only the top contestant may derive peer-generated psychological value from disclosure. We assume that \( p_2^{R,WD} = p_3^{R,WD} = p_4^{R,WD} = 0 \). Under the partial disclosure scheme, the identities of the top two contestants, but not their rankings, are publicly announced, creating psychological value from public recognition. Hence, we assume that \( p_1^{R,PD} = p_2^{R,PD} \) and \( p_3^{R,PD} = p_4^{R,PD} = 0 \). Finally, under the full disclosure scheme, the rankings (winner, runner-up, and bottom-two) of all contestants are publicly announced. As a result, a significant peer-generated psychological value can exist for all ranks.

We summarize the above assumptions on the psychological value parameters below:

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4 This model can be thought of as a more general version of the privilege contest model in Schroyen and Treich (2013).
**Assumption 1:** Peer-generated psychological values \( p_{j}^{R,D} \) have the following properties:

1) Under *no disclosure*, \( p_{1}^{R,ND} = p_{2}^{R,ND} = p_{3}^{R,ND} = p_{4}^{R,ND} = 0 \). Under *winner disclosure*, 
\[ p_{2}^{R,WD} = p_{3}^{R,WD} = p_{4}^{R,WD} = 0. \]

2) Under *partial disclosure*, \( p_{1}^{R,PD} = p_{2}^{R,PD}, p_{3}^{R,PD} = p_{4}^{R,PD} = 0. \)

3) Under *full disclosure*, \( p_{3}^{R,FD} = p_{4}^{R,FD} \neq 0. \)

Furthermore, we can develop some intuitive hypotheses about the non-zero peer-generated psychological values under different disclosure schemes. We expect that being recognized as a contest winner will provide a participant with positive psychological value. In other words, \( p_{1}^{R,PD} \) and \( p_{1}^{R,WD} \) should be positive. 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 two. Thus, the winner’s recognition under the *WD* scheme is more exclusive and valuable, so we expect \( p_{1}^{R,WD} \) to be greater than \( p_{1}^{R,PD} \). This discussion is summarized in the following hypothesis:

**Hypothesis 1:** For a given reward structure \( R \), \( p_{1}^{R,WD} > p_{1}^{R,PD} > 0 \).

Our model extends Kräkel (2008), which considers psychological values from winning (losing) in a two-person contest. First, there is only one winner in Kräkel (2008), but we allow for multiple winners and different psychological values from achieving the first and second ranks. Second, Kräkel (2008) models only two contestants, so each player always knows the other’s status. The information structure in our 4-person contest is much richer. We introduce four types of disclosure schemes and permit disclosure-specific psychological values.

Next we examine the optimal choice of effort in these contests. Our analytical method follows Kalra and Shi (2001). Given the assumptions on \( s(e) \), the distribution of \( \epsilon \), incentive plan \( R \), and disclosure scheme \( D \), equilibrium effort level \( e^* \) can be determined by the following equation:

\[
\sum_{j=1}^{4} \left( (u(100 - e^* + R_j) + o_j^R + p_j^{R,D}) \right)^{5-2j} + \frac{1}{4} u'(100 - e^* + R_j) = 0. \quad (5)
\]

This can be rewritten as:

\[
3(u(100 - e^* + R_1) + o_1^R + p_1^{R,D}) + u(100 - e^* + R_2) + o_2^R + p_2^{R,D} - 4(u(100 - e^*) + o_3^R + p_3^{R,D}) = 5e^* \sum_{j=1}^{4} u'(100 - e^* + R_j). \quad (6)
\]
Risk-Neutral Agents

Here we consider the special case in which the agents are risk neutral; that is, \( u(x) = x \). Following (6), the contestants’ optimal effort level is given by the following equation:

\[
e^* = \frac{3R_1 + R_2 + 3o_1^R + o_2^R - 4o_3^R + 3p_1^{RD} + p_2^{RD} - 4p_3^{RD}}{20}.
\]  

(7)

Now, given Assumption 1, we can characterize the optimal effort level under each disclosure scheme. The optimal effort choice under the no disclosure, winner disclosure, partial disclosure, and full disclosure schemes are denoted by \( e^{R,ND} \), \( e^{R,WD} \), \( e^{R,PD} \), and \( e^{R,FD} \), respectively, where \( R \in \{HRS, LRS\} \). Then,

\[
e^{R,ND} = \frac{3R_1 + R_2 + 3o_1^R + o_2^R - 4o_3^R}{20},
\]  

(8.1)

\[
e^{R,WD} = \frac{3R_1 + R_2 + 3o_1^R + o_2^R - 4o_3^R + 3p_1^{RD}}{20},
\]  

(8.2)

\[
e^{R,PD} = \frac{3R_1 + R_2 + 3o_1^R + o_2^R - 4o_3^R + 4p_1^{RD}}{20},
\]  

(8.3)

\[
e^{R,FD} = \frac{3R_1 + R_2 + 3o_1^R + o_2^R - 4o_3^R + 3p_1^{RD} + p_2^{RD} - 4p_3^{RD}}{20}.
\]  

(8.4)

From these equations, it is clear that Hypothesis 1 has direct implications for the equilibrium efforts and vice versa. First, according to equations (8.1) and (8.2), the hypothesis \( p_1^{R,WD} > 0 \) implies that equilibrium efforts \( e^{R,WD} \) should be greater than \( e^{R,ND} \). Conversely, if \( e^{R,WD} \) is found to be greater than \( e^{R,ND} \), then that hypothesis is confirmed. Similarly, according to equations (8.1) and (8.3), \( p_1^{R,PD} > 0 \) implies that the equilibrium efforts \( e^{R,PD} \) should be greater than \( e^{R,ND} \) and the converse again holds. Lastly, by equations (8.2) and (8.3), if \( e^{R,PD} \) and \( e^{R,WD} \) are equal, then \( p_1^{R,WD} = \frac{4}{3} p_1^{R,PD} \), which would confirm our hypothesis that \( p_1^{R,WD} > p_1^{R,PD} \). We summarize the above in the following Proposition:

**Proposition 1:** With risk-neutral agents, for a given reward structure \( R \),

1.1. \( e^{R,WD} > e^{R,ND} \) if and only if \( p_1^{R,WD} > 0 \),

1.2. \( e^{R,PD} > e^{R,ND} \) if and only if \( p_1^{R,PD} > 0 \)

1.3. \( e^{R,PD} > e^{R,WD} \) if and only if \( 4p_1^{R,PD} > 3p_1^{R,WD} \).

Parts 1.1 and 1.2 indicate that efforts will be higher under winner and partial disclosures, respectively, than under no disclosure if and only if there is a positive psychological impact from being publicly recognized as a winner. This is rather intuitive, as the effect on utility of that positive impact is equivalent to that of an increase in the value of the first prize (under WD) or the first and
second prizes (under PD). Part 1.3 indicates that effort under partial disclosure will be higher than under winner disclosure unless the psychological effect of being recognized alone as the first-place finisher (under WD) is greater than that of being recognized as one of the top two finishers (under PD) by a factor of at least 4/3. The intuition behind that result is that PD is more likely to result in some form of recognition (and resulting psychological benefit), so it induces more effort unless the effect of shared recognition is substantially ‘diluted’ relative to that of exclusive recognition.

At this point, we cannot compare between effort levels under full disclosure and any other disclosure scheme. We can hypothesize the signs of parameters \( p_1^{R,FD}, p_2^{R,FD}, \) and \( p_3^{R,FD}, \) but their relative values are unknown and hence we cannot make inferences about the values of \( e^{R,FD} \) based on equation (8.4) without multiple additional assumptions. In essence, the multitude of psychological value parameters limits the scope of inferences.

As both own and peer-generated psychological values can be different when we are comparing two incentive schemes for a given disclosure scheme, comparing across reward spread treatments are more difficult. Hence, we do not present any formal hypothesis in that context. In a symmetric equilibrium, all agents exert the same level of effort. Then, the ranking will basically depend on luck and one may expect that a more equitable contest will provide a greater level of psychological motivation. If this effect is strong enough, agents may exert more effort under the low reward spread treatments.

4. Experimental Results

In this section, we analyze the data gathered in the experimental sessions using the model described above. First, we examine the effort levels chosen by the subjects to identify differences among the eight treatments (two reward structures × four disclosure schemes). Using no disclosure as a baseline, we are interested in observing whether subjects choose higher effort levels under the partial disclosure and winner disclosure schemes. Second, we use the data to estimate the psychological value parameters and to test the predictions from Hypothesis 1 about the relationships between the peer-generated psychological values.

All of the data analysis omits contest periods 1-5 and 21-25 from each session, which are treated as practice periods because the subjects’ earnings from the sessions were not dependent on their performance in those rounds. As we do not find any effect of the order of the reward structures, we pool the data from all four sessions under each disclosure scheme.
Effort Decisions and Psychological Motivations

We begin by examining the subjects’ mean effort levels under each treatment, presented in Table 1. We can see that subjects chose significantly higher effort levels under the winner disclosure and partial disclosure schemes than under the no disclosure scheme for both reward structures (significant at 5% or less). However, there was no significant difference in effort between winner disclosure and partial disclosure under either reward structure. By Proposition 1, this confirms that our experimental results are consistent with the predictions made in Hypothesis 1. Even our weak recognition manipulation results in significant differences in effort choice, indicating that psychological motivations have a significant impact on sales agents’ effort decisions.

Table 1: Summary of Individual Effort Choice

<table>
<thead>
<tr>
<th>Mean Effort</th>
<th>No Disclosure</th>
<th>Winner Disclosure</th>
<th>Partial Disclosure</th>
<th>Full Disclosure</th>
<th>All Disclosures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Reward Spread</td>
<td>55.0</td>
<td>60.3</td>
<td>59.2</td>
<td>58.5</td>
<td>58.3</td>
</tr>
<tr>
<td></td>
<td>(34.3)</td>
<td>(29.8)</td>
<td>(32.4)</td>
<td>(32.9)</td>
<td>(32.4)</td>
</tr>
<tr>
<td>Low Reward Spread</td>
<td>58.8</td>
<td>65.2</td>
<td>64.3</td>
<td>58.4</td>
<td>61.7</td>
</tr>
<tr>
<td></td>
<td>(33.5)</td>
<td>(26.3)</td>
<td>(28.6)</td>
<td>(31.0)</td>
<td>(30.1)</td>
</tr>
<tr>
<td>Observations</td>
<td>720</td>
<td>720</td>
<td>720</td>
<td>720</td>
<td>2,880</td>
</tr>
<tr>
<td><strong>p-value for</strong></td>
<td><strong>3.5%</strong></td>
<td><strong>0.1%</strong></td>
<td><strong>0.2%</strong></td>
<td><strong>99.1%</strong></td>
<td><strong>0.0%</strong></td>
</tr>
<tr>
<td>H₀: HRS – LRS = 0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard deviations in parentheses
Sample sizes apply to each reward spread.

As discussed after Proposition 1, the theoretical model does not offer any predictions about the relative effort levels under full disclosure and the other disclosure schemes without further assumptions. However, the experimental data offers observations about these comparisons and about the relative effort levels chosen under the high and low reward spreads. Continuing to use no disclosure as a baseline, effort tends to be higher under the full disclosure scheme when the reward spread is high (p-value = 5.4%), but not when the rewards are spread more evenly.
Lastly, we observe higher effort under the low reward spread than under the high reward spread under all disclosure schemes, with the exception of full disclosure.\(^5\)

In summary, our experimental results show that effort levels are higher when the contest winner or winners (but not the losers) are publicly recognized than when they are not. This offers supporting evidence for Hypothesis 1, that these public recognition programs generate positive psychological motivations. Furthermore, the data shows that effort is generally higher when contest rewards are more evenly distributed. However, this effect is dependent on the extent to which the contest results are publicly disclosed.

**Estimating Psychological Value Parameters**

We can further use our experimental results to estimate some of the psychological value parameters (\(o\)'s and \(p\)'s) introduced above. Specifically, we can substitute the subjects’ effort choices under different experimental treatments into the appropriate equations (8.1) ~ (8.4) to estimate these parameters. First, for each contest period played under the no disclosure condition, we insert each subject’s effort choice and the appropriate rewards \(R_1\) and \(R_2\) (according to the reward scheme for the period) into equation (8.1) to calculate the value of \(3o^R_1 + a^R_2 - 4a^R_3\) (which we will call the \(o\)-index) for that subject and period. We then take the mean of these values as the estimate of the \(o\)-index under each reward scheme. The \(o\)-index represents the net effect of an agent’s psychological motivations on her effort. As noted earlier, under the no disclosure condition, there is no public disclosure of contest outcomes, and therefore the psychological motivation represents a baseline level resulting only from the anticipation of learning her own rank. This baseline psychological motivation is assumed to be the same across all disclosure schemes.

Second, for each period played under the winner disclosure scheme, we substitute each subject’s effort choice, the rewards \(R_1\) and \(R_2\), and the estimate of the \(o\)-index into the equation for \(e^{R,WD}\). This allows us to calculate the value of \(p_1^{R,WD}\) for that subject and period. We then take the means of these values to estimate this psychological value parameter \(p_1^{R,WD}\) under each reward structure. Following an almost identical procedure, we can use the data under partial disclosure to estimate the psychological value parameter \(p_1^{R,PD}\) under each reward structure.

\(^5\) As a robustness check, we also analyze the impact of the reward spread on effort choice using a panel regression that controls for individual fixed effects. Observations regarding the impact of the reward spread remain unchanged.
Lastly, we take a similar approach for the periods played under full disclosure to estimate the value of \(3p_1^{R,FD} + p_2^{R,FD} - 4p_3^{R,FD}\) (the FD-index) under each reward scheme. The FD-index represents the net effect of peer-generated psychological motivations on a participant’s effort under FD.

The psychological value index and parameter estimates (means) are summarized in Table 2. Since the index/parameter values do not appear to follow a normal distribution (i.e., they are not symmetric or unimodal), the table also includes medians and significance results based on the non-parametric sign test.

| Table 2: Estimated Intrinsic Motivation Parameters under Risk Neutrality |
|---------------------------------------------------------------|-----|-----|-----|-----|
|                  | \(o\)-index | \(p_1^{R,WD}\) | \(p_1^{R,PD}\) | FD-index |
| **High Reward Spread**  | Mean     | -19.2 | 35.1*** | 21.0*** | 68.3*** |
|                      | Median   | -20.0 | 33.1*** | 24.8*** | 99.2**  |
| **Low Reward Spread**   | Mean     | 368.3*** | 42.7*** | 27.5*** | -7.6 |
|                        | Median   | 412.0*** | 54.6*** | 55.9*** | 23.7 |
| Observations          |          | 720   | 720   | 720   | 720   |
| **\(p\)-value for \(H_0: HRS - LRS = 0\)** | t-test | 0.0%  | 44.2%  | 42.1%  | 2.5%  |
|                       | Mann-Whitney | 0.0% | 70.7%  | 89.0%  | 0.5%  |

Notes: ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively, based on t-test for means and sign test for medians.

Sample sizes apply to each reward spread.

Table 2 shows that the estimates of \(p_1^{R,WD}\) and \(p_1^{R,PD}\) are positive and significant for both reward structures. This indicates that both winner disclosure and partial disclosure induced positive peer-generated psychological values and motivations. The participants desired the opportunity to be publicly recognized for their achievements. Furthermore, there is significant evidence (not shown in Table 2) that \(p_1^{R,WD}\) is greater than \(p_1^{R,PD}\). The Mann-Whitney test rejects the hypothesis (with \(p<1\%\) under LRS and \(p<5\%\) under HRS) that these estimates are from the same distribution. This suggests that being recognized as the sole winner provides greater peer-generated psychological value than being recognized as one of the top two finishers. This could
be because disclosing the top two without distinguishing between them dilutes the value of finishing in first place. These results support Hypothesis 1.

Table 2 also shows that the $o$-index, the net effect on effort of learning one’s own rank, is not significant under the high reward spread, but is quite large and highly significant under the low reward spread. This indicates that, apart from the peer-generated psychological motivations induced by public disclosure, there may be other sources of psychological motivations. However, such motivations seem to be crowded out when the reward spread is high. In other words, the psychological motivation provided by learning one’s own rank when the reward spread is low appears to be undermined by the economic incentives of the high reward spread.

Lastly, the net effect of full disclosure on effort (the $FD$-index) is positive under the high reward spread, but is not significant under the low reward spread. Thus, when the reward spread is low, fully disclosing the contest outcome does not lead to any significant peer-generated psychological motivation. However, when the reward spread is high, full disclosure induces positive and significant peer-generated psychological motivations. The $FD$-index ($3p_{1,FD} + p_{2,FD}^R - 4p_{3,FD}^R$) measures the net effect of positive emotions from being recognized as a winner and negative emotions from being revealed as a loser. The net effect mainly depends on peer-generated psychological values from being the top winner ($p_{1,FD}^R$) and a non-winner ($p_{3,FD}^R$). As full disclosure includes a distinction between the winner and runner-up, it is likely that the peer-generated psychological value for top winner ($p_{1,FD}^R$) is much greater under the high reward spread (when the winner gains far more than the runner-up) than under the low reward spread.

5. Quantifying Psychological Motivations: An Indirect Approach

So far, we have taken a direct approach to modeling and estimating psychological motivations and their impacts on selling effort. Using the no disclosure scheme as a baseline, we are able to identify and estimate the peer-generated psychological values induced by the winner disclosure and partial disclosure schemes, to test theoretical hypotheses regarding these peer-generated psychological values, and to demonstrate the effects of psychological motivations on selling efforts. However, our analysis also uncovers a critical drawback of the direct approach: the plethora of psychological value parameters leads to limited identification. Specifically, for the psychological values of knowing one’s own result ($o_j^R$), we can estimate an index (the $o$-index) but cannot separately identify each of the individual parameters. Similarly, for the peer-generated
psychological values under the full disclosure scheme, we can estimate an index (the FD-index), but not the psychological value of recognition for reaching ranks 1, 2, and 3 or 4. These identification issues will become worse as the number of contestants increases or as the contest becomes asymmetric (e.g., Chen et al. 2011). Even for the partial disclosure and winner disclosure schemes, identifying the peer-generated psychological values relies on the set of restrictions imposed in Assumption 1.

In this section, we present a novel, indirect approach to studying the impact of psychological motivations. The main objective of this approach is to estimate a single, unique psychological motivation parameter for each regime characterized by a reward structure and a disclosure scheme. Instead of directly modeling psychological values through an agent’s utility function, here we capture the psychological motivations through a change to the agent’s marginal cost of effort. More specifically, we assume that all psychological payoffs from exerting effort $e$ in a contest characterized by $R$ and $D$ can be summarized by a parameter $\gamma_{R,D}$ representing the marginal benefit (or cost) from exerting each unit of effort. Thus, the psychological payoff from exerting effort $e$ is $\gamma_{R,D} \times e$. If $\gamma_{R,D}$ is positive, then there is psychological benefit from exerting effort in addition to the economic benefit; otherwise, there is a psychological cost.

The psychological component is not outcome-specific in this formulation, as it represents the agent’s net expected psychological payoff when she chooses her effort level. Nevertheless, an agent’s effort directly affects the probability distributions of different contest outcomes, thereby indirectly affecting her net expected psychological payoff. When a contest’s reward or disclosure scheme changes, the psychological payoffs from different outcomes change. As effort directly affects the probability distribution of different outcomes, such a change in the contest design (either in reward or disclosure scheme) can affect the net marginal return from exerting effort, effectively making effort exertion more or less costly. Hence, modeling psychological motivation through a change in effort cost indeed captures changes in the outcome-dependent psychological payoffs, albeit indirectly. Importantly, modeling psychological motivation with a single parameter makes the model tractable and parsimonious. This benefit becomes more salient when the number of agents $N$, and hence the number of psychological value parameters resulting from the direct approach, described in Sections 3 and 4, increases.

The value of the psychological motivation parameter $\gamma_{R,D}$ is specific to reward structure $R$ and disclosure scheme $D$. A change in the reward distribution or the adoption of a different
disclosure scheme could change the level of psychological motivation, as suggested by the experimental results shown in Section 4. Thus, the total payoff from earning a reward of \( r \) by exerting effort \( e \) in a contest characterized by \( R \) and \( D \) is

\[
u(w + r - e) + \gamma_{R,D} \times e.
\]

Hence, the agent will choose \( e_i \) to maximize her expected utility, given by

\[
\sum_{j=1}^N Pr_j(e_i, e_{-i})u(w + r - e) + \gamma_{R,D} \times e_i
\]

Our analysis approach is similar to that in Section 4. We restrict attention to symmetric equilibria, in which each agent expends the same amount of effort \( e_k = e^*, \forall k \). The first-order condition is given by:

\[
\sum_{j=1}^N \left( Pr_j(e_i, e_{-i}) \left( \frac{\partial u(w + R_j - e_i)}{\partial e_i} + \frac{\partial Pr_j(e_i, e^*)}{\partial e_i} u(w + R_j - e_i) \right) \right)_{e_i = e^*} + \gamma_{R,D} = 0 \quad (9).
\]

Therefore,

\[
\sum_{j=1}^N \left( \frac{N-2j+1}{e^*N(N+1)} u(w + R_j - e^*) \right) = \gamma_{R,D} = 0 \quad (10).
\]

The above equation can be rewritten as follows:

\[
e^* = \frac{\sum_{j=1}^N \frac{N-2j+1}{e^*N(N+1)} u(w + R_j - e^*)}{\gamma_{R,D}} = \frac{\sum_{j=1}^N (N-2j+1) u(w + R_j - e^*)}{(N+1)\left( \sum_{j=1}^N u'(w + R_j - e^*) - N\gamma_{R,D} \right)} \quad (11).
\]

Equation (11) provides the equilibrium effort given exogenously-determined reward structure \( R \) and disclosure scheme \( D \). Several features of this approach are worth noting. First, the indirect approach adopted here follows the property that at the equilibrium effort level, the marginal value of incremental effort equals the marginal cost. An increase in equilibrium effort due to psychological motivations can be modelled either through an increase in marginal value or a decrease in marginal cost. The direct approach in Sections 3 and 4 models changes in the marginal values of outcomes, and the indirect approach in this section models changes in the marginal cost of effort. Second, a benefit of the indirect approach is that if an agent’s utility function and initial wealth level from a given contest \((R, D)\) are known, then we can back out her psychological motivation parameter \((\gamma_{R,D})\) from her optimal effort choice. We summarize this in Lemma 1.

**Lemma 1** Suppose agents play symmetric strategies. If we observe an agent’s optimal effort choice and know her utility function, then the psychological motivation parameter is identified.

**Proof:** Equation (11) characterizes the unique symmetric equilibrium. It implies that


\[ \gamma_{R,D} = \sum_{j=1}^{N} \left( \frac{u'(w + R_j - e^*)}{N} - \frac{N - 2j + 1}{N(N+1)e^*} u(w + R_j - e^*) \right). \]

In our experiment, \( w \) equals 100. If we know the utility function \( u \) and the agent’s effort choice from contest \((R, D)\), all parameters on the right-hand side are known. Then, the psychological motivation parameter \((\gamma_{R,D})\) can be calculated easily.

Next, we use Lemma 1 to infer the psychological motivation parameter values from our empirically-observed effort decisions. Our goals are to characterize the effect of the contest design and disclosure scheme on the net impact of psychological motivations and to discuss the implications of such results on the optimal design of contests, including both the reward structure and the disclosure scheme.

**Estimation of Psychological Motivation Parameters**

Using Lemma 1 and the observed effort choices in our experiments, we now estimate \( \gamma_{R,D} \). To do so, however, we need to make an assumption about each agent’s economic utility function, \( u \). As is common in the literature, we first assume that all subjects are risk neutral, so \( u(x) = x \). We then relax that assumption, allowing subjects to have heterogeneous levels of risk aversion.

**Risk Neutrality**

Under risk neutrality, an agent’s effort choice in the symmetric equilibrium of our experiment will be \( e^* = \frac{3R_1 + R_2}{20(1 - \gamma_{R,D})} \). Therefore, the psychological motivation parameter in our experiment is given by the following equation: \( \gamma_{R,D} = 1 - \frac{3R_1 + R_2}{20e^*} \). We use this to calculate the value of \( \gamma_{R,D} \) for each subject in each period. Assuming that each observed \( \gamma_{R,D} \) equals the true value of the parameter plus a zero-mean error term, we can estimate the psychological motivation parameter for each contest characterized by \( R \) and \( D \). One issue, however, is that the range of possible estimates skews strongly to the left. For example, under the HRS, the maximum, median, and minimum efforts (100, 50.5 and 1) give estimates of 0.44, -0.11 and -55, respectively. As a result, a small set of observations with large negative values of \( \gamma_{R,D} \) pulls the mean of the estimated parameter far below the median under each treatment. Therefore, rather than considering the mean estimates to examine how psychological motivation differs across treatments, we present the medians and use the Mann-Whitney two-sample statistic to test the hypothesis that the estimates under different treatments are from the same distribution. More specifically, the test indicates whether one set of estimates tends to have higher values than the other.
Table 3 presents the median estimated value of $\gamma_{R,D}$ under each treatment. The psychological motivation parameters mirror the mean individual effort choices directionally across disclosure schemes. For example, we find significantly higher values of the psychological motivation parameter under the winner disclosure and partial disclosure schemes than under the no disclosure scheme for both reward structures. Using no disclosure as a baseline, psychological motivation tends to be higher under full disclosure when the reward structure is HRS, but not when it is LRS. Also, across all disclosure schemes, the LRS invokes significantly higher values of the psychological motivation parameter than the HRS. This suggests that psychological motivation, in part, drives the higher efforts that we observe under the LRS (as seen in Section 4), under the assumption that subjects are risk neutral. As an alternative to using the Mann-Whitney test, we can compare the means of the skewed distributions of parameter estimates by dropping extremely low values of $\gamma_{R,D}$ from each treatment. For example, if we drop the lowest 10% of values of $\gamma_{R,D}$ from each treatment, the mean values of the parameter and the comparisons of means across treatments are qualitatively the same as those in Table 3.\textsuperscript{6}

<table>
<thead>
<tr>
<th>Median $\gamma_{R,D}$</th>
<th>No Disclosure</th>
<th>Winner Disclosure</th>
<th>Partial Disclosure</th>
<th>Full Disclosure</th>
<th>All Disclosures</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Reward Spread</td>
<td>-0.02</td>
<td>0.07***</td>
<td>0.07***</td>
<td>0.07***</td>
<td>0.07***</td>
</tr>
<tr>
<td>Low Reward Spread</td>
<td>0.34**</td>
<td>0.40***</td>
<td>0.42***</td>
<td>0.33***</td>
<td>0.38***</td>
</tr>
<tr>
<td>Observations</td>
<td>720</td>
<td>720</td>
<td>720</td>
<td>720</td>
<td>2,880</td>
</tr>
<tr>
<td>$p$-value for $H_0$: HRS – LRS = 0</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

Notes: ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively, based on sign test.

Sample sizes apply to each reward spread.

\textsuperscript{6} As an example, for contests with a high reward spread and full disclosure, the lowest 10% of $\gamma_{HRS,FD}$ take values of -4.6 or lower.
**Risk Aversion**

Above, we have presented the psychological motivation parameter estimates assuming risk neutrality. This assumption, which substantially simplifies the analysis, can be restrictive. Now we extend the analysis by relaxing the risk-neutrality assumption. In the experiment, we included a risk-attitude elicitation round, allowing us to measure the individual-level risk preferences of the subjects.

In the risk-attitude elicitation round, we elicited each subject’s certainty equivalent for each of three lotteries, using the Becker-DeGroot-Marschak mechanism. A subject’s reported willingness-to-pay, or certainty equivalent, for a lottery that took a value of 0 with probability 1 – \( p \) and a value of 20 points with probability \( p \) is used to estimate a CRRA risk coefficient, as follows: Suppose a subject’s preference can be characterized by the utility function \( u(x) = x^{1-\rho} \) and the subject reports a certainty equivalent of \( c \) for that lottery. Then, \( p20^{1-\rho} = c^{1-\rho} \), implying that \( \rho = \frac{\ln(20)+\ln(p)-\ln(c)}{\ln(20)-\ln(c)} \).

We estimate \( \rho \) this way for each subject, for each of the three lotteries. Since we are interested in identifying the effects of risk aversion, we use the maximum of each subject’s three estimates (i.e., the most risk-averse estimate) to represent their risk attitude for our analysis. Table 4 summarizes these risk coefficients for all of our experimental subjects.

<table>
<thead>
<tr>
<th>Risk coefficient (( \rho ))</th>
<th>No Disclosure</th>
<th>Winner Disclosure</th>
<th>Partial Disclosure</th>
<th>Full Disclosure</th>
<th>All Disclosures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.15</td>
<td>0.25**</td>
<td>0.23**</td>
<td>0.28***</td>
<td>0.23***</td>
</tr>
<tr>
<td></td>
<td>(0.89)</td>
<td>(0.73)</td>
<td>(0.65)</td>
<td>(0.43)</td>
<td>(0.69)</td>
</tr>
<tr>
<td>Median</td>
<td>0.31***</td>
<td>0.45***</td>
<td>0.37***</td>
<td>0.37***</td>
<td>0.37***</td>
</tr>
<tr>
<td>Observations</td>
<td>48</td>
<td>48</td>
<td>48</td>
<td>48</td>
<td>192</td>
</tr>
</tbody>
</table>

**Notes:** Standard deviations are presented in parentheses.

***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively, using t-test for the means and sign test for the medians.

---

7 Our results do not change qualitatively if we use another function of the three risk-aversion parameters instead.
Both the mean and the median values of the risk coefficients for all subjects together are significantly positive at the 1% level, indicating that subjects were largely risk-averse. Although the mean value of the coefficient is not significant for the no disclosure scheme, there are no statistically-significant differences in either the median or mean values across disclosure schemes. This is not surprising, given that subjects were assigned to them randomly. Furthermore, under our experimental parameters, the range of possible values of $\rho_i$ has its maximum at 0.93 and its minimum at -22.5, so it is not surprising that the mean value is below the median under each disclosure scheme. Since the theory developed in Section 3 applies only to risk-averse and risk-neutral individuals, we drop subjects with negative risk coefficients (i.e. those who are risk-seeking) from the empirical analysis presented below.

Before examining the psychological motivation parameters under risk aversion, we first re-visit the mean effort levels chosen by the subjects under each treatment. This is to ensure that restricting the sample to risk-neutral and risk-averse subjects does not change any of the key observations from Table 1. Table 5 confirms that the directional results discussed in Section 4 continue to hold.

**Table 5: Summary of Individual Effort Choice Excluding Risk-Seeking Subjects**

<table>
<thead>
<tr>
<th>Mean Effort</th>
<th>No Disclosure</th>
<th>Winner Disclosure</th>
<th>Partial Disclosure</th>
<th>Full Disclosure</th>
<th>All Disclosures</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Reward Spread</td>
<td>53.5 (34.5)</td>
<td>60.0 (30.2)</td>
<td>60.1 (31.5)</td>
<td>58.6 (32.1)</td>
<td>58.1 (32.2)</td>
</tr>
<tr>
<td>Low Reward Spread</td>
<td>58.2 (34.1)</td>
<td>63.7 (26.9)</td>
<td>63.0 (28.5)</td>
<td>58.1 (30.4)</td>
<td>60.8 (30.2)</td>
</tr>
<tr>
<td>Observations</td>
<td>600</td>
<td>615</td>
<td>630</td>
<td>645</td>
<td>2,490</td>
</tr>
<tr>
<td>$p$-value for $H_0: HRS - LRS = 0$</td>
<td>1.7%</td>
<td>2.2%</td>
<td>8.8%</td>
<td>77.5%</td>
<td>0.3%</td>
</tr>
</tbody>
</table>

*Notes:* Standard deviations in parentheses

Sample sizes apply to each reward spread

Next, we estimate the psychological motivation parameters under the assumption that subjects are heterogeneously risk averse. Suppose again that each agent’s utility can be described by a CRRA utility function. That is, $u_i(x) = x^{1-\rho_i}$, where $\rho_i$ denotes agent $i$’s CRRA risk
coefficient, as discussed above. While we allow the risk coefficient to vary across agents, capturing the heterogeneity of subjects’ risk aversion, we assume that each agent believes that all other agents have the same $\rho_i$ as she does. We further assume that the agent never updates this belief based on the game outcomes. As the agent does not know which other agents are competing in a round with her and never observes other agents’ actual effort choices or outcomes, this is a reasonable assumption that allows us to focus on a symmetric equilibrium.

Proceeding from equation (11), agent $i$’s optimal effort choice, $e_i^*$, solves the following:

$$e_i^* = \frac{3(w_i+R_1-e_i^*)^{1-\rho_i}+(w_i+R_2-e_i^*)^{1-\rho_i}-4(w_i-e_i^*)^{1-\rho_i}}{5(1-\rho_i)\sum_{j=1}^{4}(w_i+R_j-e_i^*)^{1-\rho_i}-20\gamma_{RD}}$$  (12)

This then implies that

$$\gamma_{RD} = \frac{5(1-\rho_i)e_i^*\sum_{j=1}^{4}(w_i+R_j-e_i^*)^{-\rho_i}-3(w_i+R_1-e_i^*)^{-\rho_i}-(w_i+R_2-e_i^*)^{-\rho_i}+4(w_i-e_i^*)^{-\rho_i}}{20e_i^*}$$  (13).

Thus, as suggested by Lemma 1, we can estimate $\gamma_{RD}$ for each subject in each period by substituting the subject’s effort choice and estimated risk-aversion parameter, along with the experimental parameters, into equation (13). In order to proceed, however, it is necessary to restrict the values of certain parameters. First, the estimate of $\gamma_{RD}$ is undefined when a risk-averse subject ($\rho_i > 0$) chooses the maximum possible effort of 100. Hence, we cap the effort level at the next-highest possible effort choice of 99 for our empirical estimations. (We substitute effort choice of 100 by 99 in the analysis.) Moreover, as mentioned above, we drop 26 (13.5%) of our 192 subjects due to negative risk coefficients, in order to focus only on those who are risk-averse or risk-neutral. The excluded subjects are distributed roughly evenly among the treatments, with between 5 and 8 individuals omitted from each disclosure scheme.

Table 6 presents the median estimated values of $\gamma_{RD}$ under CRRA for each treatment. First, although the values look relatively small, all are significant at 1% using the sign test, with at least 66% of the estimated parameter values greater than zero under each treatment, except for the no disclosure-HRS combination (57%). Second, comparisons of $\gamma_{RD}$ across disclosure schemes

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8 If we relax this assumption, we can still determine equilibrium effort choices once we specify each agent’s belief about the other agents’ risk preferences. However, the equilibrium, from each agent’s point of view, will no longer be symmetric.

9 Again, instead of analyzing the median, we can alternatively handle the skewed distribution of $\gamma_{RD}$ estimates by dropping the observations with the lowest values from each treatment, and performing $t$-tests on the means of the remaining values. If we drop the lowest 5% of observations from each treatment, the results are qualitatively the same as those shown.
yield results similar to those under risk neutrality, although somewhat weaker once risk aversion is accounted for. Specifically, there is no longer a significant difference in the psychological motivation parameters between the no disclosure and winner disclosure schemes under the HRS. One possible explanation for this result is that a high reward spread naturally creates a winner-take-all feeling and, as a result, adding a winner disclosure can become redundant.

Third, as in the analyses under the risk-neutral case, psychological motivations under the LRS are lower for no disclosure and full disclosure than for winner disclosure and partial disclosure, but some of those differences are now only marginally significant (p-values below 10%). More specifically, partial disclosure leads to a (weakly) higher psychological motivation parameter than any other scheme under both reward structures. Moreover, winner disclosure and full disclosure lead to (weakly) higher psychological motivation parameters than no disclosure under both reward structures.

Overall, recognizing the winners in some form clearly increases psychological motivation relative to not publicly announcing any information about the contest outcome. It also appears that recognizing both winners without divulging their ranking (partial disclosure) succeeds in providing the highest level of psychological motivation.

Furthermore, the psychological motivation parameter continues to be significantly higher under the LRS than under the HRS for each disclosure scheme. This suggests that, even after accounting for risk aversion, psychological motivation plays a part in driving the higher efforts that we observe under the LRS. Theory models show that when players are risk neutral, a winner-take-all reward (high reward spread) structure maximizes effort. The experimental literature, however, finds robust evidence that providing multiple large rewards leads to higher levels of effort. Typically, such results are attributed to risk aversion (Lim et al. 2009). Our finding that the psychological motivation parameters are higher for the lower reward spread treatment, even after incorporating risk aversion, suggests that such results should not be solely attributed to risk attitudes.\(^1\)

\(^1\) Note that the magnitudes of the estimated parameter \(\gamma\) are smaller in Table 6 than in Table 3. This does not necessarily imply that risk aversion leads to a smaller impact of psychological motivation on effort choice. How the effort level enters the equation for psychological motivation is different under risk neutrality and risk aversion. As a result, the numbers in the two tables may not be comparable. Nevertheless, this may also imply that psychological motivation goes hand-in-hand with loss aversion for such small-stakes situations, supporting our evidence of psychological motivations significantly affecting effort choice. We thank an anonymous referee for pointing this out.
Table 6: Median of Estimated Psychological Motivation Parameter ($\gamma_{R,D}$) under CRRA

<table>
<thead>
<tr>
<th>Median $\gamma_{R,D}$</th>
<th>No Disclosure</th>
<th>Winner Disclosure</th>
<th>Partial Disclosure</th>
<th>Full Disclosure</th>
<th>All disclosures</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Reward Spread</td>
<td>0.01***</td>
<td>0.01***</td>
<td>0.03***</td>
<td>0.02***</td>
<td>0.01***</td>
</tr>
<tr>
<td>Low Reward Spread</td>
<td>0.03***</td>
<td>0.03***</td>
<td>0.04***</td>
<td>0.03***</td>
<td>0.03***</td>
</tr>
<tr>
<td>Observations</td>
<td>600</td>
<td>615</td>
<td>630</td>
<td>645</td>
<td>2,490</td>
</tr>
</tbody>
</table>

$p$-value for $H_0: HRS - LRS = 0$

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>1.1%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

Notes: ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively, based on sign test

p-values based on Mann-Whitney test

Sample sizes apply to each reward spread.

The higher level of psychological motivation observed under the low reward spread reveals an interesting form of motivation crowding-out through incentives. In the existing literature on the crowding out of motivation, psychological motivation is often found to be undermined when the amount of monetary incentive is increased. In contrast, in our study, the total amount of rewards remains the same under the two schemes. Rather, the level of psychological motivation is reduced when the spread of prizes is increased from $LRS$ to $HRS$. Thus, crowding out of motivation occurs in a contest with highly-unequal prizes, relative to one in which the prizes are more evenly distributed.

6. Conclusions and Discussion

Our theoretical analysis and laboratory experiments have demonstrated how the reward structures and disclosure schemes in sales contests can affect the participating agents’ psychological motivations, and hence their effort decisions. Our results show that, first, psychological motivations do contribute to effort decisions. The psychological motivation parameters that we estimate are significant under virtually all experimental conditions, including the no disclosure condition that is closest to the theoretical benchmark.

Second, we find that the incentive structure can affect the levels of psychological motivations. More specifically, when the reward spread is low, psychological motivation tends to
be higher. It is worth noting that past research tends to attribute high efforts observed under low reward spread to agents’ risk aversion. Our result shows that, even after controlling for risk aversion, a low reward spread could lead to higher effort through enhanced psychological motivation.

Third, we show that the choice of disclosure scheme can affect the level of psychological motivation. Disclosure schemes, which do not change financial incentives, can affect an agent’s effort only through peer-generated psychological motivations. Among many results regarding disclosure schemes, we find that, overall, having a recognition program can enhance psychological motivation and increase effort (as compared to having no public disclosure). This result provides strong support for the wide acceptance of recognition programs in industry. We also find that, among the disclosure schemes examined in our study, across many conditions, *partial disclosure* performs at least as well as any other disclosure scheme. This result is consistent with the advice of industry experts (Zoltners et al. 2011) and may help explain why President’s Club-style recognition programs are the most popular in practice.

Finally, we develop a flexible framework to estimate a single parameter that quantifies the scale and economic impact of psychological motivations. This framework can easily be extended in future research to investigate such motivations in other contexts. Within the sales management domain, future research may examine the level of psychological motivations associated with straight commission schemes, quota-based compensation schemes, and team-based incentive schemes. The framework can also be extended to study agent behavior in public economics (e.g., the psychological motivation to contribute to crowd funding).

The contributions of this paper have a number of implications for sales management. Most generally, the significant effect of psychological motivations 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 psychological impacts of both the distribution of prizes and the public announcement of outcomes. In determining the optimal prize distribution for a contest, sales managers should watch for the possibility of crowding out psychological motivation not only through larger prizes, but also through more uneven distributions of a fixed prize pool. 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, but that announcing the
identities of the non-winners may be counterproductive. Managers should also be mindful that the psychological effects of public announcement 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 two separate decisions. For example, a manager designing a sales contest can maximize psychological motivation by distributing rewards among multiple winners and publicly recognizing all of them (without “shaming” the lower finishers). 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. Lastly, we believe that our indirect model can be a useful tool for managers interested in understanding the psychological motivations of salespeople in their own particular contexts. For example, beyond contest design, a manager could use this approach to study potential differences in psychological motivations for salespeople selling different products (e.g. new vs. established brands) or to different types of customers (e.g. large vs. small, new vs. repeat purchasers). The parsimonious nature of the model allows it to be applied broadly and it is designed to focus less on the psychological motivations themselves than on the practical outcome of those motivations—their net effect on effort.

References


Appendix: Experimental Instructions (as provided to subjects)

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, parts (or all) 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 100 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 \( e \), out of 100, 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 \( \epsilon \) is distributed according to a logistic distribution with mean of zero and variance of \( \pi^2/3 \). Specifically, the probability distribution function (pdf) is \( f(x) = \frac{\exp(-x)}{(1+\exp(-x))^2} \). 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 100 (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 \( \epsilon \) 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.

**Risk-attitude Elicitation Round**

After the end of 40 periods of sales contest, you will individually participate in a risk-attitude elicitation round with three periods where, in each period, you will report your willingness-to-pay for a lottery. These are individual lotteries which take a value of 0 with probability $1 - p$ and a value of 20 points with probability $p$. The probability of winning 20 points, $p$, will be different for the 3 different lotteries — the possible values are 30%, 50%, and 80%. For each given lottery, you will report your willingness-to-pay, which has to be an integer between 1 and 19. Independent of your reported willingness-to-pay, the computer will choose a number between 1 and 19. If this number is above your reported willingness-to-pay, you will be paid this number in points. If it is below your reported willingness-to-pay, you will be paid according to the lottery. Thus, it is optimal to truthfully report your willingness-to-pay. You will be paid according to one randomly chosen period of this round at the end of the session.

**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.