The Thrill of Victory: Measuring the Incentive to Win

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Abstract: There is ample evidence that incentive-pay structures, such as tournaments, result in increased performance. Is this due to selection or increased individual effort, and is any increased individual effort caused by pecuniary incentives or merely thirst for the thrill of victory (TOV)? Prior literature has not separated the different effects. We look at performance in horse and dog racing and find that only horses, controlled by jockeys during the race, exhibit performance corresponding to pecuniary incentives, while both respond to selection and TOV. The results show that pay structures do matter.

1. Introduction

Tournament theory is held to apply in almost all labor/leisure settings. The literature is robust with industrial and managerial applications.[1] The one place that tournament theory is less accepted is in the actual tournament setting. For instance, some athletes claim they do not vary their effort levels: they claim they exert maximum effort in every contest.[2]

While we may doubt this claim, the argument helps frame the problem of understanding incentive-based performance schemes. First, there is little doubt that higher pay creates selection effects. Higher prizes attract better competitors who naturally exhibit higher performance. Competitors may also exert more individual effort, but this may be a result of sorting as well. Winning may be its own reward and the heat of competition alone may drive individual performance. It is arguable that when a field of superstars is assembled, they will fight more aggressively among themselves to claim the top spot regardless of the marginal monetary payoff. The extreme test of tournament theory is to see if it has predictive power over and above a selection effect based on ability and any performance increases induced by the thrill of victory (TOV). This is a test of tournament theory that has not previously been identified.

The policy implications are important on several fronts. Performance pay schemes for existing workers are wasteful if there is no scope for adjustment in individual behavior. Furthermore, if competition alone spurs performance outside of monetary consideration, firms need only to match talent optimally within the

[1] See O'Keeffe, Viscusci, and Zeckhauser (1984), Malcomson (1984), Main, O'Reilly, and Wade (1993), Murphy (1999), Knoeber and Thurman (1994), Ferrall (1996), and Brickley, Linck, and Coles (1999) to list a few.

[2] See discussion in Maloney and McCormick (2000), and Lynch and Zax (2000).

workforce and need not worry about the precise structure of rewards. However, if monetary incentives such as those embedded in tournament prizes drive performance, then pay structure is critical.

We test this tripartite taxonomy of performance—the selection effect based on ability, a TOV effect based on the heat of competition, and a pecuniary incentive effect based on the marginal cost-benefit calculation identified in the tournament model. We search for the effects in horse and dog racing to see how much of the variation in outcomes can be explained by each effect. We compare horse and dog races because it seems likely that the performance of horses, managed by jockeys during the race, will be more responsive than dogs to marginal monetary rewards. We find that horses, unlike dogs, can be enticed to respond with individual effort to pecuniary incentives over and above selection and the TOV effects. Our results imply that the implications of tournament theory for the structure of prizes are important.

The paper is laid out as follows: Section 2 discusses the methodology and the relation of our work to prior research. Section 3 refines the theoretical structure that we implement empirically. Section 4 discusses the data. Section 5 describes the regression results. Finally, Section 6 provides some brief conclusions.

2. Theory & Prior Research

The mass of empirical research shows that as pay goes up, so does performance. However, our problem is to parse the relationship between performance and pay into three components: selection, TOV, and incentives. Our empirical approach is to account for selection effects as comprehensively as possible. In addition to controlling for basic things like age and gender, we devise an ability index for animals across races. Given these controls, we then look for ways to capture the TOV effect. As the closeness of a contest tightens, competitors will be forced to exert more effort to taste the sweetness of victory. We capture this using the distance separating the animals at various points along the course and by the number of position changes throughout the race. Finally, we account for the pecuniary incentive effect using the marginal payoffs net of cost, as identified by the tournament model.

This approach gives us a strong test of the tournament model. Although selection and relative competitiveness are built into the tournament model, we distil each out separately as stand-alone hypotheses. We test the tournament model to see if it has explanatory power purely on the basis of marginal pecuniary incentives. Moreover, we carry out the experiment in two venues: one where we think the revelation of pecuniary incentive outcomes of the tournament theory sort are likely (horse racing) and one where we think that they are unlikely (dog racing).

2.1. Prior Research

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 we are addressing is the extent to which tournament structures achieve this result simply because tournaments 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 linked to monetary pay structures. That is, when the gap in tournament prizes gets larger, do individuals work harder and is any increase in effort a result of monetary rewards as opposed to competitive instincts? It is possible that higher pay brings better competitors together, who then perform better personally because of the heat of competition.

Nearly all of the theoretical tournament literature simply assumes that individuals can respond to incentives by varying their effort and does not try to separate the various effects.[3] Empirical work on the tournament model has addressed the issue; however, it has never staged a complete test of the competing hypotheses. Nearly all of the evidence (cited in note 1 above) that shows the productivity effect of promotion in the context of tournament theory can be rationalized as a selection effect. The tournament setting selects people who will work more hours and more days. Most past 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: 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.[4] Their motivation was to acquire human capital from on the job training.

An early test of the tournament model, by Ehrenberg and Bognanno (1990), shows that there is 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. They find that the prize gaps affect

[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] 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.

performance. More recent work has been less conclusive.[5] Moreover, selection effects are not explicitly accounted for.

Knoeber and Thurman (1994) find that the level of pay, holding constant 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 this is evidence that workers can and do marginally adjust their behavior. However, their data do not allow them to control for selection effects.

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. Lynch and Zax (2000) dispute this finding when 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 relationship between effort and prizes in the tournament model depends on ceteris paribus conditions which include the number of other contestants and their abilities. For example, when a particular runner competes 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 relationship found by Lynch and Zax can be explained by imperfect specification of the estimation.

This paper is about the specific case of tournament compensation and performance. The more general issue regards the incentive effects of performance-based compensation for which some research has been done. Prendergast (1999) surveys many papers that find performance responses from incentive-based compensation.[6] 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 low quality workers being replaced by superior workers. The rest is attributed to individual response. However, this is not undeniable evidence that individuals respond directly to incentive pay. The individual response to incentives that he finds could be due to the heat of competition. Bringing more productive people together in a competitive setting

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[5] Bronnars and Oettinger (2001).

[6] See Lazear (1996), Paarsch and Shearer (1999), Banker, Lee, and Potter (1996), Fernie and Metcalf (1999), McMillan, Whalley, and Zhu (1989), Groves, Hong, McMillan, and Naughton (1995), Kahn and Sherer (1990), and Foster and Rosenzweig (1994). More recent papers include Banker, Lee, Potter, and Srinivasan (2001), Brickley and Zimmerman (2001), and Lemmon, Schallheim, and Zender (2000).

could induce better performance not because of the monetary reward but because of the TOV effect.

Guryan, Kroft and Notowidigdo (2009) perform a study concerning incentives similar to the TOV effect. They investigate how randomly assigned competitors in golf respond to each other in the first two rounds of golf tournaments. They find no evidence of what are called "peer effects." We feel that animal racing offers a better environment for isolating TOV/peer effects than early rounds of golf tournaments. However, the authors raise important questions and complete investigation deserves further consideration.

3. Models of Performance & Estimation Strategy

Performance in racing is speed. Speed is affected by the type of track, track conditions, and the like. Speed is also a function of distance: longer races are run more slowly. Other readily identifiable characteristics like age and sex are correlated with speed; for instance, males are on average faster than females. We use these to the extent possible to control for speed across races. Additionally, because wagers are made on these races, we are able to construct a unique measure of ability by comparing the gambling odds of one participant to another, even inter-race. We use this ability index to measure the selection effect.

3.1. Measuring Selection

We build an ability index from the odds data where we observe the probability that competitor *i* will win race *r* relative to the probability that competitor *j* will win that race:

$$ODDS_{ijr} = \frac{\Pr_{ir}}{\Pr_{jr}}$$

If competitors exert maximum effort every time then their performance is determined solely by ability and the realization of within-race idiosyncratic shocks dubbed "luck."

For the pure selection hypothesis, we assume the analog of the discrete choice literature's independence of irrelevant alternatives (IIA) which in this context would be independence of irrelevant animals in the race. That is, the odds of horse *i* winning over horse *j* is independent of the other competitors in the race. Under this assumption, odds reveal ability in the following way:

$$ODDS_{ijr} = \frac{A_{ir}}{A_{jr}}$$

where A_{ir} is the ability of competitor *i* in race *r*. This provides an unambiguous ability rating of competitors in a race, relative to a baseline competitor in the race. If that same baseline competitor ran in every race, then ability ratings would clearly be comparable across races because each would be relative to the same common baseline competitor.[7]

Unfortunately, our data do not have this natural baseline. Nonetheless, we can still construct an ability rating that is comparable across races, as illustrated in the undirected graph displayed in a Figure 1. In this figure, we represent a simplified conceptualization of our data: each competitor in a given race is a node, when two competitors run against each other in a race, they are linked by their odds, and when the same competitor runs in multiple races then those nodes are linked. A comparable ability rating can be constructed for all competitors who are connected by a (sequence of) link(s). [8] The top panel displays the simplest type of connected data: when there is a common competitor in all races. The next panel shows data when all nodes are connected via a network of competitors, rather than a common baseline, which has the potential to exhibit a much more complicated topology. The third panel has two disjoint sets of competitors, yielding an unconnected graph.

[7] This actually assumes that ability is invariant across races occurring at different points in time. As discussed below, the odds data is not consistent with such time-invariant ability. We address this concern below.

[8] This sufficient condition is equivalent to there existing a "degree of separation" between any two competitors, where the degree of separation between Competitor A and Competitor D is equal to the number of links traversed along the shortest path from (one of) Competitor A's node(s) to (one of) Competitor D's node(s). If this sufficiency condition is violated (that is, if the graph is not connected) then the famed "six degrees of separation" hypothesis would not hold (at least within our data set).

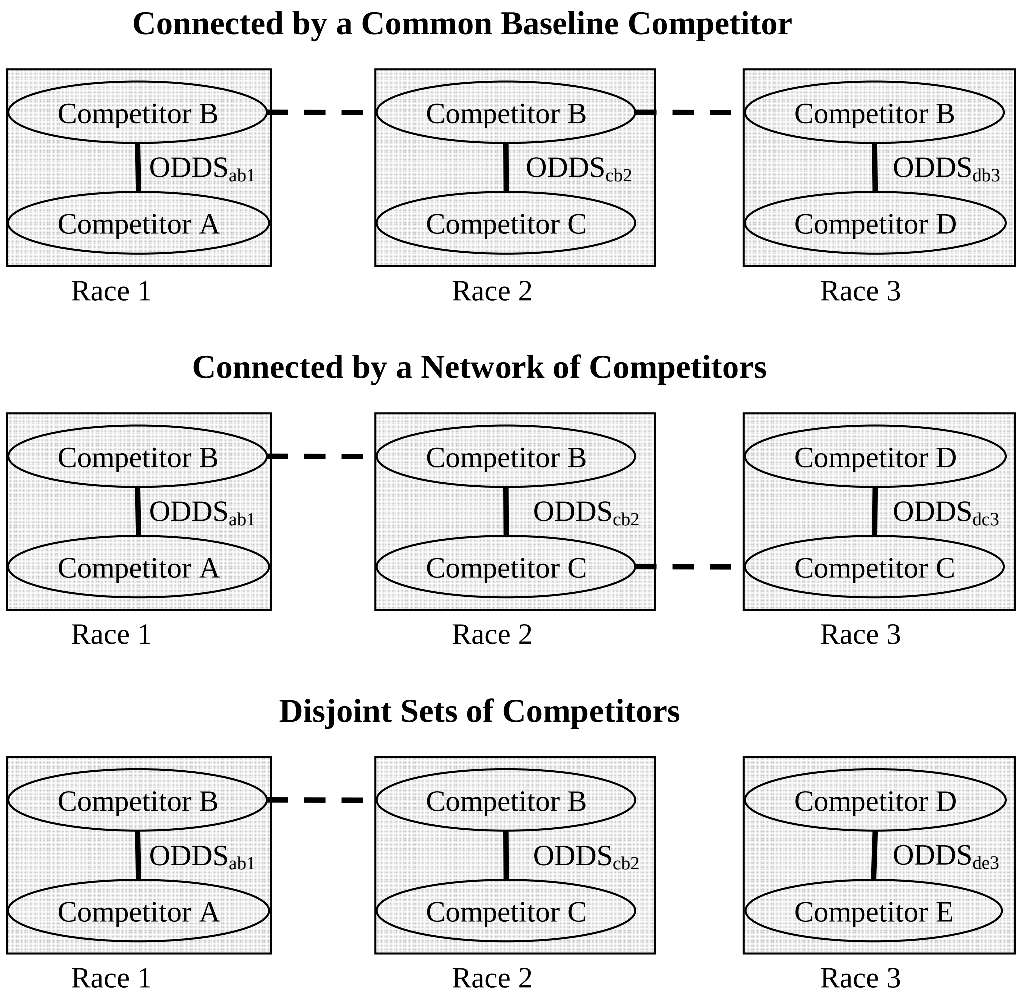

Figure 1. Networks of Competitors Based on Odds

Our data contains features from both of the bottom panels of Figure 1, i.e., both disjoint sets of competitors and a complex network of linked competitors. We address the problems implied by disjoint sets of competitors in the empirical section. We use a dummy variable indicating membership to a disjoint set of competitors. This picks up the average performance of members of that group, which can be compared to the average performance of members of a different group.

The complex network of linked competitors in our data generates an additional complication. Multiple pathways between nodes can produce different implied ability ratings when a competitor's ability varies over races (e.g., due to an injury, excelling in wetter race conditions, etc). Indeed, our odds data do not support the assumption that ability is race-invariant. We model ability across races in the simplest way possible: ability is amplified or dampened by an idiosyncratic factor observed by those who make the odds (bettors) but unobserved to the econometrician. Let υ_{ir} be the unobserved i.i.d. ability adjustment factor:

$$ODDS_{ijr} = \frac{A_i \upsilon_{ir}}{A_j \upsilon_{jr}}$$

Logging the odds gives us an equation that we can use to estimate each A:

$$\ln ODDS_{ijr} = \ln A_i - \ln A_j + \underbrace{\left(\ln \upsilon_{ir} - \ln \upsilon_{jr}\right)}_{Noise}$$

We obtain an adequately large number of pairwise comparisons, *M*, by collecting the log odds across all of the *R* races:

$$M = \sum_{r=1}^{R} \frac{N_r \left(N_r - 1\right)}{2}$$

where N_r is the number of competitors in race *r*. Placing these pair-wise comparisons into a large matrix, we recover ability ratings (relative to our group membership) by a large regression:[9]

$$E\left(\begin{bmatrix} \ln ODDS_{1,2,1} \\ \vdots \\ \ln ODDS_{I,I-1,R} \end{bmatrix}\right) = \begin{bmatrix} 1 & -1 & \cdots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \cdots & 1 & -1 \end{bmatrix} \begin{bmatrix} \ln A_1 \\ \ln A_2 \\ \vdots \\ \ln A_{I-1} \\ \ln A_I \end{bmatrix}$$

3.2. The Thrill of Victory

Next, we turn to the second or TOV hypothesis. The basic idea is that the heat of competition itself will draw forth extra effort. When competition is intense, participants will work harder than when the outcome is obvious. There are several ways to measure this.

[9] The specification above lacks a row identifying the baseline competitor. Which competitor is chosen as the baseline (ln α = 0) for each disjoint ability group is immaterial.

One way is the disparity of the field. This can be measured ex ante by the variance in the odds of winning across the entrants. It can be measured ex post by the variance of performance at the finish. Moreover, because of the richness of the horseracing data, the TOV hypothesis can be measured by the disparity of performance during the race.

The data that we have for horse racing allow us to know the relative position of each horse at each mark along the race course and by how much it was ahead of the horse trailing it. We also know the time at each mark for the fastest horse. Using these data we look at the closeness of the race at the mark for the stretch run (last furlong). The hypothesis is, the tighter the race at the stretch, the faster the race will be run overall and from the stretch on.

We measure closeness for the i^{th} animal by the sum of the distances of each animal in the race from the leader. For horses, we make this calculation at the home-stretch mark and at the finish line. Unfortunately, we do not have race results of this quality for dogs. However, the closeness of the race at the end is highly correlated with the closeness at the stretch-run mark. So, for horses we compare the results of using closeness at the stretch-run mark to closeness at the end of the race. For dogs, we then use closeness at the finish to see how dogs compare to horses.

We recognize that this is not a perfect measure of closeness for dogs, and we exploit additional information in the dog data. Fortunately, the data include the rank-order position of the dogs at way-points during the race. Lead changes at the distance marks around the course are a theoretical proxy for the closeness of the race, albeit a noisy one.[10] There should be a positive relation between lead changes and the closeness of the competitors at any point on the race course. To implement this, we calculate the Euclidean distance between an animal's rank at one mark and its rank at the preceding mark and then average it across the animals in the race.[11] That is,

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[10] The intuition connecting position changes to closeness is clear; the probability of a position change is increasing in the closeness of the pack. At one extreme is the tightest of all possible races, where any small differences in luck would result in widespread position changes. At the other extreme is the blow-out race, where the distances between the competitors steadily grows throughout the race so that no position changes occur. The noisiness of a measure based on position changes results from the fact proximity makes a position change more probable but may not materialize. This results in some relatively tight races with fewer position changes than would be expected. Moreover, position changes should also be less informative because they are ordinal data, rather than the cardinal data that we can use to construct closeness measures at the straight away mark. See Marden (1995) for a full development of the statistics describing changes in noisy rank-order positions and using those statistics to test the true underlying closeness of whatever is being ranked.

[11] Note that this measure is the L^2 norm metric corresponding to Spearman's distance (of the Spearman rank correlation coefficient), which is essentially the Mean Square Error of using the ranks at the previous mark to predict the ranks at the next mark.

$$L_{rk} = \frac{\left[\sum_{i=1}^{N_r} \left(p_{ik} - p_{ik-1} \right)^2 \right]^{1/2}}{N_r} \tag{1}$$

where L_{rk} is the lead-change statistic for race r between mark k and k-1, p_{ik} is the position of horse i at mark k, and N_r is the number of animals in race r.

We find for horses that the closeness of the race at the home-stretch mark is strongly correlated to the rank-order position changes that have occurred during the race. We can make a fair comparison between horses and dogs in their competitive responsiveness to closeness using rank-order position changes and validate it with the observed closeness at the home-stretch mark for horses.

3.3. The Incentive Effect

Modeling the incentive effect based on the Lazear-Rosen hypothesis is straight forward. The problem faced by the handler of animal i is to find the level of effort that maximizes the expected prize net of the cost of effort (*NP*):

$$E(NP) = w_1 \Pr\left(i \;\; places \; 1^{st}\right) + \cdots + w_k \Pr\left(i \;\; places \; k^{th}\right) - C\left(m_i; A_i\right)$$

where w_k is the prize paid to k^{th} place and A_i is heterogeneous ability causing different riders and/or trainers to select different levels of effort. Note that we have embedded ability in the cost function. The first-order condition for the optimizing behavior of the rider or trainer is:

$$\sum_{k=1}^{4} w_k \frac{\partial \Pr\left(i \;\; places \; k^{th}\right)}{\partial m_i} = \frac{\partial C\left(m_i; A_i\right)}{\partial m_i} \tag{2}$$

We make the standard assumptions that cost is increasing in effort, convex, and ability decreases marginal cost. These assumptions fill in the details about the right-hand side of equation (2); note that ability is directly accounted for there.

Marginal revenue is increasing in effort because the probability of winning is increasing in effort. Because the probability of winning is bounded above at 1, marginal revenue is globally concave.[12] This implies that the optimal effort in the Lazear-Rosen model equates marginal revenue to the marginal cost of effort.

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[12] Except for some irrelevant local non-concavities in expected revenue. Theoretically, these can appear when the realized distribution of ability in a race is over-dispersed. Such local non-cavities are irrelevant to our empirical work because they are never observed. The theoretical implication is that there can be some non-monotonicities in the comparative statics for ability, i.e.

In order to make this behavioral equation operational, we need to model the resolution of the tournament and fill in the details about the left-hand side of equation (2). Animal i beats animal j if $(m_i + \varepsilon_i) > (m_j + \varepsilon_j)$, where m_i is effort, unobserved by the econometrician but known to the handlers, and ε_i is luck, unobserved by the econometrician but revealed to the handlers. In general, the probability that animal i places first is the result of an N-dimensional integral:

$$\Pr\left(i\ places 1^{st}\right) = \int_{m_i+\varepsilon_i>m_j+\varepsilon_j} pdf\,(\underset{Nx1}{\varepsilon})d\varepsilon$$

In order to make this problem empirically tractable, researchers either assume homogeneity in ability or impose a particular structure on the distribution of luck. Since heterogeneity is everywhere observable in empirical work, most empirical researchers impose structure on the distribution of luck. We begin by following this approach.

3.4. Ex-Ante Marginal Revenue

We assume that luck is i.i.d. across the field according to an extreme value distribution. This produces the familiar logit form for the predicted probability of animal i winning the race:

$$\Pr\left(i\ places 1^{st}\right) = \frac{e^{m_i}}{\sum_{j=1}^{N} e^{m_j}}$$

This immediately implies the ex-ante marginal effect of effort on the probability of placing first:

$$\frac{\partial \Pr\left(i\ places 1^{st}\right)}{\partial m_i} = \frac{e^{m_i}}{\sum_{j=1}^{N} e^{m_j}}\left[1 - \frac{e^{m_i}}{\sum_{j=1}^{N} e^{m_j}}\right] \qquad (3)$$

Equation (2) is our behavior function in which effort is implicitly a function of ability, prizes, and the quality of the field. Equation (3) identifies the left-hand

an increase in ability (ceteris paribus) may not always increase effort. For instance, if 1 competitor is already a shoo-in for a winner-takes-all race, then an increase in her ability may not increase her effort because the opposition will increase their shirking so much that the shoo-in can also shirk. See the mathematical appendix for a further development.

side of equation (2) and makes it an estimable form for the behavior of the jockey or handler in their choice of effort as a function of ability and the parameters of the race. The IIA property of luck's distribution allows us to compute the ex-ante probability of animal *i* finishing at any place, as well as the marginal effect of effort on the probability of placing k^{th}, from the ex-ante probability of each animal winning 1^{st} place.[13] We observe the ex-ante probability of each animal winning through the gambling odds. Therefore, we can use those data to construct the ex-ante marginal revenue of effort.

3.5. Ex-Post Marginal Revenue

We also want to calculate the marginal revenue facing the jockey after the realization of luck in the first part of the race, but ex-ante gambling odds (alone) cannot capture information on the luck realized in the first part of the race. Hence, we must adapt our ex-ante model for marginal revenue to incorporate the information revealed in the first part of the race. We begin the development of our model of ex-post marginal revenue with the probability of placing k^{th} under homogeneous ability as derived in Krishna and Morgan (1998):

$$\Pr\left(i\ places\,1^{st}\right) = E_{\varepsilon_i}\left[cdf_1^{\,N-1}\left(m_i + \varepsilon_i - m_{-i}\right) - \underbrace{cdf_0^{\,N-1}\left(m_i + \varepsilon_i - m_{-i}\right)}_{0}\right]$$
$$\Pr\left(i\ places\,2^{nd}\right) = E_{\varepsilon_i}\left[cdf_2^{\,N-1}\left(m_i + \varepsilon_i - m_{-i}\right) - cdf_1^{\,N-1}\left(m_i + \varepsilon_i - m_{-i}\right)\right]$$
$$\vdots$$

Where the *cdf*s are the cumulative probability distributions for the k^{th} order statistic in an i.i.d. sample of size N-1. Taking the derivative implies the marginal effect of effort on the placing probabilities in the symmetric equilibrium:

$$\frac{\partial \Pr\left(i\ places\,1^{st}\right)}{\partial m_i} = E_{\varepsilon_i}\left[pdf_1^{\,N-1}\left(\varepsilon_i\right)\right]$$
$$\frac{\partial \Pr\left(i\ places\,2^{nd}\right)}{\partial m_i} = E_{\varepsilon_i}\left[pdf_2^{\,N-1}\left(\varepsilon_i\right) - pdf_1^{\,N-1}\left(\varepsilon_i\right)\right]$$
$$\vdots$$

[13] 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 Animals. This allows us to compute the probability of an animal winning second place given some other animal won first place: the probability of beating the remaining animals. The remainder of the computation involves going from the conditional probability to the joint probability and then onto the marginal probability. See the mathematical appendix for further development.

Unfortunately, theorists have not achieved such a derivation for the case of heterogeneous ability. In an attempt to construct general approximations for the ex-post marginal revenue, we must consider the implication of heterogeneity in our data that is absent from the preceding theoretical derivation. We do not know the functional form of the expected distribution of the luck order statistics when there is heterogeneous ability.[14] We address this problem in our reduced-form context by selecting the normal kernel as a reasonable proxy for the order statistic's probability density function. The challenge is to set the location and scale parameters of that normal kernel so that it effectively addresses both the heterogeneity in ability and luck realized thus far.

We choose a reasonable location for the center of the normal kernel for the k^{th} order statistic's distribution. We center it on k. In doing so, we make the plausible assumption that the mode of the 2nd order statistic's pdf occurs at the effort level, measured in terms of position rank, exerted by the competitor currently running in second place. Although using absolute position data would be more informative in centering the order statistic distributions, we only observe the position rank in the dog data. Thus, we are constrained to model ex-post marginal revenue as a function of position ranks.

We also must choose the scale parameter for the normal kernel approximation to the order statistic density. We need to capture the key feature of the order statistic densities being closer together when races are tighter. Given that the k^{th} order statistic's distribution is centered at k, its closeness to the $k + 1$ order statistic's center can be measured in terms of the spreads of the two densities. Increasing the variance of those order statistic distributions effectively brings their centers closer together, relative to the rest of the probability mass, and makes the race more competitive. Hence, we model the scale of these kernels as a function of the instability of ranks at previous marks, as well as the place under consideration:

[14] The Bapat–Beg Theorem provides a theoretical description of the order statistic distributions when heterogeneous ability generates performance data that is not i.i.d. Unfortunately, it is not operational in our context. The computational complexity is prohibitive.

$$MR^{ExPost} = w_1\left[\frac{\partial \Pr\left(i\ places\, 1^{st} \middle| p_i, L_r\right)}{\partial m_i}\right] + w_2\left[\frac{\partial \Pr\left(i\ places\, 2^{nd} \middle| p_i, L_r\right)}{\partial m_i}\right] + \cdots$$

$$\frac{\partial \Pr\left(i\ places\, 1^{st} \middle| p_i, L_r\right)}{\partial m_i} \approx \beta_1 \phi\left(\frac{p_i - 1}{\sigma_1^2}\right)$$

$$\frac{\partial \Pr\left(i\ places\, 2^{nd} \middle| p_i, L_r\right)}{\partial m_i} \approx \left[\beta_2 \phi\left(\frac{p_i - 2}{\sigma_2^2}\right) - \beta_3 \phi\left(\frac{p_i - 1}{\sigma_1^2}\right)\right]$$

$$\vdots$$

$$\sigma_k^2 = \omega_0 + \omega_1 L_r + \omega_2 k$$

Where ϕ is the normal kernel, p_i is the rank of the position of competitor i at the previous mark, σ^2_k is the scale parameter for order statistic k, L_r is our lead change measure of the instability of ranks at previous markets, and the parameters of this approximation are given by β and ω. Although the luck realized up to that point might push the ex-post marginal revenue of effort away from its ex-ante counterpart, they should be equal in expectation. Hence, we can choose the parameters of our ex-post marginal revenue to minimize the L^2 distance between our parameterized approximation of ex-post marginal revenue and its ex-ante counterpart:

$$MR_i^{ExPost}\left(\hat\beta, \hat\sigma^2\right) = w_1\left[\hat\beta_1 \phi\left(\frac{p_i - 2}{\hat\sigma_1^2}\right)\right] + w_2\left[\hat\beta_2 \phi\left(\frac{p_i - 2}{\hat\sigma_2^2}\right) - \hat\beta_3 \phi\left(\frac{p_i - 1}{\hat\sigma_1^2}\right)\right] + \cdots$$

$$\begin{bmatrix}\hat\beta \\ \hat\sigma^2\end{bmatrix} = \underset{\beta,\sigma^2}{\arg\min}\, \frac{1}{N}\sum_{i=1}^{N}\left[MR_i^{ExPost}\left(\hat\beta, \hat\sigma^2\right) - MR_i^{ExAnte}\right]^2$$

3.6. The General Model

We overlay the three hypotheses into a single estimating equation for competitor i in race r:

$$s_{ir} = \kappa + \theta T_r + \underbrace{\alpha \ln A_i + \delta D_i}_{Selection} + \underbrace{\gamma c_r}_{TOV} + \underbrace{\pi MR_{ir}}_{Pecuniary\ Incentives} + v_{ir} \qquad (4)$$

where s is speed, T are track conditions including distance, c is our measure of closeness of the race to capture the thrill of victory, MR is the marginal revenue of effort which measures the incentive effect, and ν is a random error term. D is a set of dummies measuring ability categorically (e.g., age, grade, gender). It also includes ability group, which along with A, our ability rating, are used to directly measure the selection effect.

It is important to recognize how the three models overlay in equation (4). The Lazear-Rosen model has a selection component and a relative-performance component. Participants make a cost/benefit calculation on the optimal expected effort and then decide whether the expected payoff covers their cost. If not, they do not participate. This is selection. Similarly, the L-R model accounts for the relative performance of others as shown in equations (2) and (3) in a similar manner to the TOV effect. The prediction made by Lazear and Rosen is that all participants shirk the more heterogeneous talent is in a given contest.

In other words, the tournament model itself includes a selection and a TOV-like effect. Our methodology is to control for these two effects separately by using our ability index for selection and closeness for TOV. Accounting for these, we examine the strength of the marginal cost/marginal benefit calculation of the tournament model in affecting behavior. While our independent measures of selection and TOV may not be perfect, they are separate in construction from the pecuniary incentive measure in the main analysis. Moreover, the comparison of horses to dogs further isolates the three forces.

4. Racing Data

The horse race data are from 712 races conducted at Churchill Downs in 1994.[15] The 566 races used paid to four places, had all horses finish the race, had no multiple entries by the same owner, had no ties in the prize winning places, and had no other anomalies that caused the prize, purse, and the odds to diverge substantially.[16] The 566 races were comprised of 27 stakes, 186 allowance, 2 starter allowance, 289 claiming, and 62 maiden races.[17] Table 1 shows the summary statistics on the races and on the horses in the races.

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[15] 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.

[16] 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.

[17] 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.

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 horse racing data allow us to characterize the race at the beginning and over the course of the home stretch (last furlong). Table 1, Panel b shows the number of feet that each horse is behind the leader at the home-stretch mark. It also shows the speed of each horse over the home stretch. Note that average speed is lower and the variation is higher over the home stretch compared to the race overall. Table 1, Panel a shows our measure of the closeness of the contest. We calculate this measure at the stretch mark and at the finish line. Of course, the stretch mark is preferred but we also use closeness at the finish in order to compare horses to dogs. Closeness is the sum of distances from the leader for all animals in the race. The variance of 1st place probabilities across each race is an ex-ante measure of expected closeness.

The dog racing data is taken from <http://www.greyhound-data.com>, a website run by an international consortium of greyhound enthusiasts. It tracks individual dog performance over time at racetracks around the world. The data that we use are for the Jacksonville, FL racetrack for the year 2006. The Jacksonville racetrack management was kind enough to supply us with purse and prize data. At the Jacksonville track, the purse is a fixed percentage of the betting pool (slightly less than 4 percent).

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.

Table 2 shows the summary statistics for the dogs and for the races. This table is similar to the one for horses except that we do not have as much detail for dogs concerning performance during the race. We do not know elapsed time at each mark throughout the race nor do we know the distance between dogs. However, we do know the dogs' relative positions at each mark and we know the time to finish for each dog.

All but two of these races have eight dogs (two races had 7). Dogs are graded and raced within their grade. 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. There are 925 different dogs in the sample. Only 5 percent raced once; 50 percent raced 9 or more times; and 10 percent raced 16 or more times. The average number of days between races was 6.

5. Results

Tables 3, 4, and 5 show the regressions of speed for horses and for dogs. In these regressions we allow the data to speak in as many ways as we can in order to compare the three hypotheses of selection, TOV, and pecuniary incentives, and to contrast these effects between horses and dogs.

Table 3 shows three regressions, two for horses and one for dogs. The dependent variable in all three is speed over the entire race. We measure closeness for horses at both the home-stretch mark and at the finish line. For dogs we are only able to measure closeness at the finish line. All regressions have an extensive set of controls for race-level and individual animal factors. All horse regressions include fixed-effects for turf type and condition, distance, gender, and age groups. The dog regression includes age and fixed effects for grade, distance, and gender. These controls, not reported but available upon request, are significant at 1 percent level. We report the coefficient estimates for our measures of pecuniary incentives, TOV, and selection. We use the ability index and groups as the selection measure.

The results shown in Table 3 are strong evidence in favor of the effect of tournament prizes on performance. Several points are salient: controlling for selection and TOV, pecuniary incentives are positive and statistically significant in influencing the way horses are managed by jockeys during the race. On the other hand, incentives have zero effect on the revealed performance of dogs, while selection is predictive of performance and dogs do appear to respond to the thrill-of-victory.

The coefficients on both incentives and TOV are small, but this is because the standard deviation of speed is small. The best way to interpret the coefficients is in terms of standard deviation changes. For instance, the coefficient on incentives for horses averages 0.595×10^{-2}. The standard deviation of the log of the incentive measure is one, and the standard deviation of the log of speed is 0.024. Hence, a one standard deviation change in the log of marginal revenue translates into 25 percent of a standard deviation change in log speed. By similar calculation, a standard deviation change in the log of TOV (closeness) translates into 8 percent of a standard deviation change in log speed for horses.

The coefficient estimates and associated *t*-statistics give us some indication of the relative magnitudes of the incentive, TOV, and selection effects. However, a more revealing description may be found in a variance-decomposition analysis. At the bottom of Table 3, we show the R^2 attributable to incentives, TOV, and selection. The R^2 from these three factors is the share of the variance in speed explained by these effects together using both their independent variation and their covariation. For instance, of the overall R^2 in the first horse regression, which is 0.752, 0.175 is attributable to the combined selection, TOV, and incentives effects.

We decomposed this explained variation into the three independent sources of variation and, for the sake of comparison, normalized their magnitudes so that they sum to one. These percentages are shown in Table 3. For the first horse regression, incentives account for 25 percent, TOV accounts for 8 percent, and selection accounts for 67 percent of the total R^2 explained by these factors. We see about the same magnitudes of effects in the second horse regression. In the dog regression incentives have no part in explaining variation in speed. In relative importance, TOV explains 10 percent and selection 90 percent.

As noted above, all regressions have control variables that account for variations in speed that are not the result of the thrill-of-victory or monetary rewards. These controls vary based on the data available. We add as many controls as possible in order to rule out spurious correlation between speed and our main variable of interest, marginal revenue. All horse regressions include dummy variables for turf type and condition, distance, gender, and age groups.[18] The dog regression includes age and dummy variables for grade, distance, and gender. For both horses and dogs, males run faster than females, and speed is slower for longer races.

As we discussed in section 3.1, our odds-network measure of ability may not be unique. There can be non-intersecting groups of animals, and even if all animals do intersect, the overlaps may be too minimal to generate a consistent measure of ability subject to the noise of inter-race variation for each animal. To account for this we do a two-step estimation procedure. In the first step, we regress speed on the ability index and capture the residual. In the second step, we cluster the animals based on residuals and assign a group label. For horses there are two very distinct groups. We find that 99 percent of the races are comprised of only one or the other cluster assignment. Group assignments for dogs are less distinct: 75 percent of the races have three-quarters of the dogs in the race drawn from one group, but ten percent of the races have dogs evenly split between the two groups. Nonetheless, the group assignment is statistically significant in predicting speed and therefore is an appropriate control for the null hypothesis.

The results in Table 3 show the coefficient estimates for the ability index, the ability-group assignment, and the interaction of these two. The group assignment is an intercept shifter; the interaction allows the speed-ability relation to vary between the groups. The three ability measures taken together are statistically significant, generally of the anticipated sign, and capture a large amount of

[18] We tried individual horse age, but the age groups used by the track to designate races is more informative.

variation in speed. This latter point is our main concern. Our goal in measuring ability is to absorb as much of the variation in speed as possible that comes from the simple assignment of participants to contests.

The problem in the dog regression is that we do not have a closeness measure that captures the TOV effect in the midst of the contest. Nonetheless, concerns about this problem are largely mitigated by reference to the consistency of the horse regressions in this regard. Note that the closeness of the race for horses has nearly identical elasticities whether measured at the stretch mark or at the finish line. While closeness at the finish line does seem to capture the TOV effect and adequately compare horses to dogs, we go on to exploit the lead-change dimension of the dog data as a further test.

Table 4 attacks the deficiency in the dog data. For dogs we do not know relative speeds around the track. However, we do know position changes, and we can compare the effect of position changes for dogs to the same statistic for horses. This gives us an intra-race measure of closeness that is similar for both venues.

A statistic for lead changes at the distance marks around the course is calculated as shown in equation (1). All dog races report relative positions at three way marks. Hence we calculate two lead-change statistics. The lead-change statistic between the stretch mark and the middle mark is labeled *Lead Change* (*n*-1). The lead-change statistic between the first and middle mark is labeled *Lead Change* (*n*-2). Way marks are reported variously for horse races depending on the length. There maybe two, three, or four. We use the same terminology in reporting the lead-change statistic.[19]

Empirically we do find that lead changes are positively related to the measures of TOV used in Table 3 for horses. The correlations are not particularly large (circa 0.2) but highly significant especially in the comparison of stretch-mark closeness and prior lead changes.

Table 4 exploits the theoretical relationship between lead changes and closeness to better compare horses and dogs. The models are identical to those shown in Table 3 except that the lead changes at various points around the race course are substituted for our other TOV measures. Regressions (1) and (2) are for horses; regression (3) is for dogs.

Table 4 shows several important findings: incentives are significant in predicting performance for horses and not for dogs, and lead changes have the predicted effect on speed. More lead changes are associated with faster races. It is true that the lead-change measures are not perfectly mirrored between horses and dogs. Lead changes early in the race have a more statistically significant effect for horses, while later in the race for dogs. Nonetheless, the evidence shows that

[19] We exclude the shortest races which only report two way marks from this exercise because there are too few observations.

using similar intra-race comparisons of the closeness of competition for horses and dogs, we still see that there is a thrill-of-victory effect for both and yet no marginal revenue effect for dogs, while there is one for horses.

Finally, Table 5 considers an alternative measure of the incentive effect. In these regressions we recalculate marginal revenue based on the changes in the probability of winning as revealed at the stretch mark as described in section 3.5. Speed over the home stretch is regressed on this revised estimate of marginal revenue. Because we are looking at speed over the stretch run, we also include speed up to the stretch mark in these regressions.[20] Because of data limitations, we can only do this for horses.

The results show that intra-race pecuniary incentive effects are positive and statistically significant in explaining performance over the home stretch. Even at this point in the race, horses are managed by their jockeys based on monetary incentives. The TOV effect is largely diminished when the incentive effect is included in the regression, though the TOV effect is statistically significant when the incentive effect is omitted. This is probably because marginal revenue calculated at the stretch mark is highly dependent on closeness at this point. Even so, in the horse-race of relative effects, pecuniary incentives beat out the pure thrill of victory.

6. Conclusions

This paper investigates the performance effects of incentive-based pay schemes on horse and dog race participants. There is much evidence that incentive pay increases performance. However, there are three alternative hypotheses that deliver this result. One is a pure selection effect: higher pay brings forth better talent that reveals higher productivity. Secondly, this may even occur at the individual level. The competitive setting of incentive contracts may induce extra effort through the better matching of talent and the creation of heated contests—we call this second hypothesis the Thrill-of-Victory (TOV) effect.

Finally, there is the pecuniary incentive effect: the Lazear-Rosen tournament model says that monetary inducements elicit marginal performance effects. In this model, participants weigh the marginal payoff against the marginal cost of effort and vary their level of exertion from one contest to the next.

We compare these theories to see which best organizes the data. The policy issue is important because if performance is purely a selection or TOV phenomenon, incentive pay for existing workers is inefficient and the organization of the labor force is more important than the pay structure. If the

[20] Its effect is negative and highly significant. When horses go out fast they tire more toward the end.

tournament model drives performance, then pay structure is critical. A complete test of these alternatives has not yet been presented in the literature.

We conduct our test of the hypotheses by looking at horse and dog racing. We structure the test to account for selection phenomena using a unique ability index. We account for the TOV effect by looking at the closeness of the contest as it unfolds. Finally, we include the incentive effect based on the structure of the tournament model. We compare horses to dogs as it is reasonable to imagine that horses can be managed by jockeys in a way that balances marginal monetary costs and benefits, while dogs whose handlers are not with them during the race cannot. Moreover, the marginal cost of effort for horses—the threat of breakdown—is substantial, raising the stakes for optimal effort adjustment, while the marginal cost for dogs is much lower.

Our results robustly support the conclusion that the tournament model has predictive power over and above selection and TOV phenomena. We find that performance in horse races is consistent with the prediction that jockeys are adjusting effort to equate marginal monetary benefits and costs. Of course, selection—measured by ability—is highly predictive of performance. And both horses and dogs do exhibit behavior consistent with a thirst for the thrill of victory. However, dogs do not appear to respond to monetary rewards in addition to the selection and TOV effects.

Obviously, the three effects are intertwined. Tournament theory predicts a selection effect and a response similar to the TOV effect. Our research design of comparing horses to dogs is advantageous in addressing this point. The tournament effect appears only in horseracing where intra-race marginal control is possible and where the marginal cost of mistakes is high. Moreover, even when the tournament response is not observed, we still observe a TOV effect. Thus, while the three effects may not be perfectly parsed, they are observed separately.

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Table 1. Summary Statistics on Horse Races

Variable	*Mean*	*Std Dev.*	*Minimum*	*25th*	*Median*	*75th*	*Maximum*
Panel a: Statistics on Races							
Distance	4881.90	748.81	2970	3960	4620	5610	9240
Field-size	10	2	4	9	11	12	12
Purse ($1000s)	28.75	26.12	7.32	14.82	24.1	33.5	233.95
Closeness							
Stretch Mark	542	257	6	380	582	792	1512
Finish Line	562	251	6	415.5	596	980	1472
Betting Pool ($1000s)	153.41	110.14	45.36	109.36	132.65	163.2	1029.65
Panel b: Statistics on Horses							
Speed:							
Home Stretch	49.70	3.86	22.7	48.35	50.08	51.78	61.48
Over Whole Race	53.47	1.25	48.89	54.35	53.57	52.61	56.90
Behind the Leader at the:							
Stretch Mark	56.97	47.89	0.00	18.00	48.00	86.00	274.00
Finish Line	59.71	48.95	0.00	20.50	52.00	87.75	332.00
Fillies	0.44	0.50	0	n/a	n/a	n/a	1
Ability	0.00	0.90	-2.90	-0.58	0.07	0.64	3.20
Odds	20.45	24.91	0.30	4.90	11.00	25.70	260.50

Notes: 566 races, 5504 observations on horses. Purse, prizes, and betting pool in 1994 dollars. Races restricted by age; 3 year olds and up made up 60 percent of the races. Speed in feet per second. Odds are the pari-mutuel betting odds of winning 1st place. Ability broken into two groups with 25 percent of the horses in the faster group.

Table 2. Summary Statistics on Dog Races

Variable	*Mean*	*Std Dev.*	*Minimum*	*25th*	*Median*	*75th*	*Maximum*
Panel a: Statistics on Races							
Purse	499.93	287.17	0.04	253.82	491.49	755.78	981.49
Closeness at the Finish	53.40	20.00	12.3	38.82	51.09	65.42	144.3
Panel b: Statistics on Dogs							
Speed Over Whole Race	51.96	0.79	48.62	51.44	52.00	52.51	54.74
Feet Behind the Leader	6.68	5.10	0.00	2.44	6.19	10.06	29.89
Age	31.15	8.54	16	25	29	38	64
Female	0.49	0.50	0	n/a	n/a	n/a	1
Ability	0.00	0.47	-1.72	-0.29	-0.01	0.25	2.4
Odds	8.45	6.49	0.20	2.50	6.90	10.90	99.90

Notes: 1037 races, 8318 observations on dogs. Purse in 2006 dollars. Closeness is measured as the sum of the distances from the winner. Speed in feet per second. Feet Behind the Leader is at the finish. Age in months. Ability broken into two groups; the faster group comprises 87 percent of the dogs. Odds are the pari-mutuel betting odds of winning 1st place.

Table 3. Speed of Horses & Dogs Racing

	(1)	(2)	(3)
	Dependent Variable: *Speed over the Race*		
Independent Variables:	*Horses*	*Horses*	*Dogs*
Pecuniary Incentives	0.579	0.610	-0.006
	(0.056)	(0.057)	(0.018)
Thrill-of-Victory (TOV)			
Closeness at Stretch Mark	0.335		
	(0.069)		
Closeness at Finish Line		0.307	0.285
		(0.078)	(0.048)
Selection			
Ability	0.246	0.222	0.987
	(0.064)	(0.065)	(0.099)
Ability Group	1.494	1.476	1.352
	(0.097)	(0.099)	(0.091)
Ability × Group	0.075	0.077	0.226
	(0.047)	(0.047)	(0.105)
R^2	0.752	0.751	0.509
R^2 from Incentives, TOV, & Selection	0.175	0.174	0.128
Percent of Independent Variation in:			
Incentives	24.9%	31.0%	0.0%
TOV	8.3%	6.5%	10.5%
Selection	66.8%	62.5%	89.5%

Notes: All coefficients are 10^2. Robust standard errors clustered on races in parentheses below coefficients. Speed, incentives, and closeness in logs. Observations: 5504 for horses; 8318 for dogs. All horse regressions include fixed effects for turf type and condition, distance, gender, and age groups. Dog regression includes age and fixed effects for grade, distance, and gender. All controls are significant at 1 percent level. Closeness is the negative of the sum of distances from the leader. The sign is switched to aid interpretation: the prediction is that the closer the race, the faster the race. R^2 from incentives, TOV, & Selection is the share of the variance in speed explained by these three effects together using both their independent variation and their covariation. We decomposed this explained variation into the three independent sources of variation and, for the sake of comparison, normalized their magnitudes so that they sum to one.

Table 4. Speed Based on Position Changes

Independent Variables	(1) *Horses*	(2) *Horses*	(3) *Dogs*
Incentives	0.585	0.791	-0.018
	(0.073)	(0.080)	(0.018)
TOV			
Lead Changes *n*-1	0.504	0.572	0.169
	(0.054)	(0.070)	(0.060)
Lead Changes *n*-2	0.006	-0.260	1.050
	(0.110)	(0.176)	(0.026)
Lead Changes *n*-3	-0.034		
	(0.151)		
Selection			
Ability	0.190	0.034	0.700
	(0.079)	(0.115)	(0.097)
Ability Group	1.639	1.575	1.436
	(0.122)	(0.178)	(0.085)
Ability × Group	-0.101	0.127	0.242
	(0.063)	(0.092)	(0.102)
R^2	0.739	0.590	0.616
Observations	2481	3014	8311

Notes: All coefficients are 10^2. Robust standard errors clustered on races in parentheses below coefficients. Speed and incentives in logs. Speed is measured over the whole race. Lead changes are the square root of the average squared position changes over the second last leg (*n*-1), the one before (*n*-2), etc. All horse regressions include fixed effects for turf type and condition, distance, gender, and age groups. Dog regression includes age and fixed effects for grade, distance, and gender. All controls are significant at 1 percent level.

Table 5. Speed for Horses Based on Marginal Revenue Calculated at the Stretch Mark

	Dependent Variable: *Speed over the Home Stretch*			
Independent Variables	(1)	(2)	(3)	(4)
Incentives	3.610	3.455		
	(0.314)	(0.311)		
TOV				
Closeness at Stretch Mark	-0.346		0.533	
	(0.247)		(0.245)	
Closeness at Finish Line		0.125		0.918
		(0.281)		(0.270)
Selection				
Ability	0.484	0.508	1.005	0.999
	(0.202)	(0.202)	(0.205)	(0.204)
Ability Group	3.731	3.688	3.692	3.577
	(0.461)	(0.460)	(0.452)	(0.447)
Ability × Group	0.162	0.161	0.021	0.026
	(0.226)	(0.226)	(0.229)	(0.226)
R^2	0.740	0.739	0.716	0.717

Notes: All coefficients are 10^2. Robust standard errors clustered on races in parentheses. Speed, incentives, and closeness in logs. Closeness is the negative of the sum of distances from the leader at the mark for all horses in the race. Observations: 5484. All regressions include fixed effects for turf type and condition, distance, gender, age groups, and speed up to the stretch mark. All controls are significant at 1 percent level.