Abstract

We use experiments to study how changes in the degree of competition and bonus structure affect worker effort. We find that individuals behave quite differently than expected by extant theory: most individuals use a coarse strategy that entails choosing only maximal or minimal effort. We thus find that we maximize total effort by providing higher levels of worker competition while simultaneously rewarding the best performer relatively less. In some cases, awarding the largest bonus to the second best performer is best. This structure elicits 62% more total effort per bonus dollar than our baseline winner-takes-all case.

Key Words: Heuristic, Coarse Decision Making, Contest, Tournament, Personnel Economics

JEL: DO3,M5

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"People rely on a limited number of heuristic principals which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations." Tversky and Kahneman (1974)

Many economic models prescribe sharp incentives. Incentives in the "real world," however, tend to be softer. For example, to align incentives and maximize performance, employees should be made residual claimants of a firm. However, we see few examples of material employee ownership of firms. In fact, Kim & Ouimet (2009) report a mere 18% of all workers own any of their employing firm’s shares. Similarly, although performance based labor contracts should often be used over flat salaries, we find little evidence of such contracts in the workplace. Lemieux, McCleod and Parent (2009) report only 14% of workers receive any type of performance pay—which includes bonuses, piece rates, or commissions.

Labor tournaments with steep incentives offer another approach to maximizing effort. However, this high powered structure is not so apparent in practice. Two employees of similar activities but varying effort can both advance to subsequent positions. Seniority can sometimes trump performance for advancement. And a higher position, though accompanied with higher pay, when paired with greater responsibility may not be such a steep jump in reward, if any.¹

Why are soft incentives so pervasive? We argue soft incentives result when considering the interaction of employee heterogeneity and competition. In particular, if a firm sharpens its incentives—by giving a greater share of the bonuses to the top performer(s) or increasing the number of workers competing over a set of bonuses—the most able are incentivized but the rest give up due to discouragement. Recent theoretical developments suggest this latter effect can overcome the former (e.g., see Moldovanu & Sela (2001) and Minor (2012)). Ideally, we would like to manipulate firm compensation and ownership to understand the value of soft incentives in practice. In addition to the difficulty of having firms agree to our running experiments on their workers, even with such permission, it would be difficult to manipulate worker ability, let alone identify its precise value. This is important because prescribing soft incentives relies on accurately knowing worker types. We can instead use the laboratory to not only vary reward structure and degree of competition, but also assign heterogeneous worker ability. In this spirit, we explore experimentally the effects of different organizational forms on effort—the effects of the degree of competition and the

¹See Prendergast (1999) for further examples of surprisingly soft incentives within the firm.
distribution of the bonus schedule on effort.

We find simultaneously increasing the degree of competition and softness of incentives increases overall effort. In fact, we observe the greatest effort by offering a larger second than first prize, generating some 62% greater effort than the winner-takes-all baseline case. However, we also find some important, systematic deviations from theory.

In some settings, we find "overbidding" (i.e., over exertion), which is ubiquitous in past contest experiments (e.g., see Morgan et al. (2010) for a collection of such findings); but in other settings, we find "underbidding" (i.e., under exertion) vis-à-vis the Nash equilibrium benchmark. All the while, instead of contestants using a continuum of effort levels as predicted by extant theory, contestants instead choose effort in a binary fashion. In particular, players tend to use a "coarse" strategy of simply choosing between maximal or minimal effort.

There is a growing exploration of "coarse" decision making. Such approaches can include "coarse matching," where, for example, utility companies ration electricity to a much smaller set of matching classes than optimal, and yet still capture the majority of gains (see McAfee (2002)). Similarly, "coarse" decision making can lead to coarse contract sets. Rogerson (2003) shows a simple pair of procurement contracts secures the vast majority of gains available from an unconstrained set of contracts. Chu and Sappington (2007) show another example of simple contracts capturing the majority of optimal contract surplus.

In addition to rationalizing the existence of simpler contracts and strategies than optimal, "coarse" decision making can help explain some anomalies. Mullainathan et al. (2008) directly model agents as coarse thinkers that use a more discrete state space than available. This model explains the emergence of uninformative advertising and firm product branding. In another case of coarse decision making, Gennaioli and Schleifer (2010) provide rationale for several insurance purchasing puzzles.

In light of our experimental results, this paper explores a simple model of coarse decision making in a contest setting. Our model of coarse strategy is motivated by the heuristic of attribute substitution, which is well documented by psychologists (see Kahneman(2003)). A manifestation of this heuristic is to replace a probabilistic assessment of an individual's type by a stereotype. In our model, a player assumes all of his competitors are some representative type (i.e., her stereotype), forgoing an assessment of a probabilistic outcome over multi-dimensional type space. If a person uses the heuristic of playing as if her
opponents are some representative type\textsuperscript{2}, the best response choice of effort is simple: exert maximal effort when she is more talented than such type and provide minimal effort when less skilled. Thus, coarse decision making in competition leads to coarse play endogenously.

We test the this alternative model of effort not only using our own data, but also using the data of similar experiments (Noussair and Silver (2006) and Müller and Schotter (2010)). We find our coarse model better explains subjects' behavior than the Nash predictions.

There has been considerable interest in exploring contests experimentally. Recently, the focus has become exploring different contest and incentive designs, and their effect on effort. For example, Cason, Masters & Sheremeta (2010) compare a winner-takes-all scheme to alternative schemes of piece rates and sharing prize mass proportionally based on output: Freeman & Gelber (2010) study a winner-takes-all versus multiple prize contest. They find that when contestants know their type and the realized types of their competitors, a multi-prize contest elicits more effort from the less able and less effort from the most able compared to a winner-takes-all contest. Müller & Schotter (2010) study private values contests with a constant degree of competition and compare equal to winner-takes-all prizes. They also test the monotonic prize structure from Moldovanu & Sela (2001). Finally, Dechenaux, Kovenock, and Sheremeta (2012) provide an extensive survey of contest experiments.

This recent experimental work has consistently identified a "discouragement" effect. That is, as incentives become sharper, the most able try harder, but the less able try less, or even give up. However, these findings remain largely unexplained. One purpose of this paper is to identify why we witness this behavior. We find the discouragement effect can be driven by coarse strategy and may be even harsher than theory predicts—not only does it mean lower effort, but often no effort at all.

These past experimental studies often hold the level of competition constant and thus are not able to identify how this interacts with the incentive and discouragement effect. Hence, another purpose of this paper is to determine the interaction effect of competition and incentives. We find that when we optimally design incentives, we must determine not only the reward structure but also the best degree of competition.

To our knowledge, this paper is also the first to provide experimental results on non-

\textsuperscript{2}Camerer and Lovallo (1999) coin the term "reference group neglect" to describe this idea of making competitive decisions based on some group other than the actual group one is competing against. In the case of our model, the supplanting reference group is a set of homogeneous representative types.
monotonic prize contests. In practice, it may sometimes be best to be second best. For example, in some settings the second firm to innovate can reap the better reward. In other settings with common rewards, the highest effort may yield extra responsibility or work, creating a net worse reward than second best. See Minor (2012) and cites therein for more examples of non-monotonic prize structures, as well some references to theoretical studies in non-monotonic rewards.

The paper proceeds as follows. Our first section introduces the theory of the trade off between the incentive and discouragement effect. In section two, we explain the experimental design and report our initial results. Section three introduces a simple coarse strategy model to explain the data, as well as the outcomes of other experiments. Section four then tests the explanatory power of the model, as well considers some alternative models. The final section concludes. All proofs are relegated to the appendix.

1 Theory

Consider a setting where contestants exert effort and are awarded a bonus in rank order of their effort. In practice, this includes settings where effort can be ranked, even if measured imprecisely. For example, consider a team setting where employee activities are not easily quantifiable but the manager can assess each employee’s relative contribution to the project.

The cost of effort $x$ is linear. Employees have privately known heterogeneous effort cost types $c$ drawn from a uniform distribution with support $[5, 1]$. Agents face one or two bonuses, depending on the treatment, with common values $V_1$ and $V_2$. For simplicity, we assume a base wage of zero throughout. Although $V_1$ is awarded for the greatest effort and $V_2$ for the second greatest effort, they need not be monotonically ordered in terms of value. A contestant then faces the following objective function:

$$\max_x F_1(b(x)^{-1}) \times V_1 + F_2(b(x)^{-1}) \times V_2 - c \cdot x$$

The CDF $F_1(x)$ ($F_2(x)$) is the probability of placing 1st (2nd) given effort $x$. The term $b(x)^{-1}$ is the inverse of the equilibrium effort function. The general procedure for finding this effort function involves taking the first order condition (FOC) and then integrating down the FOC to an arbitrary cost type $c$. The equilibrium effort function can be pinned down by assuming that the highest cost type in equilibrium exerts zero effort.
Assuming $V_1 \geq V_2$, we get the following equilibrium effort $b(c)$, as originally outlined in Moldovanu and Sela (2001):

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

We define

$$A(c) \equiv (N - 1) \int_c^1 \frac{1}{a} (1 - \frac{c - .5}{1})^{N-2} \times 2da$$

and

$$B(c) \equiv (N - 1) \int_c^1 \frac{1}{a} (1 - \frac{c - .5}{1})^{N-3} \times [(N - 1) \frac{c - .5}{1} - 1] \times 2da$$

with $N \in \{3, 6\}$ contestants. We name this effort function $b(c)$ since we also at times refer to effort choices as "bids" due to a contest’s similarity (and sometimes equivalence) to an all pay auction.

To examine the full contract space of two prizes, we want to allow for the possibility of a larger second prize. Minor (2012) identifies a mechanism to accommodate this case. In particular, when we have $V_1 < V_2$, a pooling interval endogenously emerges where some measure of the most able types $c \in [.5, c^*]$ all exert the same effort up to some marginal cost type $c^*$ that is indifferent to pooling or providing effort as under $V_1 \geq V_2$. All types $c \in [c^*, 1]$ still provide effort levels as given by $b(c)$ above. We also want to allow for the possibility of effort capacity constraints. Many settings—whether it be maximal physical strength or a maximum of 24 hours in a day—have some maximum of possible effort.

In Figure 1, we show theoretically predicted efforts for two experimental treatments of $N = 3$ and one with a single bonus for the greatest effort and another with equal bonuses for first and second greatest effort. Compared with an equal bonus scheme, the winner-takes-all (i.e., WTA) setting induces the greatest effort for the lowest cost types (i.e., the most able) but less effort for all other costs types. Hence, we see an immediate trade-off in designing rewards: as we sharpen the incentives via shifting the bonus mass to first place, we increase the effort of the most able, but disincentivize all the others. We term the former the "incentive effect" and the latter the "discouragement effect."

[Figure 1 about here]
We will explore these effects, as well as contestant behavior and contest design in more general terms through controlled laboratory experiments, which we turn to now.

2 Experimental Design

In total, we conducted eight experimental sessions. Our 141 Subjects were undergraduate and graduate students from UC Berkeley. Sessions lasted approximately 45 minutes and subject payment averaged approximately $15 per subject. Subjects were not allowed to participate more than one time. The experiments were programmed and conducted with the software z-Tree developed by Fischbacher (2007).

We designed the experiments to operationalize the notion of individuals competing for rewards under different theoretically important settings. The experiment had a within subject design: subjects were randomly allocated cost types over time. This allows us to identify the discouragement and incentive effects while controlling for a subject’s unobserved heterogeneity.

The experiment also has a between subject element: We varied the competitions across the dimensions of prize structure, soft or hard effort cap, and the degree of competition (i.e., number of contestants). This variation is important to be able test primary contest design effects on subjects.

We use a chosen effort design. The importance of this is several fold. First, the theory relies crucially on knowing the participant types, which we readily know from having assigned them. Second, since types are randomly allocated, it is much easier to determine the effect of type on outcomes rather than just its correlation. Achieving these two conditions would be extremely difficult in a real effort setting, yet alone a field or natural experiment.

Sessions varied on the dimensions of bonus allocation, number of contestants (i.e., degree of competition), and the presence of effort capacity constraints. Since these contest games are complex and require learning, we allowed subjects to compete over 30 periods. For the bonus allocations, we simply changed the distribution of a constant $400 (in experimental units) bonus, which amounted to a per period bonus of $2 US dollars. The winner takes all (WTA) treatment awarded $400 per period to the most chosen effort. In the equal prize (EP) treatment, $200 is awarded to each of the top two effort subjects. Finally, the larger second prize (SP) contest awarded $260 to second greatest effort and $140 to the greatest. We also varied treatments across 3 and 6 subject groups to study the effects of changing the degree of competition.
Finally, all but the first two sessions had a total effort capacity constraint of 240 per period. This was done to allow us to explore how constraints affect optimal incentive structure. Theory predicts when competitors have no constraint, such as 24 hours per day or some maximal physical strength, the optimal structure is to only offer a WTA bonus structure. However, once agents have limits, it is best, in theory, to offer softer incentives. Table I shows a summary of all 8 sessions and the corresponding treatment.

Table I about here

Subjects were given an endowment of $300 experimental units each period. In each period, a subject was randomly assigned a cost type $c$, which was drawn from a uniform distribution with support $[.5, 1]$. Each player knew only their own cost type and then the distribution from which the other two (or five) contestants’ cost types were drawn. After learning their own cost type, subjects chose how much effort to exert. In addition to his cost type, the subject’s endowment value, the value of the bonus, and a calculator, should he need to calculate his cost of effort, were all displayed. On this screen, the player would then enter his effort. After all subjects submitted their chosen effort, the next screen revealed all three (or six) chosen levels of effort, as well as the calculation of the subject’s winnings for that particular period:

$$V - c \times e + W$$

where $V$ is the value of any bonus awarded, $c$ is his cost type, $e$ is his chosen units of effort, and $W$ is that period’s endowment.

Play continued to the next period where all subjects were again randomly assigned another cost type from the same distribution, independent of past periods of play and independent of the other players. Subjects’ final payoffs were based on six randomly chosen periods. This was done to limit the chances of any type of dynamic strategy and to limit income effects. At the end of the 30 periods of play, subjects took a short questionnaire and risk test. The risk test was a coarse version of Holt & Laury (2002). Rather than providing all 10 lotteries from their original study, we offered subjects half of these. While parsimonious, this still allowed us to categorize a subject’s risk attitude. Our aim was not to have a precise measure of risk aversion, but instead be able to identify risk neutral from risk averse and risk seekers.
2.1 Experimental Results

Table II reports our aggregate effort findings vis-à-vis the Nash Equilibrium benchmark predictions. In some cases, we observe overbidding, which has been the historical standard (e.g., see Crawford and Iriberri (2007) and cites therein). However in other cases, we observe underbidding. As we will soon see, such underbidding is explained by coarse strategy.

[Table II about here]

In our main treatments under effort capacity constraints, we see that competition and softer incentives work relatively better than predicted. In fact, comparing the baseline of a winner-takes-all (WTA) contest with three players to the contest with a larger second prize and six players shows 62% increased revenue. Roughly 80% of this 62% increase is from increased competition (i.e., moving from three to six players with a fixed prize mass) and 20% from changing the prize structure from WTA to a larger second prize. Recall that the first WTA treatment has no capacity constraints, so it is not directly comparable to the large second prize contest with capacity constraints. Results also suggest flatter incentives work worse than predicted in the absence of capacity constraints.

Thus, we find support that increased competition and softer incentives in the face of capacity constraints increase revenue; however, subjects are clearly acting differently under some settings.

2.1.1 The Nature of Effort Disparity

When analyzing subject effort choices individually, many seem to be using a threshold strategy. That is, there seems to be some cutoff cost type for each participant: when she inherits a cost type below this cutoff type, she exerts very high levels of effort, and when her realization is above this cost type, she abstains (i.e., exerts zero effort or close to it).

For example, Figure 2 shows a particular subject’s effort choices for a given cost type she inherits. Actual effort exerted is denoted by the diamonds. The dashed line is the Nash Equilibrium predicted effort, labeled NEBid. Note we also report the last 15 periods of play, as by then subjects had stabilized their strategy, as we discuss in our econometric section. Finally, the solid line labeled Capacity denotes the maximally allowed effort. As can be seen, the subject exerts maximal effort when she realizes cost types below the average cost type of .75, and then provides no effort for type realizations above this.
In Figure 3, we describe the effort choices of a subject with a very high threshold—at about a .85 cost type. When more advantaged (i.e., having a lower cost type) she exerts maximal effort and otherwise zero.

The final example in Figure 4 shows a subject with a very low threshold. Here there is a soft capacity constraint, only limited by the endowment and cost type, as opposed to the other two subjects who faced hard constraints of 240 maximal effort units.

Of course, these are only anecdotes. Overall, it appears that 1/2 to 2/3 of the subjects exhibit similar threshold behavior. As another measure of coarse play, if one considers the six treatments with common maximal effort of 240, we find roughly 48% of all effort choices are either zero or maximal (i.e., 240). Figure 5 reports the entire distribution of efforts for these sessions. As can be seen, there is a strong tendency to play maximal and minimal effort levels.

To verify these subjective observations quantitatively, a simple threshold effort strategy, as outlined explicitly in our next section, compared to actual effort, carries a mean squared error of 2115.61 across all sessions, assuming all players use the threshold strategy. In contrast, the Nash Equilibrium predicted effort compared to actual effort carries a mean squared error of 5226.04. We now explore a simple model of coarse strategy to better understand this threshold behavior.

3 A Coarse Strategy Model

For a player, calculating a best response over continuous type space is a complex calculation. Indeed, the expected effort given in Table II must be calculated numerically. It is plausible that contestants use a heuristic to calculate a best response. We begin with the starkest version, simply collapsing one’s action space from \([0, \text{max}_e] \rightarrow \{0, \text{max}_e\}\). That
is, rather than choosing from a continuum of possible effort, the player simply restricts himself to maximal and minimal effort. The agent problem is

\[
\max_{x \in \{0, \text{max effort}\}} \pi = P_1(x) \times V_1 + P_2(x) \times V_2 - c \cdot x_i
\]

where \(P_i\) is the probability of winning \(i\)th place given effort \(x\), which is a vector of the agent’s effort and his opponent’s efforts.

Now define \(B \equiv P_1(x_{\text{max}}) \times V_1 + P_2(x_{\text{max}}) \times V_2\), the gross expected benefit from providing maximal effort \(x_{\text{max}}\). Define \(c^*\) such that \(B = c^* x_{\text{max}}\). It then follows that there exists a unique \(c^*\) such that for all \(c \leq c^*\) the agent chooses \(x = \text{max effort}\) and \(x = 0\) otherwise. Of course, \(c^*\) might be the maximal or minimal cost type.

It would be interesting to know when the coarse strategy of simply choosing from the collapsed action set of \(\{0, \text{max effort}\}\) arises endogenously. One condition that yields this is to assume that \(P_1\) and \(P_2\) are uniform distributions in one’s own effort. This yields \(\frac{\partial \pi}{\partial x} = \frac{V_1}{a_1} + \frac{V_2}{a_2} - c\), where \(\frac{\partial P_i}{\partial x} = \frac{1}{a_i}\). Consequently, we again get the bang bang solution for maximal or minimal effort depending on \(c\). However, in this case, the subject is making an error in assuming the probability functions are uniform in his own effort. Nonetheless, this would be an understandable heuristic for contestants since cost types are drawn from a uniform distribution.

In a similar spirit to above, Baharad and Nitzan (2008) propose a model where homogeneous players have distorted probabilities and compete over a single prize. They find theoretically that different levels of over and under bidding arise as a function of contest size. In our experimental results, we find over and under bidding for both large and small contests. Instead, we find the over or under bidding is mostly a function of the distribution of the prize. This difference in our results to theirs is not surprising, however, as we are instead studying the setting of heterogeneous contestants and contests with more than one prize.

A second assumption that generates the strategy set \(\{0, \text{max effort}\}\) endogenously is motivated by the well established heuristic of attribute substitution (see Kahneman (2003)). In this case, competitors play as if all the other players are some representative type. For example, a player might assume all of her opponents are the average cost type .75. As shown in the appendix, the best response under such a heuristic is to again choose \(\text{max effort}\) when her cost type \(c \leq r\) and \(0\) otherwise, where \(r = .75\) (i.e., her representative type). We will use this latter interpretation for clarity in what follows: our estimation of one’s threshold
(or representative) type.

4 Estimating Representative Types

In this section, we estimate players’ representative true types \( r_i \). To do so, we use what we will call an Absolute Error Minimization (AEM) algorithm. Intuitively, we are finding for each subject the cost type that minimizes the summed absolute value of errors, where errors are defined as the difference between actual efforts chosen and the efforts that would be chosen if the player held the posited cost type as her representative type. In particular, this algorithm minimizes the following loss function over 30 periods of effort for a given contestant \( i \):

\[
\min_{r_i} \left[ \hat{b}_{i,t} - \left( I_{\hat{c}_{i,t} < r_i} \times M_i \right) \right] \times \left( 1 - I_{\hat{c}_{i,t} = r_i} \right)
\]  

(1)

The term \( \hat{b}_{i,t} \) is the observed effort, which is then compared to the expected effort \( I_{\hat{c}_{i,t} < r_i} \times M_i \). The indicator function \( I_{\hat{c}_{i,t} < r_i} \) takes on the value of 1 when realized cost type \( \hat{c}_{i,t} \) for contestant \( i \) for period \( t \) is less than the posited representative type \( r \), and 0 otherwise. Therefore, when \( \hat{c}_{i,t} > r \), the expected effort is zero and when \( \hat{c}_{i,t} < r \) the expected effort is \( M \). Recall \( M \equiv \min \{ \kappa, \frac{V_{\max}}{r_i} \} \) and thus varies across sessions and individuals, but not periods. For the knife edge case \( \hat{c}_{i,t} = r \), coarse strategy rationalizes any choice of effort and thus there is no error. Thus the indicator \( I_{\hat{c}_{i,t} = r_i} \) causes exclusion of these cases in the error minimization routine.

We use an absolute value loss function rather than squared deviation loss function since the former is less sensitive to outliers. This estimation procedure will identify the true \( r_i \) if subjects make errors that are no greater in magnitude than half the maximal effort, as the next proposition shows.

**Proposition 1** If the effort error \( \varepsilon_t < \frac{M}{2} \) for all periods \( t \) and \( \kappa \leq \frac{V_{\max}}{r_i} \) then the AEM algorithm identifies the true representative type \( r_i \)

**Proof.** See appendix. ■

This proposition says that as long as the contestant is "close enough" (i.e., not off by more than 1/2 of the total possible effort choice) to using the coarse strategy, the algorithm identifies the true \( r_i \) for such person. The results of this AEM algorithm are reported in Figure 6, which shows the empirical distribution of \( \hat{c}_i \), the estimate of the true \( r_i \):
Interestingly, as Figure 6 shows, there are three groupings of estimates of the representative type $r_i$. A large mass of players are just around the mean of the representative types at $\bar{c}_i = .75$. There is also a substantial grouping just below $\bar{c}_i = 1$. These can be thought of as chronically overconfident subjects—they are exerting maximal effort as if they are always facing the least able opponent. Finally, there is a smaller group of people close to $\bar{c}_i = .5$, playing as if all others are almost the most able type. This players exert little or no effort unless they find themselves realizing a cost type draw of the highest ability. In total, the mean of the entire distribution of $\bar{c}_i$ is .76, remarkably close to the simple average of all possible costs types. The average player is playing as if she has a representative type of (approximately) the average player—when she is stronger than average she goes "all in" with maximal effort and when she is weaker than average she offers minimal effort.

4.1 Coarse Strategy Model Goodness of Fit

We now consider the original Nash Equilibrium baseline predictions versus the actual revenue, but now add the predicted revenue assuming an average representative type of .75. This is reported in Table III.

Those cases where effort are both over and under the Nash prediction are all rationalized by the simple coarse strategy model.

In addition, we can consider the mean squared error of the model’s effort predictions compared with the Nash ones. Table IV records the mean squared errors from these models, partitioned by sessions. However, we combine sessions 5 and 6 and then 7 and 8, as they are the same treatment. For the first session, comparing the coarse strategy model and the Nash Equilibrium model, the latter provides a better fit for describing the data. For all other seven sessions, the coarse strategy model provides a much better fit.

A next natural question is how prevalent this coarse strategy is outside of our laboratory. To address this, we obtained data from the Noussair and Silverman (2006) study, hereafter...
NS. Their subjects were from Emory University. Additionally, they had an entirely different framing—that of a private values all-pay auction. Thus, players in their setting realized valuations as opposed to cost types. Players also received an initial endowment as opposed to our periodic endowment. Finally, their study was a paper and pencil experiment versus ours, which was computerized. Despite these differences, we found a great similarity to their subject’s behavior and ours. Within their treatments, for the last 15 periods of bidding, the mean squared error of actual bidding to the Nash prediction is 42,086.74. This error is much higher than for our treatments because their bidding ranges from zero to 1,000 versus ours is zero to 600 for the most able type (and 300 for the least able type). In comparison, the coarse strategy model yields an error of 23,847.69, roughly half the Nash prediction error.

In addition to NS, Müller & Schotter (2010), hereafter MS, find the same coarse strategy as in our study—individuals seem to go "all in" or abstain depending on their skill level. Their setting is a private values all-pay contest with equal or winner-takes-all prizes and a constant group size of four contestants. They also have quadratic vs. linear costs as opposed to our hard and soft capacity constraints with linear costs. We are able to compare our coarse strategy revenue predictions to their Nash predictions. These are summarized in Table V below.

[Table V about here]

For the treatment with linear costs and with a single WTA prize, their Nash Equilibrium prediction for revenue is 1.452: their actual revenue average is 2.391. In contrast, if we use their data with the coarse strategy model, it predicts average revenue of 2.234.

Another possibility is that the coarse strategy is just a manifestation of risk aversion. Fibich et al. (2006) show bidding should be greater for the most able types and less for the least able types under risk aversion compared to the traditional Nash prediction. However, this risk aversion prediction is still a smooth degradation of effort and not the sharp step bidding function that we observe in the data. In addition, lower cost individuals in the experiments tend to put in less effort than the Nash prediction and higher cost ones higher than Nash efforts, which would be predicted from risk seeking. Moreover, we can reject subjects were risk seeking from their risk tests which labeled most everyone risk neutral to risk averse.

We also conducted regression analysis on individuals’ representative types and found it is not explained by subjects' level of risk aversion. In addition, we regressed individual
effort choice on subject risk and demographic variables, with session fixed effects and lagged effort. Representative type has a strong and substantial effect on effort, while degree of risk aversion does not. Although subject gender does not matter\(^3\), being Caucasian or an economics or business major also contributed to greater effort choices. These regressions were omitted for sake of brevity but are available from the author upon request.

Although it seems many are engaged in this coarse strategy, not all players follow such a strategy. We now consider what proportion of different player behaviors best represents the data—allowing not just for coarse strategy but also Nash behavior, and an additional category we label noisy players, who choose effort randomly over the entire effort support.

### 4.2 Estimating the Proportion of Player Types

For this first analysis, we estimate from the entire subject pool the proportion of players behaving as coarse players, Nash players, and noisy players.

To do so, we use a non-linear least squares pooled panel regression. To account for potential serial correlation and idiosyncratic errors, we cluster the standard errors on subject. In particular, our model is as follows:

\[
\min_{\gamma_1, \gamma_2} Q \equiv \sum \left[ \text{effort}_{i,t} - \gamma_1 \left( I_{\tilde{c}_{i,t} < r_i} \times M_i \right) + \gamma_2 \left( b_{NE}(\tilde{c}_{i,t}) \right) + (1 - \gamma_1 - \gamma_2) \cdot n_t + e_{i,t} \right]^2
\]  \hspace{1cm} (2)

Again, we have \( M_i \equiv \min \{ \kappa, \frac{V_{\max}}{r_i} \} \). The term \( I_{\tilde{c}_{i,t} < r_i} \) is an indicator function taking on the value 1 when realized cost type \( \tilde{c}_{i,t} < r_i \) and zero otherwise. Each \( r_i \) is estimated in a first step according to the algorithm (AEM) outlined in the previous section. We denote \( b_{NE}(\tilde{c}_i) \) as the Nash Equilibrium predicted effort (or bid) given realized cost type \( \tilde{c}_i \). The third term \( n_t \) is the mean of the effort support, for the mean type of a given session—i.e., the expected effort from a noisy player.\(^4\) For the first two sessions, \( n_1 = 200 \) and \( n_2 = 133.33 \). However, for all other sessions due to the hard capacity constraint of 240, we have \( n_t = 120 \). Finally, the error term \( e_{i,t} \) is clustered by individuals.

We are estimating the parameters \( \gamma_1 \) and \( \gamma_2 \) to predict the proportion of coarse strategy and Nash players, respectively. This implies that \( 1 - \gamma_1 - \gamma_2 \) is the proportion of noisy

\(^3\)This is contrast to many experiments that have found a difference. See Ong & Chen (2012) and cites therein for such cases.

\(^4\)If instead \( n_t \) is drawn from an IID uniform distribution with the same support, the results are qualitatively the same.
players. Regression results suggest that 57% of subjects are coarse players, 16% are Nash players and, and balance are noisy players. When estimating these parameters on an individual session basis, for all but the first two sessions, we cannot reject the null hypothesis that the proportion of Nash players is zero. Meanwhile, the proportion of coarse players is always highly significant.

For the above estimates, we are using the last 15 periods of effort decisions; the first 15 periods are much nosier, as commonly found in contest and auction games. Indeed, if we use all 30 periods we estimate 50% are coarse players and just 10% are Nash players. This means that some subjects that were flagged early as noisy players learn to be coarse strategy players or Nash players for the last 15 periods.

4.3 Empirical Best Response

An alternative to using a heuristic when facing a complex problem is to learn a best response based on history. In particular, since players did receive feedback after each period, it is reasonable to assume some were experimenting with different strategies of when to play higher or lower efforts and, over time, they learn the best response. From the data, we can calculate such best responses. There is one complication from the original model since now players can pool at different effort levels—i.e., in the original model, every effort level was unique to a given type. For example, now there is some mass of players choosing zero effort, as well as other mass points throughout the effort space. Thus, the expected payoff in general (for two prizes) becomes

\[
\pi_i(x) = \sum_{i=0}^{N-1} \frac{V_1}{i+1} \binom{N-1}{i} m(x)^i p(x)^{N-1-i} \\
+ \sum_{i=0}^{N-2} \frac{V_2}{i+1} \binom{N-1}{i} \binom{N-2}{i} m(x)^i p(x)^{N-2-i}(1 - p(x) - m(x)) - c_i x
\]

For example, for sessions seven and eight, the calculation becomes
where $p(x)$ and $m(x)$ are then observed empirically. From this, we can estimate the best response of effort $x^*$ for a given player with cost type $c_i$. To ease computation, we divide the possible best response type space into cost type increments of .05. This means a cost type $c_i \in [.5, .55)$ is given the same best response effort level. We then go through the same exercise as in the previous section to estimate the proportion of the population playing this strategy, which we report in Table VI below.

Interestingly, the estimate of those players using coarse strategy—60%—is almost the same as before when not including the possibility of using the empirical best response as a strategy. Similarly, the estimate of those players using the Nash Equilibrium strategy is similar to before, falling from roughly 16% to 14% of the population. However, it is now estimated that some 11% of the players are playing an empirical best response strategy. As before, there are fewer "noise" players when we only consider that last 15 periods.

When conducting the same analysis on a per session basis, we cannot reject the null hypothesis that no player is playing the Nash Equilibrium in five of eight sessions. Similarly, we cannot reject the null that no players are playing the empirical best response players for five sessions. As before, we can reject the null that no players are playing the coarse strategy for any given session.

### 4.4 Level-$k$ Auctions

Our work is related to the so called cognitive hierarchy model. Crawford and Iriberri (2007) make the important contribution of extending the complete information setting of this model to the case of symmetric first and second-price auctions with incomplete information (and a single object), which they call level-$k$ auctions. In the cognitive hierarchy setting,
there are different levels of player sophistication. The first level player (i.e., level 0) acts as an anchor player that is assumed to mechanically mix over some distribution, often assumed to be uniform. The second level, level 1, then best responds as if all other players are level 0 players. A third level of players, level 2, then best respond based on all other players being level 1 players, and so on for \( k \) levels of players. Empirically, most players tend to fall within the first two levels.

For our analysis, the contest is isomorphic to an all-pay auction with multiple objects and (possible) bidding constraints, which are not studied by Crawford and Iriberri (2007). Extending \( k \) level thinking to all pay auctions with bidding constraints and multiple objects is beyond the scope of this paper. However, the above analysis of empirical best responses can be viewed as a version of \( k \) level thinking with \( k = 1 \) and with an all pay auction with multiple prizes and (possible) bidding constraints. However, rather than a uniform distribution for level 0 players, we consider a more complex case where level 1 players are best responding to the actual distribution of play. We have evidence that in 3 of the 8 sessions, some players are doing this. For all sessions, our best estimate is roughly 11% of the population is playing this way.

If we instead, assume a uniform distribution of mixing for level \( k = 0 \), it is straightforward to show for the case of capacity constraints and a single prize, level 1 players should bid at capacity. Meanwhile, level 2 players should bid zero. However, of the 48 subjects included in these single prize treatments, no subject always chooses maximal effort and only one chooses to always bid zero. That is, only roughly 2% of the population in these sessions is following a level \( k \) thinking strategy. With a less strict requirement of choosing within 5% of the required strategy (i.e., rather than requiring 240 or 0, we allow effort \( x \in [218, 240] \) or \( x \in [0, 12] \), respectively), we do not admit any additional players. Thus, it seems that in this different setting of an all pay auction and a single prize, subjects are not using a level \( k \) thinking strategy.

Overall, our results suggest that the predominate strategy played in our treatments is a coarse strategy.

5 Discussion and Conclusion

We explored the behavior of subjects competing under varying degrees of competition and distributions of rewards. As predicted by Minor (2012), a contest with more players and a larger second than first prize yields the greatest effort for a given prize budget. Adding more
competitors pushes the most able to work even harder, but the lesser able are discouraged and thus work less or give up. However, if when adding more competitors we also reward the best relatively less, the less able are encouraged to continue to work, while the best are still motivated to work from the increased competition. In short, using these two levers in tandem allows the contest designer to capture the incentive effect while blunting the discouragement effect. In our experiment, the net result is that increased competition combined with rewarding the best relatively less works even better in practice than theory would suggest. This results from most subjects playing a simple coarse strategy: when they are more able than some representative type, they choose maximal effort, and they choose roughly zero otherwise. The net difference of these two extremes is even more effort than predicted. We find this coarse strategy also better explains behavior in other experiments in addition to our own.

To the extent that these findings carry over to the field, they have some important incentive design implications for managers. For example, a firm finding itself with a long list of "slackers" producing minimal effort might make the wrong decision by firing them and hiring new workers. However, firing the "slackers" and hiring new workers could result in simply more "slackers," as the real problem is the firm design and not the type of workers. Instead, the firm may need to increase the degree of competition. In a sales organization, for example, this would mean making sales regions over which salespeople compete for bonuses larger (but not too large), resulting in more salespeople competing for the same bonuses. As another example, if a firm’s turnover is very high, instead of the cause being workers lacking the skill to make the cut, it could be that the firm needs to provide more rewards to others besides top performer.

However, whatever the case, the manager should use these two forces in concert—more competition and more of the reward given to second best—to maximize worker efforts.

For further research, it would be interesting to better understand the source of representative types—perhaps they come from one’s competitive experience or perhaps more from the type and framing of a particular competitive event. Similarly, it would also be interesting to discover how malleable these beliefs are. Can a designer manipulate a person’s representative type, and if so, how? These would have very important implications.
Appendix

6.1 A Representative Type Model

We solve the model of coarse decision-making assuming a player has some representative cost type \( r \) for all other players. The first question is how would a population of representative types play against one another? The following Lemma characterizes this world.

**Lemma 2** A population \( N \) of type \( r \) compete via a mixed strategy characterized by effort support \( e \in [0, \delta] \cup \{ M \} \), where \( M \equiv \min\{\kappa, \frac{V_{\text{max}}}{\tilde{\pi}}\} \) and \( \delta \in (0, M] \)

**Proof.** We first find a symmetric equilibrium where bidders\(^5\) have an atom at \( \kappa \), the maximal bid, and spend the balance of their bidding mass mixing over a continuous bidding support that is a subset of the entire possible bidding space \( x \in [0, \kappa] \) with cumulative distribution function (CDF) \( G(x) \). We will show that bidding either \( \kappa \) or from \( G(x) \) produce an expected payoff of zero.

We denote \( \binom{N-1}{j} \) to mean of the \( N-1 \) other players, \( j \) bid zero. \( V \) is the total prize mass for an arbitrary \( k < N \) prizes (i.e., \( V = \sum_{k} V_k \)). Thus given the probability \( p \) of playing \( M \), with \( M = \kappa \), we have the equality:

\[
\binom{N-1}{j} \cdot p^{N-1} \cdot \frac{V}{N} + \binom{N-1}{1} \cdot (1-p) \cdot p^{N-1} \cdot \frac{V}{N-1} + \ldots
\]

\[
+ \binom{N-1}{N-1} (1-p)^{N-1} \cdot V_1 - \tilde{\pi} \cdot M = 0
\]

The left hand side of the equality (LHS) represents all of the possibilities of prize sharing, where the first term is the expected prize if all \( N-1 \) players and player \( i \) bid the maximum \( M \). The final LHS term is if all bid 0 save bidder \( i \), who bids \( M \). This then means player \( i \) receives the first prize \( V_1 \).

The above expression has at least one zero since the LHS is continuous and we have \( p = 0 \Rightarrow V_{\text{max}} - \tilde{\pi} \cdot \kappa > 0 \) (since \( \kappa < \frac{V_{\text{max}}}{\tilde{\pi}} \)) and with \( p = 1 \Rightarrow \frac{V}{N} - \tilde{\pi} \cdot \kappa < 0 \) (since \( \frac{V}{N \tilde{\pi}} < \kappa \)). Denote \( p^* \) as a solution to above.

\(^5\)For this proof, to increase expositional ease, we frame contestants as bidders in an auction where their effort choice is their bid.
We next find the mixing strategy drawn from $G(x)$ with effort support $e \in [0, \delta]$. We write expected profit of mixing from $G(x)$ as:

$$E(\pi) = (1 - p^*)^{N-1} \cdot F(x)^{N-1} \times V_1$$

$$+ (N - 1) \cdot (1 - p^*)^{N-1} \cdot G(x)^{N-2} \cdot (1 - G(x)) \times V_2$$

$$+ (N - 1) \cdot (1 - p^*)^{N-2} \cdot p^* \cdot G(x)^{N-2} \times V_2 - \overline{c} \cdot x = 0$$

We can first find the bidding support by setting $G(x) = 1$, which gives $\delta$, and $G(x) = 0$. We also need to show $G(x)$ is increasing in $x$ over the bidding interval since it is a CDF, which is readily verified by the implicit function theorem. Hence, the symmetric equilibrium has players bidding $\kappa$ with probability $p^*$ and then draws a bid from $G(x)$ with probability $1 - p^*$.

For cases with $\kappa \geq \frac{V_{\max}}{r}$, it is easily shown the bidding support has no atom and $e \in [0, \frac{V_{\max}}{r}]$. Whichever the case, we get bidding support $e \in [0, \delta] \cup \{M\}$, where $M \equiv \min\{\kappa, \frac{V_{\max}}{r}\}$ and $\delta \in (0, M]$. ■

The term $\kappa$ allows for a (potentially) binding capacity constraint. Many competitive settings have hard effort caps: from electioneering (e.g., contribution caps as explored in Che and Gale (1998)) to labor settings (e.g., 24 hours per day), or simply a common budget constraint. In other settings, there is a soft effort cap: expending a cost of effort equal to the value of the maximal reward. In the latter case, the effort cap varies across types, whereas in the former everyone maintains the same cap. Whichever the case, in a symmetric equilibrium, $r$ types mix over an effort distribution with lower support of zero effort and upper support of the maximal level $M \equiv \min\{\kappa, \frac{V_{\max}}{r}\}$. With coarse decision making, when facing such a field of players, the best response is greatly simplified, as shown in the following proposition.

**Proposition 3** An individual with effort cost level $c$ and representative type $r$ best responds with effort $e$ as follows, where $M \equiv \min\{\kappa, \frac{V_{\max}}{r}\}$:

- $c < r$ exert $e = M$
- $c > r$ exert $e = 0$
\[ c = r \text{ exert } e \in [0, \delta] \cup \{M\} \]

**Proof.** If \( c = r \), we are in the case of Lemma 1 and the result follows. Assume now \( c < r \). Note from Lemma 1, if \( c = r \), then the marginal benefit equals marginal cost for all \( e \in [0, \delta] \). Hence, with \( c < r \), profit is strictly increasing in \( e \) yielding \( \delta \) as the optimal effort choice over \([0, \delta]\). With soft effort caps, \( \delta = M = \frac{V_{\text{max}}}{r} \). Consider when \( \delta < M \), which occurs with a (binding) hard effort cap of \( \kappa \).

To see effort \( M \) provides greater expected payoff write

\[
E[\text{Benefit}|\kappa] - \kappa c - (E[\text{Benefit}|\delta] - \delta c) = E[\text{Benefit}|\kappa] - \kappa r (1 - \Delta) - (E[\text{Benefit}|\delta] - \delta r (1 - \Delta)) = E[\text{Benefit}|\kappa] - \kappa r - (E[\text{Benefit}|\delta] - \delta r) + (k - \delta)\Delta > 0
\]

where \( c \equiv r (1 - \Delta) < r \)

The final inequality follows from \( \kappa > \delta \) and \( E[\text{Benefit}|\kappa] - \kappa r - (E[\text{Benefit}|\delta] - \delta r) = 0 \). Thus, whenever \( c < r \), playing \( M \) dominates any other action. Similar logic shows when \( c > r \), choosing effort of zero dominates any other choice. \( \blacksquare \)

The proposition suggests that if an individual has \( c < r \) her marginal cost is always less than her marginal benefit at \( e \in [0, \delta] \): this means her expected payoff is strictly increasing up to effort level \( \delta \), the upper support of the representative type’s mixing distribution. If there is a binding effort cap, \( \delta < M \), there is a disjoint jump in expected payoff by exerting effort \( M \) over \( \delta \).

When playing as if the entire field of competitors are of type \( r \), the individual has a sharp strategy: maximal effort \( M \) or minimal effort \( 0 \) when better or worse than the representative type, respectively.

**6.1.1 An algorithm for finding a subject’s representative type**

**Proposition 1** If the effort error \(|\varepsilon_t| < \frac{M}{2}\) for all periods \( t \) and \( \kappa \leq \frac{V_{\text{max}}}{r_r} \), then the AEM algorithm identifies the true representative type \( r_t \)

**Proof.** Assume the contestant’s true representative type is \( r_t \). By assumption, a contestant makes all effort choices with absolute errors \(|\varepsilon_t| < \frac{M}{2}\) for all \( t \in T \), where \( T \) is the set of
all periods. Consider now minimizing the sum of absolute estimation errors \( \sum_T |\varepsilon_t| \), where 

\[ \varepsilon_t = \hat{b}_t - b_t(r_t) \]

is the difference at time \( t \) between an observed effort choice and a coarse thinker’s effort choice, given her representative type is \( r_t \). Now choose some arbitrary \( \tilde{c} < r_t \) from the realized type space generated across all \( t \). Define \( A = A_1 \oplus A_2 \oplus A_3 \), the disjoint partition, such that all \( \varepsilon_t \in A_1 \) when \( c_t \geq r_t \), \( \varepsilon_t \in A_2 \) when \( r_t > c_t \geq \tilde{c} \), and \( \varepsilon_t \in A_3 \) when \( c_t < \tilde{c} \). Denote the number of elements in \( A \) as \( N_i \in \mathbb{N} \) for \( i \in \{1, 2, 3\} \). If we choose the posited representative type to be the true \( r_t \), we know for any \( \varepsilon_t \in A_i \), \( |\varepsilon_t| < \frac{M}{2} \) by assumption. Thus the total error when positing the true \( r_t \) is 

\[ \sum_T |\varepsilon_t| < (N_1 + N_2 + N_3) \cdot \frac{M}{2}. \]

Now consider changing our posited threshold point from \( r_t \) to some \( e_i \) such that \( \tilde{c} < e_i < r_t \) for arbitrary \( \tilde{c} \), as above. Since our sets are disjoint, \( \sum_T |\varepsilon_t| \) over the regions \( A_1 \) and \( A_3 \) are just as before. Over the region \( A_3 \), \( \varepsilon_t = M - \hat{b}_t \) and still \( M = \kappa \) since \( \kappa \) binds by assumption. Similarly, over the region \( A_1 \), still all \( \varepsilon_t = 0 - \hat{b}_t \). However, now \( \sum_T |\varepsilon_t| \) is greater over the region \( A_2 \). To see this, further partition \( A_2 = A_{2a} \oplus A_{2b} \), where \( \varepsilon_t \in A_{2a} \) when \( c_t < \bar{c}_i \) and \( t \in A_{2b} \) when \( c_t \geq \bar{c}_i \). This means \( \sum_T |\varepsilon_t| \) is greater over the region \( A_{2a} \) is just as before. However, now \( \sum_T |\varepsilon_t| \) is greater over the region \( A_{2b} \). In particular, 

\[ \sum_T |\varepsilon_t| \geq N_{2b} \times \frac{M}{2} \]

over the region \( A_{2b} \). This follows from the fact that since \( |\varepsilon_t| < \frac{M}{2} \) and \( b_t(r_t) = M \) with \( r_t \) over \( A_{2b} \), it must be that \( |\varepsilon_t| \geq \frac{M}{2} \) since \( b_t(\bar{c}_i) = 0 \) with \( \bar{c}_i \) over \( A_{2b} \), where \( b_t(x) \) is the true bid to play assuming representative type \( x \). But this means the total error \( \sum_T |\varepsilon_t| \) over the region \( A = A_1 \oplus A_2 \oplus A_3 \) is larger than before. Recall \( \tilde{c} \) is arbitrary and note the argument is virtually identical for choosing \( \tilde{c} > r_t \). ■
In addition to being robust against frequent but moderate errors, the algorithm is also robust against large but infrequent errors. To illustrate this point, consider a player who exerts effort perfectly according to a coarse strategy but has one effort choice that should have been $M$ but was instead entered as $0$. As long as the deviation is three or more cost type steps away from the true $r_i$, the estimation error minimization choice of $r_i$ is still the true representative type. This is because by choosing some estimate of $r_i$ as $\bar{c}_i \neq r_i$, we now add to the total summed error $m \times M$, where $m$ is the number of realized cost types $\bar{c}_i$ is from $r_i$. Since $m \geq 3$, we have larger error than if choosing $r_i : m \times M - M > M$. That is, by choosing $\bar{c}_i \neq r_i$ we save the error $M$ in our estimation but we now add two (or more) errors of $M$. Hence, the true $r_i$ is the resulting estimate to minimize the error. If $r_i$ is within two steps away from $\bar{c}_i$, then $\bar{c}_i \simeq r_i$, as spacing between realized costs types is small in our data. Indeed, recall for a unit uniform distribution, $E[X_i] = \frac{i}{N+1}$, where $X_i$ is the $i$th order statistic. This means that with 30 periods and $U[\frac{1}{2}, 1]$, the expected cost realizations are spaced apart by $\frac{1}{62}$. With a maximal effort error, the worst the AEM algorithm would do is miss the true $r_i$ by roughly .03, and if the maximal error occurred more than .03 away from the the true $r_i$, the true $r_i$ would be identified.

References


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[22] Minor, Dylan. 2012. "Increasing Revenue by Rewarding the Best Less (or not at all)," *working paper, Northwestern University.*


# Tables and Figures

## Table I: Summary of Treatments

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Session</th>
<th>Subjects</th>
<th>Group Size</th>
<th>1st Prize</th>
<th>2nd Prize</th>
<th>Constraint</th>
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<td>3</td>
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<td>240</td>
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<tr>
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<td>36</td>
<td>6</td>
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<td>$260</td>
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## Table II: Predicted vs. Actual Effort Levels

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<th>Treatment</th>
<th>Nash</th>
<th>Actual</th>
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<tbody>
<tr>
<td>Winner Takes All (WTA)</td>
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<td>607.65</td>
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<tr>
<td>Equal Prize (EP)</td>
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<td>Constrained WTA</td>
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<td>Constrained EP</td>
<td>468.90</td>
<td>434.36</td>
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<td>Large WTA</td>
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<td>634.40</td>
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<tr>
<td>2nd Prize&gt;1st Prize</td>
<td>518.59</td>
<td>681.43</td>
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## Table III: Predicted vs. Actual Effort Levels

<table>
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<th>Treatment</th>
<th>Nash</th>
<th>Coarse</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
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<td>565.32</td>
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<td>2nd Prize&gt;1st Prize</td>
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## Table IV: Mean Squared Error of Coarse Strategy vs. Nash Effort Predictions

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<tr>
<th>Session</th>
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<th>2</th>
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<th>5&amp;6</th>
<th>7&amp;8</th>
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<td>Nash</td>
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<td>8239.05</td>
<td>3915.09</td>
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### Table V: Muller and Schotter (2010) Data

<table>
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<tr>
<th>Treatment</th>
<th>Nash Prediction</th>
<th>Coarse Prediction</th>
<th>Actual Effort</th>
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<td>Quadratic Costs Two Prizes</td>
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<td>1.963</td>
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### Table VI: Proportion of the Population Playing a given Strategy

<table>
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<tr>
<th>Strategy Played</th>
<th>Last 15 Periods</th>
<th>All Periods</th>
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<tr>
<td>Coarse Strategy</td>
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<td>-0.0373</td>
<td>-0.0263</td>
</tr>
<tr>
<td>Empirical Best Response</td>
<td>.1078 ***</td>
<td>.1108***</td>
</tr>
<tr>
<td></td>
<td>-0.028</td>
<td>-0.0234</td>
</tr>
<tr>
<td>Uniform Mixing</td>
<td>0.1558</td>
<td>0.235</td>
</tr>
<tr>
<td></td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Observations</td>
<td>2115</td>
<td>4230</td>
</tr>
<tr>
<td>Adjusted R Squared</td>
<td>0.7519</td>
<td>0.7216</td>
</tr>
</tbody>
</table>

Notes: ***,*** represent statistical significance at 90%, 95%, and 99% confidence levels.

Clustered standard errors reported in parentheses.

Uniform mixing is the complement of the other coefficients.
Figure 1: Winner Takes All vs. Equal Prize Contest

Figure 2: Using an Average Threshold
Figure 3: Using a High Threshold

Figure 4: Using a Low Threshold
Figure 5: Distribution of Effort for Sessions 3-8

Figure 6: Distribution of Estimates for Representative Types