The Incentive Effects of Tournament Compensation Systems

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Tournament models have developed into an important component of the theoretical literature on organizational reward systems. However, with one exception there have been no empirical tests of the incentive effects of tournament models in a field setting. Drawing on a panel data set from auto racing, we show that the tournament spread (prize differential) does have incentive effects on both individual performance and driver safety, that these effects peak at higher spreads, and that controlling for the dollar value of the tournament spread, the prize distribution has little influence on individual performance.

The study of compensation and reward systems has broadened in recent years as employment and other organizational outcomes are analyzed at the level of the firm rather than the individual. Much of this work follows from the agency theory and contracting literatures that focus on how characteristics of an organization, such as its compensation system, can improve employee performance in a world of imperfect information and non-zero monitoring costs. Efficiency wage theory (Akerlof and Yellen, 1986), the temporal distribution of pay (Lazear, 1981; Hutchens, 1989), pension policies (Lazear, 1979), and the structure of managerial compensation systems (Jensen and Murphy, 1990) have all been offered as methods by which organizations attempt to align the interests of employees with the larger interests of the organization, usually defined as those of the shareholders.

Tournament models have been an important element of this larger literature for the last decade (Lazear and Rosen, 1981), examining the efficiency and incentive properties of reward systems based on rank-ordered rather than absolute individual performance. Overwhelmingly theoretical, the tournament literature has focused on organizational and individual employee characteristics (information on effort, monitoring costs, attitudes toward risk, etc.) that would affect the efficiency and incentive characteristics of such a reward system. Recent organizational research (0’ Reilly, Main, and Crystal, 1988) has compared corporate reward structures with those predicted by tournament theory, but, except for Ehrenberg and Bognanno (1990a, 1990 b), there have been no empirical tests of the incentive effects of tournament models in a field setting.

Following Ehrenberg and Bognanno (1990a, 1990 b), we draw on an athletic context, professional auto racing, because it provides an objective measure of individual performance. However, unlike the golf tournaments that were Ehrenberg and Bognanno’s focus, auto racing is characterized by across-tournament variation in both the size and distribution of the prizes. Perhaps most importantly, while still an athletic contest, auto racing has considerably more organizational content than individually focused events such as golf. Racing requires interaction with the other participants and requires cooperative as well as competitive behaviors. Similarly, even though managers may be competing with each other for a promotion, each must cooperate with the others to improve his or her own performance. Although golfers compete against one another, they play against the course. There is

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really no cooperation necessary to score well, nor will the lack of cooperation hinder a player, Our sample, however, is more like one organization that repeatedly exposes its employees (drivers) to different reward structures.

Tournament Effects on Performance

Tournament theory argues that such systems are desirable when monitoring is either unreliable or costly (Lazear and Rosen, 1981). Instead of using monitoring and supervision to enforce the implicit employment contract, the firm should rely on a self-enforcing reward structure. The appeal of successively higher salaries motivates employees to devote greater attention to organizational interests at all job levels and discourages shirking. However, contracting theories focus on the alignment of individual interests with those of the organization, because organizational shirking is more than effort aversion. An employee can expend a great deal of effort, but if it is not in the interests of the organization, shirking exists, In agency theory terms, the principal wants not only the agent's effort but the right kinds of effort (McMillan, 1992: 98-99).

Tournament structures have several important features for the purposes of this study. First, prizes are set before the tournament begins and are awarded based on the rank order at the finish, not the absolute performance of the participants. This corresponds to a fixed salary structure that does not vary with individual employee productivity in a particular job, as would a piece-rate or bonus system. Second, the absolute spread between the payoffs for each rank should affect the efforts of the participants (Lazear, 1991), since, as the salary structure becomes more compressed, there is less incentive to expend the effort required to achieve the next rank. Finally, any incentive system is likely to be an incomplete contract that may not only fail to encourage the full range of desirable behaviors but may elicit undesirable behavior as well. Milgrom and Roberts (1988), for example, showed that incentive systems can also encourage counterproductive organizational influence activities. More generally, such reward systems could result in a narrowing focus on individual goals to the exclusion of value-enhancing cooperation with coworkers. In an auto race this would take the form of unnecessary risks that jeopardize the position not only of the driver in question but of other drivers as well. In this study we consider the incentive effects of absolute spreads between ranks, explore the potential limits of any incentive effects and determine whether such effects are constant over our data, and test whether the effort-inducing effects of tournaments have a downside in terms of carelessness or negative consequences for other participants. Finally, we extend the analysis to include separate estimates of the effects of tournament structure; namely, the relative distribution of prize money to the top finishers.

METHOD

Data

To provide some breadth to our findings and to serve in part as a replication of our initial results, we used two classes of auto races in our analysis: National Association for Stock Car Auto Racing (NASCAR) and International Motor Sports Association (IMSA).

NASCAR. The NASCAR data are from the 1990 NASCAR circuit and include all but one of the 29 races held in that year (NASCAR, 1991). For estimation purposes we limited our sample to drivers that competed in at least five races, giving us a sample with 44 different drivers. The first race of the season, Daytona, was excluded because the magnitude of the purse was so much greater than any of the other 28 races.

The performance measure *(ADJUSTED FINISH)* was constructed to reflect both the order of finish and the relative speed of the race. The races were normalized with average speed of the winning car divided by the fastest winning speed in the 28 races: The fastest race was scored as 1.00, with slower races having proportionately higher values. This speed rating was then multiplied by each driver's finishing position. The result is an overall performance score that gives a 1.00 to the winner of the fastest race and higher scores to other drivers. As a result, the second lowest score could either be the second-place finisher in the fastest race or the winner of a slightly slower race, and so on. This variable was constructed to provide an individually based measure of performance, since the average speed was only available for the winning car in each race. At the same time, relying only on finishing position would not reflect any absolute changes in performance across races. While ADJUSTED FINISH is an imperfect proxy for absolute driver performance, we believe the compromise is justified, to capitalize on other virtues of the NASCAR data. However, our second data set, while considerably smaller, does provide a more desirable measure of driver performance and therefore serves as a validity check on our NASCAR results.

We defined $SPREAD(a,z)_k$ as the difference in the average prize money available per driver in positions *a* through *z* in the *kth* race and the average prize money per driver finishing below position *z* in the *kth* race. For example, if $\text{SPREAD}(1\text{–}20)_2$ is \$2000, the winnings of drivers finishing 1st through 20th in race 2 average \$2000 more than drivers with poorer finishes. Table 1 reports the mean, standard deviation, and range for these tournament characteristics. The prize data are not entirely straightforward because the reported winnings for each finishing position includes not only the prize provided by the promoter but additional contingency payments that a driver using "XYZ" parts might get for a particular finish that another driver using "ABC" parts would not receive. The largest of these (\$1OOO-\$1O,OOO) are published with the race results and have been removed from the prize data. However, not all driver-specific contingencies are identified, though they are reflected in the reported prize distribution. The reported prize distribution within each race is thus not a smoothly declining percentage of the total purse.

We have handled this problem in two ways. First, when choosing a variable to reflect the reward structure, we opted

Table 1

Relevant Descriptive Statistics for NASCAR and IMSA Races

Variable	Definition	Mean (S. D.)	Min.	Max.
NASCAR data				
ADJUSTED FINISH	The finishing position of the *ith* driver in the *kth* race times the ratio of the winning speed in the *kth* race over the *fastest* winning speed in the sample.	27.95 (18.14)	.994	105.2
SPREAD (l-1 O)	The *difference* in the average prize money available per driver in positions 1 through 10 and the average prize money per driver finishing below position 10 (in thousands).	17.11 (4.3)	12.39	32.54
SPREAD (1-20)	The *difference* in the average prize money available per driver in positions 1 through 10 and the average prize money per driver finishing below position 20 (in thousands).	11.40 (2.84)	8.34	22.04
SPREAD (1 1-20)	The *difference* in the average prize money available per driver in positions 11 through 20 and the average prize money per driver finishing below position 20 (in thousands).	4.34 (1.47)	2.16	8.79
CAUTION FLAGS	The total number of caution flags in the *kth* race.	37.89 (17.03)	10.0	75.0
PERCENTAGE OF PURSE (1-20)	The percentage of the total purse awarded to drivers finishing in positions 1 through 20.	.76 (.03)	.69	.82
RACE LENGTH	Length of race (in miles).	405.82 (117.34)	187.00	600.00
LAP LENGTH	Length of track (in miles)	1.47 (.74)	.50	2.66
IMSA data				
MILES PER HOUR	The average miles per hour for each car in the *kth* race.	64.92 (27.14)	0.0	112.90
SPREAD (l-2)	The *difference* in the average prize money available per driver in positions 1 and 2 and the average prize money per driver finishing below position 2 (in thousands).	19.16 (9.91)	.962	43.66
SPREAD (1 -5)	The *difference* in the average prize money available per driver in positions 1 through 5 and the average prize money per driver finishing below position 5 (in thousands).	11.82 (5.13)	2.84	23.73
PERCENTAGE OF PURSE (l-5)	The percentage of the total purse awarded to drivers finishing in positions 1 through 5.	.76 (.11)	.50	.92

for more aggregate measures such as the differential for the top 10 [SPREAD(l–1O)$_k$] or 20 [SPREAD(1–20)$_k$] positions, rather than attempting to estimate effects for distributional changes in a specific finishing position. We do not extend the spread beyond the top half of the field because there is little across-race variation in the distribution to the slower finishers. Second, we surveyed 12 race promoters and collected the actual prize distributions without the contingencies. The correlation between their actual distribution and our adjusted figures was .94.

Finally, we included three control variables. The first, starting position *(START POSITION)* in the race, allows for a more accurate estimate of the true incentives posed by the varying tournament characteristics. Ideally, one could vary the tournament characteristics and give every driver an equal starting position. The incentives of a particular starting position are not entirely straightforward, however. Better starting positions might provide a greater inducement, since the driver has a higher probability of finishing in the top position. Alternatively, drivers' efforts may be muted by the fact that they have already achieved a good standing and now only have to prevent a significant decline in performance. Given the definition of ADJUSTED FINISH, controlling for starting position is equivalent to estimating the incentive effects on the change in driver position. The second, *LAP LENGTH,* is included because longer tracks will have higher average speeds. If these tracks also have races with higher spreads, our estimates of incentive effects will be biased.

The third control variable was the number of caution laps *(CAUTION FLAGS)* in a race. A caution lap is run at reduced speed, with no passing allowed, as the track is cleared of debris. At a minimum, the number of caution laps should have a direct bearing on the speed of a race, so the inclusion of this variable should reduce the error variance and make our regression estimates more stable. In addition, it serves as a proxy for the costs associated with unnecessary risks that might be induced by the tournament structure and as a measure of the indirect costs of the tournament incentives.

IMSA. The IMSA data are drawn from the IMSA Gran Touring Prototype (GTP) and Camel Light categories (IMSA, 1990, 1991). Cars in these races are single-purpose factory prototypes that are fabricated from exotic materials. The races are held on road courses and include such events as the 24 hours of Daytona, as well as a number of much shorter races. Because of the race length, driving teams are typically involved, although there is always a lead driver on the team. Half of the IMSA season involves races in which drivers travel as far as they can in a fixed time period and therefore provides an absolute performance measure *(MiLES PER HOUR)* for all driving teams. Because these races are smaller in size and fewer are held each year, we have collected data for both 1989 and 1990, with each driving team required to appear at least five times over the two-year period in order to be included in the sample. The variables describing the tournament characteristics are of the same form described in the NASCAR data. However, because there are fewer entrants in each race, we only aggregated as high as the top-five finishers, instead of the first 10 or 20 finishers.

Control variables include starting position (START POSITION) but not the number of caution laps. The number of caution laps is not available because IMSA races are not run over oval courses and therefore do not require that all drivers reduce their speed over the entire course after an accident. Instead, there is a caution over only a portion of the course, an event that is not recorded in the official race statistics. Finally, lap length is not included as a control for the IMSA races because race speed is more a function of the curves on a road course than the length of the laps. In addition, we have added two other variables to the model. To develop a reasonable sample size, we used two classes of IMSA races (GTP and Camel Lights) and collected data over the 1989 and 1990 seasons. These races are typically run simultaneously on the same track, although each driver is only competing within his or her own class. There were a total of 24 (13 GTP and 11 Light) teams that competed in at least 5 of the 11 combined races over the two years. *TYPE* and *YEAR* are dummy variables that reflect these two characteristics. Descriptive statistics for all variables in the IMSA data are also reported in Table 1.

Estimation Model

Based on the discussion to this point, our basic NASCAR model would be specified such that:

$$ADJUSTED\ FINISH_{ik} = a_1 SPREAD(a,z]_k + a_2 START\ POSITION_{ik} + a_3 LAP\ LENGTH_k + a_4 CAUTION\ FLAGS_k + \sum_{i=1}^{n} DR_i + u_i \quad \textbf{(1)}$$

where ADJUSTED FINISH$_{ik}$ is the adjusted finishing position for the *ith* driver in the *kth* race, and SPREAD is defined as above. CAUTION FLAGS$_k$ is the number of caution laps in the *kth* race. STARTING POSITION$_{ik}$ is the starting position for the *ith* driver in the *kth* race, and LAP LENGTH$_k$ is the length of each lap.

Both data sets combine cross-sectional and time-series data. While reliance on cross-sectional data is common in many lines of organizational research, a significant disadvantage of this practice is the inability to rule out the effects of unmeasured individual differences that may in fact explain the observed relationship. Panel data, however, allow one to control for individual differences that are fixed over time (across races). DR_i is a vector of dummy variables for the N drivers in the sample. By including DR_i in a fixed-effects model, we were able to exclude the heterogeneity bias that might occur if individual drivers or cars were not equally fast at the start of the race. Since this is clearly the case in auto racing, and the bias associated with such heterogeneity cannot be evaluated a priori, the fixed-effects model is appropriate (Hsiao, 1986).

Given that low values of the dependent variable in the NASCAR data indicate higher individual performance, we would predict that higher values of SPREAD will increase performance $(a_i < 0)$. Nevertheless, we recognize that, at some point, higher purses may provide sufficient reward for one's current position that additional effort is unappealing, and we therefore tested the notion that an optimum tournament spread exists and that the incentive effects of widening the payoff spread will eventually erode.

The performance model for the IMSA data is similar, except that YEAR and race TYPE are included as independent variables, and CAUTION FLAGS is excluded for reasons described above. The dependent variable (MILES PER HOUR) is now a continuous measure of performance, indicating the miles traveled per hour of race time. Because the races have considerably fewer entrants than a NASCAR race, SPREAD is cumulated over no more than the top five finishers. Otherwise, our expectations for the tournament variables would be similar to a NASCAR race.

RESULTS

NASCAR

Using SPREAD to characterize the tournament incentive system, the NASCAR data support the predictions of tournament theory. The results show that increasing the absolute prize differential going to the top finishers increased driver performance. Columns 1 and 2 in Table 2 are two variations of equation 1. The column 1 model allows for different incentive effects for the SPREAD over the top 10 finishers and the next 10 finishers. The total incentive effect for drivers who might finish below 20th is the sum of the two coefficients. While the relative magnitude of the coefficients is consistent with a greater incentive effect when the payoffs go to the top 10 finishers, compared with those finishing 11–20, a joint F-test of the hypothesis that the coefficients are equal cannot be rejected. We therefore combine the two variables into SPREAD(I–20) and take column 2 as the most appropriate representation of equation 1. The control variables STARTING POSITION and CAUTION FLAGS are also statistically significant at conventional levels, though LAP LENGTH is not.

Table 2

Regression Results for NASCAR Data •

Independent variables	**Model (1)**	**(2)**	**(3)**
CAUTION FLAGS	.1676***	.1702***	.0688
	(.0419)	(.04I6)	(.0438)
START POSITION	.2254***	.2247***	.2164***
	(.07O2)	(.0702)	(.O687)
LAP LENGTH	.7730	.7742	.3704
	(.9811)	(.9807)	(.9580)
SPREAD (1-10)	–.6270***		
	(.1634)		
SPREAD (11-20)	–.5060		
	(.4588)		
SPREAD (1-20)		–1.1187***	
		(.1965)	
Splines			
LOW SPREAD (< Mean)			– 4.8444***
			(.6257)
HIGH SPREAD (≥ Mean)			– .0781
			(.2588)
R^2	.2449***	.2448***	.2761***
Adjusted R^2	.2052	.2059	.2380
Sample size	940	940	940

*$p < .10$; **$p < .05$; ***$p < .01$; two-tailed tests.

• Standard errors are in parentheses. All results are for a fixed-effects model and therefore include 43 dummy variables, one for each driver. The dependent variable is ADJUSTED FINISH.

Finally, all results in Table 2 are for a fixed-effects model and therefore include 43 dummy variables, one for each driver, A joint F-test of the dummy variables in column 2 is statistically significant in excess of the .001 level ($F_{42,893}$ = 2.52), indicating that simply pooling the data would be inappropriate. This formulation assumes that these individual specific effects are fixed over time, though an alternative approach would be to consider them as random variables. The latter approach, a random-effects model, is a plausible specification of a panel data model, though more so in data sets with few observations over time (Hsiao, 1986: 41). Using the Hausman test, we evaluated the results in Table 2 against the alternative random-effects specification and comfortably rejected the random-effects model in each case. Moreover, a comparison of the coefficients and t-values for the tournament coefficients revealed no substantive differences between the two specifications.

The organizational interest in such results is less in their statistical significance and more in their policy significance. Namely, what influence does varying the SPREAD have on driver performance? One way to evaluate the magnitude of this influence on performance is to evaluate the effect of SPREAD at the mean. The mean of SPREAD multiplied by its regression coefficient is – 12.75, or 46 percent of the mean of the dependent variable (ADJUSTED FINISH). Alternatively, comparing the change in driver performance (ADJUSTED FINISH) in races with the lowest SPREAD ($7,870) against those with the highest ($21,370) indicates that the difference in the dependent variables is 15.1, or more than 50 percent of the mean of ADJUSTED FINISH. In short, race promoters do substantially vary the SPREAD for finishing in the top half of the field, and the variation in incentives is associated with meaningful changes in driver performance.

A discussion of the policy implications raises the question of whether there is a limit to the returns from increasing the magnitude of the SPREAD. There are presumably individual limits to performance once effort is maximized, and individuals who believe they may have no chance to finish in the upper echelons may simply give up. In order to test the hypothesis that the incentive effects are not monotonic, we respecified equation 1 to allow for a discontinuity in the incentive effects. Theory provides little guidance as to the exact point at which incentive effects might diminish, much less a prediction for the specific context of auto racing. We therefore simply attempted to identify the presence of any discontinuity without overemphasizing the particular form it might take.

Our approach was to test whether the incentive effects changed over the level of SPREAD. The tournament literature suggests that if such a change occurred it would take the form of diminishing incentives as SPREAD increases. This would be reflected in the coefficient on SPREAD in equation 1 becoming less negative at higher values of SPREAD. To test this hypothesis we transformed SPREAD(I–20) into a spline function,[1] Splines were constructed by dividing SPREAD into HIGH SPREAD and LOW SPREAD. As a first approximation we chose the mean as the break point. LOW SPREAD took the value of SPREAD when SPREAD was less than the mean, otherwise LOW SPREAD would equal the mean. HIGH SPREAD would equal zero if SPREAD was less than the mean, and equal SPREAD minus the mean if SPREAD was greater than or equal to the mean. The null hypothesis is that there is no difference

1 For a complete discussion of spline functions, see Greene (1990). We adopted the particular specification of Clark (1984), since it returns the actual slopes over the range in question, rather than the difference in slopes. An alternative and perhaps more straightforward approach would have been to Include the square of SPREAD in the model. Unfortunately, the two terms were so highly correlated (*r* = .987) that reliable estimates could not be calculated.

between the coefficients for HIGH SPREAD and LOW SPREAD.

Column 3 in Table 2 reports the results of the mean-based spline function and supports the notion of an incentive discontinuity ($F_{1,892}$ = 38.67). The coefficient on SPREAD(l-20) was –1.1187, but this was in effect a weighted average of a much higher incentive effect (–4.8444) as the SPREAD is increased from values below the mean (LOW SPREAD) and a negligible effect (– .0781) for values of SPREAD above the mean (HIGH SPREAD). This is a remarkable erosion of incentive effects and no doubt reflects as much the limits of man and machine as any decision on the part of drivers to limit their efforts. The ceiling is clearly illustrated by the data, where all but three races have SPREAD(l–20) values within the range of $8,000 to $13,000. While these three races have considerably higher spreads, their ADJUSTED FINISH values are equivalent to the upper end of the larger group and therefore dramatically attenuate the overall relationship. In short, there appears to be a limit to the incentive effects of the tournament system in auto racing, and most promoters appear to have recognized it.

Impact on Race Safety

Any discussion of the incentive effects of reward structures should also include the possibility that (1) participants can focus so narrowly on individual achievements that they jeopardize the joint output of the organization, or (2) in the pursuit of greater performance, participants will take risks that the organization might not sanction. Perhaps the latter is best illustrated by the lucrative compensation structures on Wall Street in the 1980s and the excessive behavior of some employees in those firms. In auto racing it might be reflected in taking chances and unnecessary risks that jeopardize not only the individual driver but others in the field as well. To evaluate this type of tournament effect, we examined the effect of tournament characteristics on the number of caution laps in each race (CAUTION FLAGS). The assumption was that if drivers are engaging in riskier behavior, it should be reflected in more accidents, with the intensity reflected in the number of laps each race was run under the caution flag. With CAUTION FLAGS as the dependent variable and RACE LENGTH as a control variable, we developed a simple model using the tournament characteristics, including the splines, reported in Table 2. We used RACE LENGTH to pick up both the effects of races with more laps as well as races with longer laps. Whether these two dimensions were included individually or together, the pattern of results was similar to that reported in Table 3. Nevertheless, since CAUTION FLAGS is a race-level variable and the sample size is only 28, the reader should interpret these results very cautiously.

The results in Table 3 suggest that drivers did take more risks as the SPREAD increased, but only when the payoffs were very high. For example, the results in column 1 indicate virtually no relationship between SPREAD(l–20) and the number of caution laps in a race, However, columns 2 and 3 report the results of the model when SPREAD is

Table 3

Effects of Tournament Characteristics on Race Hazards in NASCAR Races •

Independent variables	Model (1)	(2)	(3)
Constant	55.387***	113.190***	98.710
	(13.950)	(35.340)	(21.610)
RACE LENGTH	– .0424	– .006	–.0127
	(.0340)	(.0387)	(.0336)
SPREAD (1-20)	– .0249		
	(1.518)		
Splines			
LOW SPREAD (< Mean)		– 7.340	
		(7.390)	
HIGH SPREAD (≥ Mean)		1.180	
		(1.610)	
LOWER SPREAD (> Mean + 1 S. D.)			– 5.450**
			(2.59O)
VERY HIGH SPREAD (≥ Mean + 1 S. D.)			4.480*
			(2.280)
R^2	.0890	.1940	.2750**
Adjusted R^2	.0163	.0934	.1840
Sample size	28	28	28

*$p<$ .10; **$p<$ .05; ***p < .01 ; two-tailed tests.

• Standard errors are in parentheses. The dependent variable is CAUTION FLAGS.

redefined as a spline function that breaks at the mean (column 2) and one standard deviation above the mean (column 3), respectively. The pattern is the same in both cases, though the difference is sharpest in column 3 when we compare races with a VERY HIGH SPREAD (one standard deviation above the mean or greater) with LOWER SPREAD (less than one standard deviation above the mean). When the spread is very high, the number of caution laps goes up substantially with the increase in spread, Since the sample mean of CAUTION FLAGS is 39.7, a $1000 increase in the spread at these very high levels increases the number of caution laps by more than 10 percent. Alternatively, in races with lower spreads (the vast majority), as the spread increases, drivers seem to drive more carefully.[2]

IMSA

The results for the IMSA data are reported in Table 4. In general they reflect a consistent incentive effect for tournament characteristics, yet they are not identical to the NASCAR findings. We first compared two measures of tournament spread, as we did in the NASCAR data. The results for each are reported in columns 1 and 2, respectively. As in the NASCAR data, the broader spread, SPREAD(l–5), has the larger incentive effect. Moreover, the substantive importance of the tournament incentives was also similar to that observed in the NASCAR sample when evaluated at both the mean and over the full sample range of incentives.

We followed our analysis of the NASCAR sample and reformulated the SPREAD(l–5) variable as a spline (column

2 We have consistently omitted Daytona from the NASCAR analysis, based on a concern that both the magnitude of the purse and the prestige of the race would distort any results. Analysis of equation 1 with Daytona in the sample suggests that the results reported in Table 2 were virtually unaffected by this decision. However, the effects of tournament spread on safety reported in Table 3 are considerably attenuated when Daytona is included in the sample. This is consistent with the high prestige of the race, which appears, in part, to offset the declining incentive effects at higher spread levels.

Table 4

Effects of Tournament Characteristics on Driver Performance in IMSA Sample •

Independent variables	Model (1)	(2)	(3)
YEAR	– 5.990	–4.540	–2.910
	(4.080)	(4.160)	(4.310)
RACE TYPE	21.430	22.980	30.960
	(21.100)	(20.670)	(21.390)
STARTING POSITION	–.183	–.187	–.171
	(.358)	(.351)	(.351)
SPREAD (l-2)	.680**		
	(.276)		
SPREAD (l-5)		1.852***	
		(.595)	
Splines			
LOW SPREAD (l-5)			4.051**
(< Mean)			(1.68)
HIGH SPREAD (l-5)			1.295*
(≥ Mean)			(.714)
R^2	.2034**	.2261**	.2355**
Adjusted R^2	.0722	.0907	.0961
Sample size	199	189	189

$^*p < .10$; $^{**}p < .05$; $^{***}p < .01$; two-tailed tests.

• Standard errors are in parentheses. All results are for a fixed-effects model and therefore include 43 dummy variables, one for each driver. The dependent variable is MILES PER HOUR.

3). The evidence of diminishing returns to incentive effects is at best modest in the IMSA sample. This is somewhat surprising, because there is what would appear to be an important distinction between IMSA and NASCAR races. NASCAR, as a sanctioning organization, devotes considerable effort to limiting the heterogeneity of the field in order to make the races closer and therefore more interesting to the fans. There is much more performance variation across racing teams in IMSA. The fixed-effects specification only controls for those differences that are constant over time. Therefore, IMSA teams could gear up for races with larger rewards for winning because IMSA rules provide them greater latitude for such temporal variation. Such an investment in response to changing tournament structure is entirely consistent with tournament theory (Lazear and Rosen, 1981: 844). However, tournament theory also predicts that organizations should not attempt to elicit effort beyond the point where the cost of that effort exceeds the benefits of the higher performance. For the most part, IMSA promoters apparently have not reached that point.

The IMSA experience raises the question of why a few NASCAR races would offer purses and spreads considerably beyond the point of diminishing returns. While we cannot answer this question with these data, we believe that it may reflect institutional influences rather than immediate performance considerations. For example, a race such as Daytona has always been the first race of the year, the most prestigious, and the most lucrative. There may have been a time when this spread was necessary to motivate drivers and racing teams to drive the best race of the year and when there was much more across-race variation in potential performance. That Daytona and a few other races have continued their historical prize structure, even as the incentive effects have diminished, suggests other benefits such as might be explained by institutional theory (Tolbert and Zucker, 1983; Fligstein, 1985).

The Role of Tournament Structure

Earlier work by Ehrenberg and Bognanno (1990a, 1990b) could not test the separate effect of tournament structure on incentive effects. Auto racing, unlike golf, is characterized by variation in tournament structure across races, so such a test is feasible. Beyond the elaboration of incentive effects in such a context, it is also important to include a measure of tournament structure to avoid a potential bias in our estimates of the incentive effects for SPREAD. For example, across tournaments with the same total prize, or compensation pool, the percentage of the total prize awarded to the top finishers is positively related to the increase in SPREAD. To the extent that increasing the distribution of the purse among the top finishers also has an incentive effect, omission of such a variable from our models could overstate the effect of SPREAD on driver performance. To test for this possibility, we reestimated equation 1 for both the NASCAR and IMSA samples, including PERCENTAGE OF PURSE *(a,z)* in the model. PERCENTAGE OF PURSE, the percentage of the purse going to the top finishers, was never statistically significant at conventional levels. While the magnitude of the change in the coefficient on SPREAD was in the expected direction in both models, the change (a 32-percent decline) was only meaningful in the IMSA sample.[3] Unfortunately, these results were very unstable and should be taken with considerable caution, but, at a minimum, they imply that future research on tournament incentive effects should be cognizant of variations in structure to avoid potential biases in estimates of the SPREAD effects.

DISCUSSION AND CONCLUSION

Despite a well-developed theoretical literature, there have been very few empirical studies of the incentive effects of tournament theory. This paper has examined these incentive effects in a context, auto racing, that allows for a direct estimate of the effects associated with varying magnitude and distribution of the tournament prize. We found that for two classes of auto racing, variation in absolute spread between higher and lower finishers has a significant influence on participant performance, both statistically and practically. Moreover, these results also indicate that the incentive effects diminish as the spread increases, though this effect is more pronounced in the NASCAR data. We also examined whether increasing the spread encourages drivers to engage in reckless behavior and found that, while there is no such overall effect, there is an increase in hazardous behavior when the spread exceeds the sample mean by one standard deviation. Finally, we found only limited evidence that tournament structure influences driver performance, though ignoring this aspect of reward structure may overstate the incentive effects of the spread variables.

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The original paper was shortened considerably for purposes of publication. A longer version, including the complete results of this analysis, is available upon request from the senior author.

We see several organizational analogies in these results. Employers want to encourage employees to take risks and to be entrepreneurial, but not to be careless in their actions. It would appear that tournament reward systems have the potential to achieve these goals. Alternatively, overly aggressive or opportunistic behavior in organizations is penalized in a variety of ways, ranging from informal sanctions by colleagues to dismissal. In an auto race, overly aggressive behavior is penalized with a “black flag” (removal of a driver from all or a portion of the race) or a “stop-and-go” penalty (when an infraction is punished by requiring the driver to come into the pits, come to a complete stop, and then continue on in the race).

Reward systems are used to motivate employees and align their interests with those of the organization. The results in this study suggest that tournament systems have considerable motivational properties. People in organizational contexts other than auto racing would no doubt give considerable attention to the possibility that extreme tournament spreads encourage inappropriate behavior on the part of employees. The results in Table 3, in particular, provide some empirical support for such concern, Our only interpretive caveat for the world of auto racing is that promoters realize that racing fans are attracted to excitement, and that often means the kinds of accidents that require caution laps. In that sense, while the behavior is not encouraged for individual drivers, it is not necessarily dysfunctional organizationally.

Caveats and Reservations

Tournament theory is an important tool in understanding reward structures if it can explain these structures in a context with both practical and academic interest. Prior research, as well as this study, has drawn on athletic contests, given the problems of testing tournament theory incentive effects in an organization. While auto racing has considerably more organizational content than typical experimental studies or individually oriented sports, the reader should be aware of the limitations of such an approach. One of the most important distinctions between athletic events and organizational life is the time frame for exercising discretionary effort. Therefore, the incentive effects of tournament characteristics may be different for athletic events. For example, tournament theory implies that employees make discretionary effort choices over a very long period. Tests of tournament theory that rely on sports data observe activities requiring relatively short bursts of effort with considerable time off between events. This contextual difference raises the question of whether similar response patterns can be expected in both contexts. In part, this problem is mitigated by the fact that racing outcomes are a joint effort of the driver and 30 or so members on each team. Moreover, since the race payoffs are posted long in advance of the races and are publicly available, a great deal of effort and resources are devoted to enhancing race performance before the race even begins.

There is also a more general problem that confronts any attempt to estimate the incentive effects of tournament structures empirically. Whether the researcher is using organizational data or sports data, one faces a “Catch-22” situation. Tournament theory predicts that tournament structures will be more likely to exist where individual effort or performance is difficult or costly to observe. Yet a test of incentive effects requires an objective measure of individual performance. The purported value of a tournament structure is that it will encourage higher effort, even when it is difficult to monitor individual behavior. A test of tournament incentive effects thus requires that greater performance be elicited when the participant knows that he or she cannot be accurately evaluated at any particular point in time. Although athletic events leave some question as to participant input, or effort, there is usually very clear evidence of performance, with auto racing being no exception. This raises the question of whether drivers respond to the greater incentives directly or, in fact, are indirectly monitored by car owners or other principals who can terminate a driver for poor performance, not just a poor finish.

Implications for Future Research

The principal goal for future research is to move beyond the convenience of athletics to organizational settings. However, such efforts will face considerable challenges. The data limitations are daunting and reflect a problem that regularly confronts researchers attempting to estimate policy effects in a reasonably competitive market. Ideally, one could randomly assign reward structures across organizations and observe their effects on performance. However, using the naturally occurring experience from the real world means that the presence of tournament structures will in part be determined by performance considerations and, if as successful as tournament theory suggests, may be most widely adopted where their effects (need) are the greatest. We can only recall the reaction of a NASCAR official when the prospect of tournament incentives was suggested to him, who said “Of course, that’s why we do it!” As a result, cross-sectional differences in performance would not necessarily reveal a positive effect for such structures. Avoiding this potential bias would require either a data set very rich in control variables or panel data with variation in tournament structures over time within observational units.

In short, the literature on organizational rewards has a well-developed theoretical model that holds the promise of illuminating compensation issues of concern both to academics and practitioners. The challenge is to extend future empirical work in a way that will prevent the literature on tournament theory from deteriorating into little more than an intellectual curiosity.

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