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Beating a Live Horse: Effort's Marginal Cost Revealed in a Tournament

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Abstract: There is ample evidence that incentive pay structures such as tournaments result in increased performance, but whether this is due to selection or increased individual effort is less clear. We show that empirical specification is the key. Misspecification masks individual effort and interprets it as selection. Looking at data on horse racing, we compare a pure selection model to the Lazear-Rosen tournament model. While both models organize the data, the tournament model does a better job, and it says that nearly two-thirds of the increased performance associated with higher prizes is due to increased individual effort. This estimate is very similar to estimates found in industrial field studies where performance pay is not structured as a tournament. We corroborate the horse-racing results by looking at dog racing. Dogs are not expected to respond as elastically as horses, and empirically they do not.

1. Introduction

Tournament theory is widely held to apply in almost all labor/leisure settings. The literature is robust with industrial and managerial applications.[1] The model has cachet.[2] The one place that tournament theory is less well received is in the actual tournament setting. Many people argue and with some evidence that competing athletes do not vary their effort levels: they claim that sporting participants go all out all the time. The Lazear-Rosen tournament model, of course, says exactly the opposite. The tournament model says that players adjust their effort in order to maximize their expected payout net of cost. So individuals should work harder when more is at stake.

These opposing views make a horse race. Which of the two models can better organize the data? We propose to answer this question by looking at data on horse and dog racing. Horse racing is an interesting venue in which to conduct our test. First, the data are rich. We know the field for each race, odds that rank the horses, and the prizes for which they are competing. However, there is an even more compelling reason to look at horse racing. Horses clearly face a substantial loss

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[1] See O'Keeffe, Viscusci, and Zeckhauser (1984), Malcomson (1984), Main, O'Reilly, and Wade (1993), Murphy (1999), Knoeber and Thurman (1984), Ferrall (1996), and Brickley, Linck, and Coles (1999) to list a few.

[2] One measure is the time line of citations to Lazear & Rosen (1981). Cumulative citations were around 10 over the first ten years; they reached 200 by 2001; and are over 800 today. On the other hand, Demsetz (1997) argues that the L-R model has more cachet than it deserves.

function associated with breaking down. Witness the 2006 Kentucky Derby winner, Barbaro, in his run at the Preakness. Hence, there is every reason to believe that their riders and handlers would be marginally sensitive to the cost of effort. On the other hand, horses are dumb animals. Even more than human competitors, it may be impossible to marginally vary effort in horses.

Dog racing complements our inquiry because dogs are not handled by humans during the race. Thus, it is much less likely that dogs adjust their behavior in response to prizes. The dog racing data that we have are not as rich as the horse racing data, but still they provide corroborative evidence.

This research is important because it shows that only by careful theoretical and empirical identification can the two competing hypotheses be distinguished. Yet, the policy implications of the two are dramatically different. If there is no scope for adjustment in individual behavior then performance pay schemes for existing workers are wasteful. On the other hand, if individuals can vary their effort then these schemes have important efficiency effects. We find that the tournament model, which accounts for both selection and individual-effort effects, is the more powerful in organizing the data.

Section 2 discusses prior research. Section 3 discusses and analyses some aspects of the horse racing data. Section 4 identifies the structure of the models and the estimation strategy. Section 5 shows the estimates and the comparison of the two models. Section 6 introduces the dog racing data and shows results using these. Finally, section 7 gives some concluding remarks.

2. Theory & Prior Research

Everyone agrees that as pay goes up so does performance. However, there are two views of why this happens. The all-out model says that individuals adjust their behavior in terms of where and how often they go to work, but when they are at work, effort is produced at a constant, fixed rate. The tournament model has the same feature in terms of selection. If the expected net payout is not high enough, workers stay home. The additional feature of the tournament model is that workers respond marginally when they are at work. So the debate is whether observed performance differences across venues are attributable only to sorting or to marginal effort responses in addition to sorting.

The trick for our research is to model the behavior underlying the two propositions especially as it applies to horse racing data and devise an estimation strategy. The all-out model is based on sorting horses across races with horses running as fast as they can in each race they enter. The tournament model also recognizes the sorting of horses across races, but identifies relative effort levels based on the quality of the other horses within the race and the structure of prizes paid across finishers. Ultimately the showdown between the tournament model and the all-out model is about prediction. We examine how well each can predict the observed speed of horses within and across races.

Almost all the existing research shows that tournament competition results in increased performance. This evidence spans almost every industrial and commercial setting including sports. Nonetheless, the issue that we are addressing is the extent to which tournament structures achieve this result simply because they provide a setting where self-selection of participants ensures that as pay increases, average ability also increases, or whether there is an individual incentive effect. That is, when the gaps get bigger in tournament prizes, individuals work harder.

Nearly all of the theoretical tournament literature simply assumes that individuals can respond to incentives by varying their effort.[3] However, it might not be so. It might be the case that tournament participants once engaged in the contest are unable to adjust marginally. Tournament prizes may draw a selection of participants into a contest, but it may be that they go flat out once the gun sounds. In this case the observed performance effects in tournament settings are merely a result of sorting. The best participants migrate to the tournaments with the highest payouts.

A number of intriguing questions are raised by comparing these competing assumptions on the behavior of tournament participants. One is, does the prize structure itself tell us which model is better? Surprisingly, at least to us, the answer is no. It turns out that it is somewhat easier to rationalize an exponentially declining prize pattern, such as the one that we see in professional golf and horse racing, in the context of the all-out model as opposed to the tournament model.[4] So we have to turn elsewhere for an answer.

The empirical work on the tournament model has addressed the issue, but it has never staged a complete test of the competing hypotheses. Nearly all of the evidence (cited in note 1 above) shows the productivity effect of promotion in the context of tournament theory can be rationalized in the all-out model. The tournament setting selects people who will work more hours and more days, but this research does not show that people work more intensively when they are on the job.

For instance, there is some evidence disputing the application of the tournament model in one of the prominent examples from the commercial sector:

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[3] In addition to Lazear and Rosen (1981), see Green and Stokey (1983), Carmichael (1983), and Nalebuff and Stiglitz (1983), and more recently Fullerton and McAfee (1999).

[4] Galton (1902) is credited with initiating the question of the optimal shape of the prize structure, which he did implicitly in the context of the all-out model. The tournament model is ambiguous about the optimal prize schedule in field tournaments and most research suggests that effort is maximized by paying all or nearly all to first place, a feature rarely observed in practice. See Clark and Riis (1998a and b), Syzmanski and Valletti (2002), and Syzmanski (2003).

up-or-out decisions at large law firms. While the treatment of associates at big law firms may appear to be a tournament where some are kept and others let go (see Ferrall, 1996), Kordana (1995) argues that this is merely selection where associates are monitored directly and the ones that leave after a given period of time came with the anticipation of leaving.[5] Their motivation was to acquire human capital from on the job training.

An early test of the tournament model by Ehrenberg and Bognanno (1990) insightfully attempted to show that there was an incentive effect on top of the selection effect. They did this by looking at the performance of golfers in the fourth round of a tournament based on their position after the third round. Their finding is that the prize gaps affect performance. More recent work has been less conclusive.[6] Moreover, the selection effect is not explicitly accounted for.

Knoeber and Thurman (1994) find that the level of pay holding constant the incremental pay does not affect performance in raising chickens. They do find that moving from a tournament-style pay structure to a relative performance pay schedule does increase performance. They claim that this is evidence that workers can and do marginally adjust their behavior. However, their data do not allow them to control for the selection effect.

The more explicit tests point out the problem with the methodology applied in the past. Maloney and McCormick (2000) report results that show individual foot racers have better times when the prizes are higher, that is, Emily Wood had a faster time in a $500/$200/$100 race than in a $200/$100/$50 event. Lynch and Zax (2000) dispute this finding also looking at foot racers. We will show that both of these studies are misspecified. Indeed, there is no reason to necessarily expect a positive correlation between effort and prizes or purse. The relation between effort and prizes in the tournament model depends on ceteris paribus conditions which include the number of other contestants and their abilities. So, for example, when Emily Wood runs in a race with a 1st place prize of $500 where she is the tenth best competitor, she may run slower than when she competes in a $200 race where she is the best. Hence, the positive relation between performance and prizes found by Maloney and McCormick and the lack of a relation found by Lynch and Zax are both spurious.

Our paper is about the specific case of tournament compensation and performance, but the more general issue is that of the incentive effects of performance-based compensation. There has been a good bit of research on this.

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[5] Ferrall (1996) attempts to compare a tournament model of promotion (the firm keeps *k* from a cohort of *n*) to promotion decisions based on a standard of performance. He models the behavior of entry-level lawyers who have unknown talent, even to themselves, so it is a model of symmetric behavior. Moreover, on close inspection his estimating form does not differentiate behavior in the two regimes, which makes the empirical results uninformative.

[6] Bronnars and Oettinger (2001).

Prendergast (1999) surveys many papers.[7] All find performance responses from incentive based compensation. Of these, only a few (Lazear 1996, Paarsch-Shearer 1999, and Fernie-Metcalf 1999) have data that allow the selection effect to be separated from individual responsiveness to incentives. In particular, Lazear finds that in the auto-glass industry about a third of the overall increase in productivity of piece rate pay came from poorer workers being replaced by superior ones.

As Prendergast says, "even in situations were there is evidence consistent with agency theory, the literature has been plagued with … identification problems where outcomes are often equally consistent with other plausible theories" (p. 11). Our results show that this is indeed true. Both models of pure selection and individual response organize the horse racing data. Nonetheless, the interpretations are substantially different. In the results that we present below, the tournament model applied to horse racing shows that two-thirds of the performance increase observed when prizes increase is due to increased individual performance and only one-third to selection. (Notice that this is very similar to Lazear's findings in the auto-glass industry). The alternative hypothesis mistakenly attributes all of the increased performance to selection.

3. Horse Racing Data

The horse race data are from 712 races conducted at Churchill Downs in 1994.[8] We used 566 that paid to four places, had no multiple entries by the same owner, ties in the prize winning places, and other anomalies that caused the prize purse and the odds to diverge substantially, and had all horses finish the race.[9] The 566 races were comprised of 27 stakes, 186 allowance, 2 starter allowance,

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[7] See Lazear (1996), Paarsch and Shearer (1996), Banker, Lee, and Potter (1996), Fernie and Metcalf (1996), McMillan, Whalley, and Zhu (1989), Groves, Hong, McMillan, and Naughton (1994), Kahn and Sherer (1990), and Foster and Rosenzweig (1994). More recent papers include Banker, Lee, Potter, and Srinivasan (2000), Brickley and Zimmerman (2001), and Lemmon, Schallheim, and Zender (2000).

[8] These data were made available to us by Raymond Sauer who obtained them when he was a Professor of Equine Studies at the University of Louisville in the 1980s.

[9] The biggest races, such as the Kentucky Derby, paid to five places. However, to maintain homogeneity in our sample for estimation purposes, we excluded the few races paying 5 places. When there are multiple horses by the same owner entered in a race, they are bet as a group so separate odds for each horse are not available. Ties happen and the prizes are shared. From our data we only know the prizes paid, not offered, so we are forced to delete races with ties. When horses break down or pull up, their finishing time is not available. While these outcomes are interesting, we omit these races for fear that they will bias the test between the two models. There is no way to treat these missing observations without favoring one model or the other.

289 claiming, and 62 maiden races.[10] Table 1 shows the summary statistics on the races. Table 2 shows the summary statistics on the horses in the races.

The most common distance is 6 furlongs (4290 feet); the second most common is 1 1/16 miles. The average field-size is ten horses. The track purse paid to the horses varied from $7,320 to $233,950. On average, first place paid 65 percent of the purse, second place 20 percent, third 10 percent, and fourth 5 percent.

The pari-mutuel betting pool varied from $45,360 to $1,721,432 with a mean of $155,004 and a median of $132,792.[11] The size of the betting pool is positively related to the purse of the race because the purse attracts faster horses. The size of the betting pool is also negative related to the disparity of horses in a race.

There are several ways to characterize the disparity of the field. One is to look at the distribution of the odds of winning across the horses. We can construct an entropy measure from the probability of winning ($prob_i$). It is $-\sum prob_i \ln(prob_i)$ across the horses in each race. The entropy of the probabilities of winning increases as the odds become more equal across the horses. Alternatively we can use the variance of the log of the probability of winning 1st place. Table 1 shows how these measures vary across the sample.

Table 3 shows a regression of the log of the betting pool on the log of the purse and the log of the entropy measure. Both entropy and the variance of the log of the probability of winning 1st place are based on bettors' predictions about the performance of each horse. Both specifications show that disparity of talent reduces spectator interest. The final regression in column (c) includes the actual race-outcome statistics in the regression. It shows that spectator interest anticipates the outcome and spectators are most interested in races that are fast, close, and have a lot of horses. By way of characterizing the magnitudes of these coefficients, a one standard deviation move in purse changes the betting pool by slightly more than 20 percent, a one standard deviation move in the variance of speed changes the betting pool by 8 percent, and a one standard deviation move in the variance of the probabilities of each horse winning changes the betting pool by 5 percent.

4. Models of Performance & Estimation Strategy

Horse *i* beats horse *j* iff:

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[10] Maiden races are for horses who have never won. In claiming races, horses entered in the race are up for sale at a posted price. In allowance races, the horses are handicapped by carrying more or less weight based age, sex, and past performance. A starter allowance race is an allowance race for horses that have started for a given claiming price or less. In a stakes race the horse owners pay a fee to be in the field.

[11] Pari-mutuel betting means that the odds on each horse are determined by the amount of money bet on each after the betting windows close just before the beginning of the race.

$$\ln m_i + \varepsilon_i > \ln m_j + \varepsilon_j$$

where m_i is effort, unobserved by the econometrician but known to the riders, and ε_i is luck, unobserved by the econometrician but revealed to the riders.

Table 1. Summary Statistics on Races

Variable	*Mean*	*Std Dev.*	*Minimum*	*Maximum*
Distance	4882	749	2970	9240
Field-size	10	2	4	12
Purse	28748	26122	7320	233950
First Place Prize	18663	16974	4758	152068
Second	5757	5273	1464	46790
Third	2889	2635	732	23395
Fourth	1440	1317	366	11698
Percent of First Place Prize to Purse	64.9	2.1	57.4	70.8
Second	20.0	1.6	15.3	25.2
Third	10.1	0.9	7.5	14.2
Fourth	5.0	0.4	3.7	6.5
Betting Pool ($1000s)	153.41	110.14	45.36	1029.65
Variance log 1st Place Probability	1.01	.38	.09	2.28
Entropy	1.88	.22	1.14	2.38

Notes: 566 races. Entropy is constructed from the probability of each horse winning; as entropy increases the disparity of talent in the race declines. Purse, prizes, and betting pool in 1994 dollars.

Table 2. Summary Statistics on Horses across Races

Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Speed	54.35	2.44	48.89	60.69
Odds	20.45	24.91	0.30	260.50

Notes: 5504 Observations. Speed in feet per second. Odds are the pari-mutuel betting odds of winning 1st place.

Let luck be iid across the field according to an extreme value distribution. This produces the familiar logit form for the predicted probability of horse i winning the race:

$$\Pr(i \text{ places 1st}) = \frac{m_i}{\sum_{j=1,N} m_j} \tag{1}$$

We observe the probability of each horse winning through the gambling odds.

Table 3. Predicting the Size of the Betting Pool

Independent Variables	(*a*)	(*b*)	(c)
Purse	0.365	0.306	0.350
	(0.042)	(0.037)	(0.041)
Entropy	0.356		
	(0.087)		
Variance of log Probability of Winning 1^{st} Place		-0.123	-0.135
		(0.043)	(0.047)
Field Size			0.400
			(0.089)
Average Speed			0.800
			(0.345)
Variance of Speed (x 100)			-12.239
			(2.182)
Intercept	7.486	8.88	4.468
	(0.517)	(0.359)	(1.402)
R^2	0.225	0.210	0.274

Notes: Size of the pari-mutuel betting pool, track purse, field size, and speed in logs. Robust standard errors below coefficient estimates. 566 observations.

To estimate total effort, we turn to the optimizing behavior of track owners. In horse racing, the track owner's profits increase with the size of the betting pool. The volume of bets are increasing in total effort if gamblers prefer to bet on the “more exciting” races and if excitement is created by the effort of the horses in the race as is revealed in Table 3. Hence, we use the observed pari-mutuel pool of wagered funds as a proxy for total effort in each race. Taking logs and rewriting, we have:

$$\ln m_i = \ln \Pr(i \text{ places } 1^{st}) + \phi \ln B + u \qquad (2)$$

where B is the betting pool of funds, ϕ is the inverse of the elasticity of the betting pool with respect to effort, and u is a white noise term that varies by race. Equation (2) is a reduced form relation between effort and betting pool. There are other characteristics of the race that affect the betting pool and the track owner's profit as shown in Table 3. Equation (2) simply argues that the sum of effort in a race can be monotonically proxied by the betting pool.

Log effort can also be estimated from information extracted from a structural model of behavior. The iid extreme value assumption on luck allows us to compute the probability of horse i finishing at any place in the money from the probability of each horse winning 1st place.[12] This allows us to work with the problem faced by horse *i*, which is to find the level of effort that maximizes the expected prize net of the cost of effort:

$$w_1 \Pr(i \text{ places } 1^{\text{st}}) + ... + w_k \Pr(i \text{ places } k^{\text{th}}) - C(m_i, \alpha_i)$$

where w_k is the prize paid to k^{th} place and α_i is heterogeneous ability causing different riders to select different levels of effort.

4.1. Case 1: The Tournament Model (Costly Effort)

Assuming constant marginal cost, β, we can write:

$$C(m_i) = \beta m_i / \alpha_i$$

where again α_i is ability.

The first-order condition for the optimizing behavior of the rider is:

$$\sum_k \frac{\partial \Pr(i \text{ places } k^{th})}{\partial \ln m_i} \cdot \frac{1}{m_i} \cdot w_k = \frac{\beta}{\alpha_i} \qquad (3)$$

where the left-hand side is the sum of the marginal effect of effort on the probability of finishing in the money weighted by the prize for that finishing position and the right-hand side is the marginal cost of effort. To simplify notation, we define *x*:

$$x_i = \sum \frac{\partial \Pr(i \text{ places } k^{th})}{\partial \ln m_i} \cdot w_k$$

which can be calculated from the observed probabilities given our distributional assumption on luck.

By logging the first order condition, we obtain an additional expression for log effort:

[12] The logit probabilities generate the well-known Independence of Irrelevant Alternatives in the context of a random utility model of individual choice. In the context of a race, the logit probabilities generate an Independence of Irrelevant Competitors. This allows us to compute the probability of a horse winning second place given some other horse won first place: the probability of beating the remaining horses. The remainder of the computation involves going from the conditional probability to the joint probability and then onto the marginal probability.

$$\ln m_i = \ln \alpha_i - \ln \beta + \ln x_i$$

Adding and subtracting the within-race mean log effort, we obtain:

$$\ln m_i = -\ln \beta + \ln x_i + \overline{\ln \alpha_i} + \left(\ln \alpha_i - \overline{\ln \alpha_i}\right)$$

In order to capture mean log ability within a race, we need to model how horses are selected into races.[13] The institutional detail of horse-racing suggests that horses are sorted into races according to their ability and that this stratification is mirrored by the purse paid to the field and horse characteristics including age and sex. In this case, we can use a simple reduced form model of selection:

$$\ln m_i = -\ln \beta + \ln x_i + \gamma Q + \left(\ln \alpha_i - \overline{\ln \alpha_i}\right) + v \qquad (4)$$

where Q are the selection criteria of purse, sex, and age, γ is the vector of elasticities of mean log ability with respect to the selection criteria, and v is a white noise term that varies at the race level.[14]

Equations (4) and (2) represent a system of equations that identifies the predicted level of effort by a horse based on the tournament model of behavior where effort is costly.

4.2. Case 2: The All-Out Model (Costless Effort)

Now let the horse's cost function be:

$$C\left(m_i, \alpha_i\right) = \begin{cases} 0 & m_i \le b\alpha_i \\ \infty & m_i > b\alpha_i \end{cases}$$

[13] If horses were randomly selected into races, then we would expect that the within-race mean log ability would equal the population mean log ability, which could be set to zero.

[14] The data are comprised of 5504 observations on individual horse performance in 566 races. There 1349 horses that raced only once, and 1420 that raced multiple times, a few as many as eight times. One might argue that ability is constant for these horses across races, but it can also be argued that ability varies based on the vagaries of life. We estimate the model both ways. The results are unaffected. See footnote 15, below. Moreover, by estimating the model in an unrestricted form, that is, treating each horse in each race as an independent observation, we then use the estimates of ability across races in tests of model fit.

where *b* is a scalar and, again, α is the ability indicator. Given this function, the optimal solution to the rider's optimization problem is simply to exert maximum effort:

$$m_i = b\alpha_i \tag{5}$$

Note that this would also be the solution to the riders problem if the objective was maximizing the probability of winning subject to the maximum effort constraint. Substitution of equation (5) into equation (1) above yields:

$$\Pr(i \text{ places } 1st) = \frac{\alpha_i}{\sum_{j=1,N} \alpha_j}$$

Logging equation (5) and performing the analogous substitutions as case 1 yields:

$$\ln m_i = \ln b + \gamma Q + \left(\ln \alpha_i - \overline{\ln \alpha}\right) + v \tag{6}$$

That is, we add and subtract the average log ability level in each race. Subtracting it from the log ability of each horse gives us a mean zero term of relative ability in a race. We then proxy for average log ability in the race using the race purse, sex, and age as the sorting mechanisms mirroring the tournament organizer. Equations (6) and (2) represent a system of equations that identifies the predicted level of effort by a horse based on the all-out model where effort is costless.

4.3. Completing the Models

We have constructed two equations for each case that predict log effort. Unfortunately, log effort is not directly observable. However, we do observe speed and it is monotonic in performance, that is, log effort plus iid luck:

$$\ln s_i = \delta T + \theta D + \lambda\left(\ln m_i + \varepsilon_i\right)$$

where *s* is speed, *T* is a set of dummies for track conditions with δ effects, *D* is a set of race distance dummies with θ effects allowing speed to slow with greater distances holding effort constant, and λ converts performance into speed. Substituting our two effort equations into the speed equation yields estimable forms for the two cases:

Case 1:

$$\begin{aligned} \ln s_i &= \delta T + \theta D + \lambda\bar{\varepsilon} + \lambda \ln \Pr(i \text{ places } 1^{st}) + \lambda\phi \ln B + \lambda\left[u + \left(\varepsilon_i - \bar{\varepsilon}\right)\right] \\ \ln s_i &= \delta T + \theta D + \lambda\left[-\ln\beta + \bar{\varepsilon}\right] \\ &\quad + \lambda \ln x_i + \lambda\gamma Q + \lambda\left[\left(\ln\alpha_i - \overline{\ln\alpha_i}\right) + v + \left(\varepsilon_i - \bar{\varepsilon}\right)\right] \end{aligned} \tag{7}$$

and Case 2:

$$\begin{aligned} \ln s_i &= \delta T + \theta D + \lambda\bar{\varepsilon} + \lambda \ln \Pr(i \text{ places } 1^{st}) + \lambda\phi \ln B + \lambda\left[u + \left(\varepsilon_i - \bar{\varepsilon}\right)\right] \\ \ln s_i &= \delta T + \theta D + \lambda\left[\ln b + \bar{\varepsilon}\right] + \lambda\gamma Q + \lambda\left[\left(\ln\alpha_i - \overline{\ln\alpha_i}\right) + v + \left(\varepsilon_i - \bar{\varepsilon}\right)\right] \end{aligned} \tag{8}$$

The left-hand side of equations (7) and (8) is observed, the last term on the right-hand side of each equation is a mean-zero iid disturbance term, and the remainder of the right-hand side is observed regressors and their parameters. Note that the only effective difference between the two models is the inclusion of ln *x* (the log marginal benefit of effort relative to effort) in the second equation of case 1, the tournament model. Its parameter, λ, also identified in the first equation, is restricted to be the same across the equations when estimated.

Each structural parameter is fully recoverable. The parameter λ is identified off of the log probability of winning in the first equation in the all-out model and also the log of the marginal benefit of effort relative to effort in the tournament model; average luck is the intercept of the first equation divided by λ; ϕ is the quotient of λ divided into the coefficient on the log of the betting pool; *u* is estimated as the race-specific mean residual (divided by λ) of the first equation, luck's deviation from the mean is the residual (divided by λ) less *u*; β (or b for case 2) is identified from the intercept of the second equation (removing mean luck as recovered from the first equation); γ are the quotient of λ divided into the coefficients on the selection criteria; *v* is estimated as the race-specific mean residual (divided by λ) of moment 2; and log ability's deviation from the mean is the residual less demeaned luck and *u* (divided by λ).

The estimation can be performed with GMM by stacking the moments. To simplify notation of the stacked equations, let *y*, *Z*, and ξ be defined as follows:

$$y = \begin{bmatrix} \ln s_i \\ \ln s_i \end{bmatrix}$$

$$Z = \begin{bmatrix} T & D & 1 & 0 & \ln \Pr\left(i \text{ places } 1^{st}\right) & \ln B & 0 \\ T & D & 1 & 1 & \left\{\ln x_i ; 0\right\} & 0 & Q \end{bmatrix}$$

$$\xi = \begin{bmatrix} \delta \\ \theta \\ \lambda\bar{\varepsilon} \\ \lambda\left[\{-\ln\beta; \ln b\}\right] \\ \lambda \\ \lambda\phi \\ \lambda\gamma \end{bmatrix}$$

where the bracketed expression are the alternative specifications for case 1 and case 2. The estimation can be performed with GMM under the appropriate moment conditions on the disturbance terms:

$$E\left(Z'\begin{bmatrix} u + (\varepsilon_i - \bar{\varepsilon}) \\ \left(\ln\alpha_i - \overline{\ln\alpha_i}\right) + v + (\varepsilon_i - \bar{\varepsilon}) \end{bmatrix}\right) = 0$$

$$E\left[Z'(y - Z\xi)\right] = 0$$

The first stage of GMM is equivalent to OLS and the second is a minimum distance estimator where distance is weighted by the inverse of the covariance of the moments. The estimator is given by:

$$\hat{\xi} = \underbrace{\left((Z'Z)\hat{V}^{-1}(Z'Z)\right)^{-1}}_{Var(\hat{\xi})}(Z'Z)\hat{V}^{-1}(Z'y)$$

where V is the covariance of the moments, estimated by:

$$\hat{V}^{-1} = Z'E\left(\begin{bmatrix} u + (\varepsilon - \bar{\varepsilon}) \\ \left(\ln\alpha - \overline{\ln\alpha}\right) + v + (\varepsilon - \bar{\varepsilon}) \end{bmatrix}\begin{bmatrix} u + (\varepsilon - \bar{\varepsilon}) \\ \left(\ln\alpha - \overline{\ln\alpha}\right) + v + (\varepsilon - \bar{\varepsilon}) \end{bmatrix}'\right)Z$$

Under the assumption of the model, the expectation of the cross-product of the disturbances works out to be the sum of the following variance-covariance matrices sandwiched by the covariates. The first matrix captures disturbances that are common across all horses in a given race; the second matrix captures how a horse's idiosyncratic luck appears in both equations and heteroskedasticity in the variance of ability across races.

$$
\begin{bmatrix}
\sigma_u^2 & \cdots & \sigma_u^2 & & & & & \sigma_{uv} & \cdots & \sigma_{uv} & & & & \\
\vdots & \ddots & \vdots & & & & & \vdots & \ddots & \vdots & & & & \\
\sigma_u^2 & \cdots & \sigma_u^2 & & & & & \sigma_{uv} & \cdots & \sigma_{uv} & & & & \\
& & & \ddots & & & & & & & \ddots & & & \\
& & & & \sigma_u^2 & \cdots & \sigma_u^2 & & & & & \sigma_{uv} & \cdots & \sigma_{uv} \\
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& & & & \sigma_u^2 & \cdots & \sigma_u^2 & & & & & \sigma_{uv} & \cdots & \sigma_{uv} \\
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\sigma_{uv} & \cdots & \sigma_{uv} & & & & & \sigma_v^2 & \cdots & \sigma_v^2 & & & & \\
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$$

5. Results

The parameters are shown in Table 4 with the standard errors in parentheses. Every parameter associated with the two models has the expected sign and all but one are statistically significant.[15] The tournament model has a higher R^2 than the all-out model. This indicates that it predicts log speed better and wins the horse

[15] As mentioned in note 14 above, we estimated the models allowing for individual horse ability to vary from race to race, as reported in Table 4, and holding individual horse ability constant across races. The latter estimates are nearly identical to those reported in Table 4: λ is slightly lower which makes the elasticities on purse and pool slightly higher.

race between the two. Although the margin does not appear large, it is statistically significant. We run a non-nested test of the two models in which the costly model shows the all-out model to be misspecified. The test begins with a slight alteration that combines the two models into one varying by the parameter, τ. This parameter indicates which model appears: $\tau = 1$ indicates the tournament model and $\tau = 0$ indicates the all-out model:

$$\ln s_i = \delta T + \theta D + \lambda\bar{\varepsilon} + \lambda \ln \Pr\left(i \ places\ 1^{st}\right) + \lambda\phi \ln B + \lambda\left[u + \left(\varepsilon_i - \bar{\varepsilon}\right)\right]$$
$$\ln s_i = \delta T + \theta D + \lambda\bar{\varepsilon} + [\cdot] + \tau\lambda \ln x_i + \lambda\gamma l Q + \lambda\left[\left(\ln \alpha_i - \overline{\ln \alpha}\right) + v + \left(\varepsilon_i - \bar{\varepsilon}\right)\right]$$

The parameter of interest is recovered with the same GMM estimation, divided by the estimated λ, and where the appropriate adjustments are made to the standard errors. The estimated value of τ is 1.327 with a standard error of 0.120; the null that the costless-effort model is correctly specified gets rejected at the .01 level.[16]

Although it is still significantly positive, the importance of the purse drops from the all-out model to the tournament model. This is exactly the result that we anticipated. The appearance of ln *x* in the second equation of the tournament model diminishes the influence of the purse. The tournament model attributes race-level variation in speed to both a selection affect (the purse drawing horses of a certain level of ability) and the marginal benefit of effort (increasing in the purse as captured in ln *x*). The all-out model can only attribute race-level variation in speed to a selection effect and hence will enlarge the importance of the selection effect. The all-out model misinterprets individual responses as selection effects.

The other selection variables, age and sex, are similar across the models and their estimated effects on speed are also consistent with our expectations. Female horses and two year olds (the omitted age group) run slower on average. Also, our controls for distance and track conditions follow the anticipated pattern. Horses run slower over longer distances and faster on turf compared to dirt.[17]

[16] A value of τ significantly different from zero says that the all-out model is an incorrect specification and, strictly speaking, a value different from one indicates the same for the tournament model. Depending on how conservative the level of significance is, the tournament model is also misspecified. Even so, we interpret the value of 1.3 to mean that the tournament model is a better specification than the all-out model.

[17] We tried many variations on the control for distance. In the end, dummy variables for different distance groups were the most parsimonious specification. We grouped races into 6 furlongs or less, 6 ½ to 7 ½ furlongs, and 1 to 1 ¼ mile, allowing races longer than 1 ¼ mile to be the excluded group. Alternative specifications for distance have virtually no effect on the estimated values of the coefficients of interest.

Table 4. Parameter Estimates for the Speed Equations from the Two Models

Parm.	*Meaning*	*Tournament Model: Costly Effort*	*All-Out Model: Costless Effort*
δ_1	Turf Surface in Good Condition	0.029	0.029
		(0.003)**	(0.003)**
δ_2	Turf Surface in Bad Condition	0.005	0.005
		(0.007)	(0.007)
δ_3	Dirt Surface in Good Condition	0.008	0.008
		(0.003)*	(0.003)*
θ_1	Short Distance	0.130	0.129
		(0.007)**	(0.007)**
θ_2	Medium Distance	0.056	0.055
		(0.007)**	(0.007)**
θ_3	Long Distance	0.031	0.030
		(0.007)**	(0.007)**
λ	Elasticity of Speed wrt Performance ($\times 10^3$)	6.371	5.680
		(.245)**	(.254)**
ϕ	Inverse Elasticity of Pool wrt log Total Effort	1.850	2.080
		(0.331)**	(0.381)**
ln β or ln *b*	ln Marginal Cost or ln Max Effort over Ability	-9.604	6.813
		(3.556)*	(4.102)
γ_1	Elasticity of Mean log Ability wrt Purse	0.606	1.915
		(0.195)**	(0.216)**
γ_2	Fillies and Mares (females)	-1.159	-1.292
		(0.263)**	(0.302)**
γ_3	Age = 3 years	5.418	6.096
		(0.640)**	(0.761)**
γ_4	Age = 3 years and up	4.552	5.103
		(0.500)**	(0.589)**
γ_5	Age = 4 years and up	4.341	4.883
		(0.533)**	(0.638)**
R^2		0.809	0.800
Correlation of Ability for a Given Horse across races		0.932	0.712
Kolmogorov-Smirnov test statistic for:			
log ability ~ log normal		0.186	0.088
luck ~ extreme value		0.106	0.111
Skewness of Luck		-0.527	-0.573
Kurtosis of Luck		4.239	4.303

Notes: GMM estimates of two equation model; absolute *t*-statistics below coefficients. Dependent variable is speed. All variables except the dummies for track are in logs. Observations: 5504. Skewness : 1.1 for extreme value, 0 for normal. Kurtosis: 5.4 for extreme value, 3 for normal. Null for Kolmogorov-Smirnov test is that the distributions are as predicted. Both tests reject the null. Significance levels shown by: one star indicates significance at the 5% level, two stars at the 1% level. Short distance is 6 furlongs or less, medium is 6 ½ to 7 ½ furlongs, and long is 1 to 1 ¼ mile. Distance longer than 1 ¼ mile is the excluded group.

The value of marginal cost in the tournament model is statistically significant at the 1 percent level. The magnitude is also economically reasonable. We can calculate the total variable cost of a horse entering a raced by the antilog of the estimated coefficient times effort divided by ability. The average over all horses is $835.[18] The favorite in the race with the field of average ability had an expected payout of $5227 and expected variable cost of $314.[19]

The all-out model says that all of the increase in effort associated with increased prizes is due to selection. The tournament model breaks the increase in effort associated with increased prizes into a selection effect and increase in individual performance. The ratio of individual performance to total can be written as:

$$\frac{\ln x_i - \ln \beta}{\ln x_i - \ln \beta + \gamma Q}$$

where the numerator is the individual performance effect and the denominator adds in the selection effects of purse, age, and sex. Based on the estimated values for γ and $\ln\beta$, and averaged over the entire sample, we find a value of 63 percent. This says that nearly two-thirds of the increase in performance associated with paying higher prizes comes from individual horses running harder.

5.1. Diagnostics

Table 4 shows the correlations of estimated ability for the same horse in different races. There are 1420 horses that raced multiple times. In our estimation process, we treated these as independent observations. By doing this, we can empirically assess how ability changes race to race, but also we can compare the two models. As shown in Table 4, the tournament model says that the correlation of estimated ability from race to race is over 0.9; the correlation of estimated ability for the same horse from the all-out model is 0.7.

Specification tests indicate a reasonable fit. Within a race, effort has a strictly positive monotonic relationship with ability in the tournament model. (Obviously, in the all-out model effort equals ability.) The following two figures show the empirical density function of log ability alongside the closest fitting log normal CDF. The tournament model is shown in Figure 1. The all-out model is shown in Figure 2. The test statistic shown in Table 4 rejects the null that log ability is distributed log normal, but the patterns shown in Figures 1 and 2 indicate that

[18] The average for log effort is 19.12; the average for log ability is 9.70.

[19] We averaged the estimated ability from the tournament model across horses in each race and then took the average of these. The favorite in the race with the field of average ability finished second.

lognormal may appeal as a rough approximation, particularly for the costless model.

Although the model specification assumes an extreme value distribution for luck, the data do not appear to be extreme value. Just as in the non-nested model specification test, the costless model is more misspecified on this dimension than the costly model. The Kolmogorov-Smirnov test statistics in Table 4 reject the null that luck is distributed extreme value. When we investigate we see that the sample skewness is about half of the magnitude of the assumed extreme value and a different sign; the luck distribution appears to be skewed left (i.e., a fat left tail) instead of skewed right. Moreover, the empirical luck distribution exhibits thinner tails (lower kurtosis) than the assumed distribution; instead, the kurtosis is somewhere in between the extreme value and normal distributions. The extreme value assumption is made in order to employ a closed form solution in the calculation of ln *x* and relating effort to odds in (2). We could, with some non-trivial degree of difficulty, relax this assumption and use a more flexible distribution of luck to derive ln *x*. This would probably improve the goodness-of-fit for the tournament model relative to the all-out model since ln *x* is a regressor in equation (7) but not in (8) and (2) is the same for both models. Since we have already found that the tournament model is superior to the all-out model, we forgo this task.

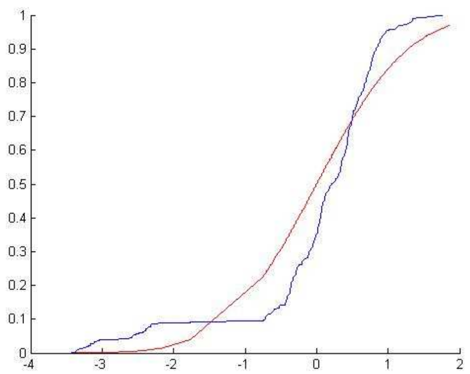

Figure 1. Empirical and Hypothesized CDF of log Ability for the Tournament Model

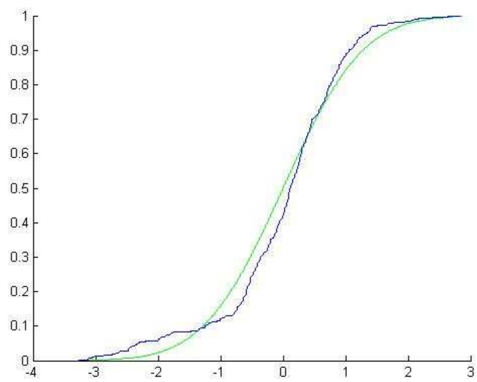

Figure 2. Empirical and Hypothesized CDF of log Ability for the All-Out Model

Finally we investigated the sensitivity of both models to the frequency of favorites winning. Both models say that a dose of luck affects the outcome and stops the finishing positions from being perfectly correlated with the odds. If the models are systematically missing something associated with favorites it should show up as a correlation between estimated luck and the average finishing position of the favorites. We define favorites as the top three and the top five horses and correlate estimated luck with the average finishing position of these horses. The correlations are uniformly zero.

5.2. Reduced Form Estimates

Further evidence comparing the ability of the two models to organize the data can be found in a reduced form estimation of the speed equation. Essentially, the tournament model says that the performance of a given horse will be affected by the performance of the competition that it faces. The all-out model makes no such prediction. One way to investigate this is to see if the revealed speed of a horse is affected by what the horses around it are doing. We regress speed on track, distance, purse, age, and sex, and on the variance of speed in the race. We alternatively use the variance of the log of the probability of winning. We use the variance of speed of all the horses and also the variance in speed in the top five favored horses.

These results are shown in Table 5. We see that variance, however measured, causes average speed to decline. The horses appear to be reacting to the competition, and based on the results in Table 4, they are reacting in a way that is consistent with the tournament model of behavior. Several specifications are shown including the ex ante prediction about variance of speed given by the variance in the betting odds. The control variable effects are nearly the same as those shown in Table 4, though the magnitudes are different because the coefficients shown in Table 4 are adjusted by the estimated value of λ.

Table 5. Reduced Form Estimates of Log Speed

Independent Variables	*Coefficient*	*Std Error*	R^2
Intercept	3.720	(0.017)	
Turf Surface in Good Condition	0.027	(0.003)	
Turf Surface in Bad Condition	0.002	(0.006)$^{+}$	
Dirt Surface in Good Condition	0.010	(0.002)	
Short Distance	0.136	(0.007)	
Medium Distance	0.060	(0.007)	
Long Distance	0.033	(0.007)	
Log of Purse	0.017	(0.001)	
Fillies and Mares (female)	-0.009	(0.001)	
Age = 3 years	0.040	(0.005)	
Age = 3 years and up	0.035	(0.005)	
Age = 4 years and up	0.043	(0.005)	
Variance of Speed Overall	-59.816	(14.743)	0.887
Alternative Specifications			
Independent Variable: Variance of Probability of Winning (× 10^2)	-0.516	(0.167)	0.882
Dependent Variable: Log Speed of Favorites			
Independent Variables:			
Variance of Speed Overall	-95.153	(14.926)	0.883
Variance of Speed of Favorites	-15.874	(7.474)$^{\#}$	0.868
Variance of Probability of Winning (× 10^2)	-0.915	(0.175)	0.872

Notes: Alternative specifications include all of the track, distance, and selection variables. Coefficient values on these variables change trivially across alternative specifications. Robust standard errors in parentheses. All coefficient estimates significant at the 1 percent level except (#) significant at the 5 percent level and (+) not significant. Favorites defined as top five horses based on probability of winning. Distance dummies defined in Table 4.

Another and possibly more powerful test of the tournament model is to look at horses that run multiple times. We have already pointed out that our correlation of estimated ability for horses that run multiple times is quite high, but we can go beyond this and look at the relation between estimated effort and the time between races. If horses vary their effort levels, then this variance should be predictably linked to the time that it takes them to recover and race again. That is, if horse *i* runs hard in one race, it will take longer to recover and the time until its next race should be longer. We measure the time between races for 1285 horses that raced multiple times within the same season (i.e., fall and spring). There are 2181 observations. We control for dirt versus turf because most races are dirt and a turf racer will have fewer opportunities. We also control for age and sex because these determine whether a horse can compete in a given race.[20]

The results are shown in Table 6. The independent variable of interest is our estimated value of effort expended by the horse in its last race. As can be seen, effort expended in the last race significantly increases the time before the horse races again.

Table 6. Time Between Races

Independent Variables:	*Coefficient*	*Std. Error*
Estimated Effort in Last Race	0.881	(0.168)*
Dirt v. Turf Race	-1.595	(0.578)*
Fillies and Mares (female)	1.050	(0.389)*
Age = 3 years	-0.137	(1.419)
Age = 3 years and up	0.817	(1.335)
Age = 4 years and up	-1.975	(1.323)
Intercept	0.260	(3.967)
R^2	0.046	
Mean of Dependent Variable	18.643	

Notes: 2181 observations on 1285 horses. Robust standard errors in parentheses. Dependent variable measured in days. One star indicates significance at the 1 percent level.

6. Dog Racing

Dog racing offers an interesting additional test of the comparison between the tournament model and the all-out model. Arguably, the effort level of horses can be controlled to some extent by the jockey. In dog racing, there are no jockeys. The dogs, when started, chase around a track after a simulated rabbit. The speed of the rabbit can be adjusted, but there is no way to make intra-race adjustments for individual dogs. The obvious prediction is that the all-out model should do a better job of predicting dog racing than horse racing.

[20] It might be argued that purse should be included as an independent variable in this regression. The control variables that we use are physical conditions of the race. That is, three year olds cannot races in a two year old race. However, three year olds can pick and choose among three-year-old races with different purses. Regardless, when purse is included, it has the expected sign (negative), is statistically significant, and does not affect the estimated coefficient on lagged effort.

Unfortunately the institutional characteristics of dog racing data make the application of our structural model problematic. In dog racing there is no independent determination of the purse and pool. The purse is a fixed percentage of the pool (slightly less than 4 percent).

Nonetheless we can estimate the reduced form model for dogs as we did for horses as reported in Table 5. The prediction in the reduced form model is that if competitors are behaving according to the tournament model, average performance will decline as the variance of performance increases. When facing more disparate competitors, workers shirk. The all-out model makes no such prediction. By using the dog racing data we can refine the prediction: dogs should be less affected by disparity of the field than horses.

The dog racing data is taken from http://www.greyhound-data.com, a website run by the international greyhound racing association. It tracks races, individual dog performance, and racetrack specific races over time. The data in question is specifically for the Jacksonville FL racetrack for the year 2006. We have data on races between June 1 and September 4. There are generally 28 races per day broken into afternoon and evening sessions. We have complete data on 1037 races on 77 days. There are two race lengths: 89 percent of the races are 550 yards; 11 percent are 661 yards.

These races all have eight dogs. Dogs are graded; dogs of similar grade are raced against each other. There are 6 grades. Dogs vary by age, sex, and weight. The youngest dog raced when it was 16 months old; the oldest when it was 64 months old. Dogs varied between 23 and 40 kg with the average at 30 kg. Males comprised 51.2 percent of the dogs in the sample. The fastest dog in the short races ran 54.7 feet per second, and in the long races, 52.7 feet per second.

Table 7 shows the reduced form regression for dogs similar to the one for horses given in Table 5. The regression shows that afternoon races are slightly faster than evening races, and that shorter races are 2 percent faster than longer ones. The grades order the quality of the dogs with the omitted class being the fastest. The slowest class, *M*, which is for dogs between one and two years old, is 2.6 percent slower than the fastest. Purse, age, weight, and sex do not predict speed, *ceteris paribus*.

The variable of interest is the variance of speed in the race. We see that it does have a statistically significant effect. As variance increases, average speed goes down. However, as predicted, the effect of variance on speed is smaller for dogs than it is for horses. Dogs do not vary their effort as much based on the performance of the other competitors as do horses. The responsiveness of dogs is approximately one-third of the responsiveness of horses.

Table 7. Reduced Form Estimate of Speed for Dogs

Independent Variables		*Coefficient*	*Std. Error*
Afternoon		0.17*	0.05
Grade	A	-0.47*	0.18
	B	-1.17*	0.18
	C	-1.71*	0.17
	D	-2.06*	0.17
	M	-2.64*	0.20
Short Race		2.17*	0.06
Purse		-0.00	0.02
Age	Average	0.28	0.19
	Variance	-0.08	0.60
Weight	Average	-0.39	0.82
	Variance	2.00	3.80
Sex	Average	-0.24	0.17
	Variance	-0.03	0.36
Variance of Speed		-21.09*	2.38
	R-squared	0.81	

Notes: 1037 Races. Dependent variable is log speed. All coefficients and standard errors except Variance of Speed are multiplied by 100 and thus are percentage effects. Purse, age and weight are in logs. Single star indicates 1 percent significance. Omitted grade is *S*, which are the fastest. Fixed effects for date.

7. Conclusions

We have investigated the performance effect of incentive-based pay schemes. Everyone agrees that incentive pay increases performance. However, there are two alternative hypotheses that deliver this result. One model is that of all-out effort. This theory claims that competitors go all out, all of the time, and the only thing that distinguishes one match from another is the sorting of participants. The other model is based on the Lazear-Rosen tournament theory. In this model, players weigh the marginal payoff against the marginal cost of effort and vary their level of exertion from one contest to the next. In the all-out model, individuals do not adjust their effort. In the Lazear-Rosen model, they do.

We compare these two theories to see which better organizes the data. The policy issue is important because if the all-out model is correct, incentive pay for existing workers is inefficient. An important feature of our investigation is the theoretical structure of the empirical investigation. The tournament model has subtle features and the contrast to the all-out model requires attention. Our results show that proper structural form is necessary to distinguish individual performance responses from field selection effects. We also exploit implications of the tournament model that differ from the all-out model to perform reduced form tests.

We examine performance in horse and dog racing. Using structural estimation in horse racing we find that the tournament model does organize the data more precisely. These estimates show that only around one-third of the performance increase resulting from higher prizes is due to the selection effect. This result is very similar to the result found in field studies such as Lazear (1996) of individual worker performance in industrial settings. The superiority of the tournament model and the point estimate of the individual versus selection effect is corroborated both in both horse and dog racing by reduced form results. Importantly we find that competitors work less hard when talent is more heterogeneous—a prediction of tournament theory—and that this effect is stronger for horses than for dogs, as we would expect because dogs are not under direct control by handlers during the race.

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