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Empirical Evidence on Information Theory and the Favorite Longshot Bias

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Abstract

Pari-mutuel betting provides a fertile testing ground for theories of how risk is evaluated in the market. Favorite longshot bias, the over-betting of longshots and under-betting favorites, is commonly observed in pari-mutual betting. Opportunities to test the predictive ability of the many theories that have been advanced over the past 60 years have been rare. This study uses data gathered from nine greyhound racing tracks in the United States and shows that bettors' decisions are consistent with the predictions of a Bayes-Nash model with symmetric information advanced by Ottaviani and Sorensen (2010). (JEL D81, D83)

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1. Introduction

Studies in pari-mutuel betting provide opportunities to observe how risk is evaluated in the market. Griffith (1949) is the first to observe that in horse track betting there is a consistent tendency for bettors to "over-bet" horses with a high pay-out ratio (low probability of winning) and "under-bet" horses with a low payout ratio (high probability of winning). This anomaly, known as the favorite longshot bias (FLB), is detected in many other studies of horse racing including Ali (1977), Snyder (1978), Figlewski (1979), Losey and Talbot (1980), Hausch, Ziemba, and Rubinstein (1981), Asch, Malkiel, and Quandt (1982, 1984, 1986), Tuckwell (1983), Ziemba and Hausch (1984, 1987), Asche and Quandt (1987, 1990), Gandar, Zuber, and Johnson (2001), and Winter and Kukuk (2006). There are a few studies that have not found evidence consistent with FLB. Three of these studies find betting patterns with a bias in the opposite direction, reverse favorite longshot bias (RFLB). Swidler and Shaw (1995) examine data from a small horse-racing track in Texas. Busche and Hall (1988) examine data from a large horse racing track in Hong Kong and Gulati and Shetti (2007) examine greyhound racing data from six tracks in the United States. Sobel and Raines (2003) find that both FLB and its opposite could be observed in a single greyhound race track, the direction of the bias depending on the whether racing took place on a weekend or not. Gramm and Owens (2005) find that FLB, while always present, is more pronounced in smaller betting pools with fewer entrants. Chung and Hwang (2010) find that a single event, a British soccer game, can produce both strong FLB in the bookmaking market and relative RFLB in a pari-mutuel setting.

A number of rigorously derived models are offered to link the FLB anomaly to rational behavior. Any taxonomy of FLB theories must begin by dividing them into three categories: rational theories consistent with the weak form of the efficient markets hypothesis, risk-adjusted rational behavior theories, and behavioral theories. Rational theories include both the informationally symmetric theories of Ali (1977), Blough (1994), Sobel and Ryan (2008), and Ottaviani and Sorensen (2009, 2010), as well as the informationally asymmetric theories of Isaacs (1953), Hurley and McDonough (1995), Potters and Wit (1996), Gandar, Zuber, and Johnson (2001), Feeney and King (2001), Koessler, Noussair, and Ziegelmeyer (2008), and Ottaviani and Sorensen (2003). Behavioral theories include (1) a form of prospect theory suggested by Griffith (1949) and Snowberg and Wolfers (2010) and (2) mental accounting suggested by Kahneman and Tversky (1984), Thaler (1985), and Thaler and Ziemba (1988). This latter class of models also includes the-value-of-bragging-rights model suggested by Canfield, Fauman, and Ziemba (1987). Finally there is a third behavior model, the risk-adjusted rational behavior theories that include Weitzman (1965), Ali (1977), Asch, Malkiel, and Quandt (1982, 1986), and Blough (1994).

The theories that are offered as explanations of FLB are not necessarily mutually exclusive. It is likely that more than one of the assumptions offered in the literature is operative during the course of a race track betting session. Asymmetric information, risk seeking behavior, bragging rights, probability measurement error, prospect theory, and mental accounting are mutually consistent theories. Given the limitations on available data it may be futile to try to reject all of the alternative explanations of FLB save one.

The underlying premise of this paper is that the preferred theory is the one that relies on the fewest assumptions about human behavior and is consistent with the largest number of empirical studies. That premise, along with our examination of greyhound racing, supports a model in which bettors are assumed to be risk neutral, to be free of measurement bias, and to estimate probabilities with equal endowments of information. It also assumes that bettors estimate probabilities initially and then adjust their beliefs toward the final odds through a Bayes-Nash process.

The next section reviews the symmetric risk neutral information model; we then describe the data and compare the characteristics of thoroughbred racing to greyhound racing; following that we describe the empirical methodology and the results. The final section concludes.

2. The Model

Let the gross payout ratio for the i^th entry be a function of the entry's relative share of the betting pool,

$$W_i = \left[(1-t) \times \sum_{i=1}^{G} X_i`\right] / X_i, \tag{1}$$

where,

W_i	=	The winnings from betting on entry i when i wins,
t	=	The percentage "take out" that the track operator retains,
X_i	=	The amount of money bet on the i^th entry,
G	=	The number of entries,
ΣX_i	=	The total amount in the betting pool across all entries.

The probability of winning implied by the pattern of wagers can be considered the market probability,

$$m_i = (1-t) X_i / \sum_{i=1}^{G} X_i = \frac{1-t}{1+O_i}, \tag{2}$$

where,

m_i	=	The market probability of entry i winning,
O_i	=	The posted odds for entry i.

In the symmetrical information models there are no inside bettors possessing information that is superior to other bettors. Each bettor makes a bet only when his subjective probability, *p,* that a horse (or greyhound) will win exceeds the market probability which is implicit in the odds posted at the betting window, $p_i > m_i$.

In the heterogeneous information models of Ali (1977) and Blough (1994) the median belief, p_i^*, of the probability of entry i winning is an accurate estimate of the actual probability of its winning. If Entry "*F*" is the favorite then the portion of people betting on *F* is $1 - F_F(\bar{p}_F)$, where $F_F(x)$ is the belief distribution of subjective probabilities of the favorite winning and $\bar{p}_F$ is the mean subjective probability that the favorite will win.

If bettors are normalized to bet the same amount then $\overline{p}_F$ is also the market probability.

$$\overline{p}_F = m_F = 1 - F_F(\overline{p}_F), \tag{3}$$

In a two-way race with even odds the accurate probabilities of Entry *1* and Entry *2* winning are $\mathrm{p}_1^* = \mathrm{p}_2^* = ½$. As the p_i^* are the medians of their respective distributions it follows that $F(\overline{p}_i) = 1 - \overline{p}_i = ½$. When, however, there is a favorite, *F*, and a longshot, *L*, then $p_F^* > ½$ and $p_L^* < ½$. It follows that

$$\begin{aligned} 1 - F_F(p_F^*) < p_F^*. \\ 1 - F_L(p_L^*) > p_L^*. \end{aligned} \tag{4}$$

From $1 - F_i(\overline{p}_i) = \overline{p}_i = m_i$ the favorite is under-bet and the longshot is over-bet. Thus, even though bettors correctly estimate the probabilities, $\left(p_F^*, p_L^*\right)$, the motivation for betting depends on the market probability relative to the true probability.

This model is extended from a two-horse race to a multiple horse race by Blough (1994). These heterogeneous belief models allow only for FLB and do not allow for the opposite kind of bias. In these models bettors who believe that the probability that the favorite will win exceeds the market probability implied by the odds bet on the favorite, otherwise they bet on a longshot. Except for the marginal bettor whose belief corresponds to the market probability all favorite bettors enjoy a consumer surplus (our term) because their belief (or reservation price) exceeds the market probability. For this reason the observed probabilities are less than the individually held beliefs. On average bettors do a better job estimating the true probability than the market probability implies. The remainder of the bettors bet on the longshots. Because the number of bettors on the longshots is lower, under certain classes of distributions the median belief is below the market belief (see Ali (1977) and Ottaviani and Sorensen (2007)).

Dynamic information is explored in a Bayes-Nash context by Ottaviani and Sorensen (2006, 2009, 2010) and by Sobel and Ryan (2008). In these models bettors are initially endowed with a set of universally held prior beliefs, say q_F, the belief that the favorite will win. Initially there is no belief distribution because prior beliefs are homogenous. Ottaviani and Sorensen (2010) characterize the betting period as one where both false and accurate signals are randomly distributed among the bettors. Johnson, O'Brien, and Sung (2010) focus on the flow of information to bettors at the Wolverhampton race track in the U.K. While they do not test for FLB, their results support their hypothesis that bettors form efficient heuristics to cope with this information flow. Ottavianni and Sorensen (2010) contend that a Baysian-Nash decision process can lead to observed FLB or RFLB depending on the quality of the information flow. Bets on a given outcome follow a binomial distribution. For *N* bettors on *K* horses with *n* bettors betting the favorite, *F*, and *N-n* betting on other horses, *L*, the distribution of the bets on the favorite follows a binomial distribution:

$$\beta_F = \frac{\Pr(\text{bet } F|F \text{ wins})^n\,[1 - \Pr(\text{bet } F|F \text{ wins})]^{N-n}}{\Pr(\text{bet } F|F \text{ wins})^n\,[1 - \Pr(\text{bet } F|F \text{ wins})]^{N-n} + (K\text{-}1)\Pr(\text{bet } F|L \text{ wins})^n\,[1 - \Pr(\text{bet } F|L \text{ wins})]^{N-n}}$$

Where,

β_F	=	The probability of a particular outcome (i.e. *F* wins and all other horses lose) and is equal to the empirical probability,
Pr(bet F/F wins)	=	The probability of a bet on Horse *F* given that Horse *F* wins,
Pr(bet F/L wins)	=	The probability of a bet on Horse *F* given that Horse *F* does not win.

β_F plays the role that the median belief does in the Ali model. It is the unbiased link between belief and empirical reality just as the median belief in the Ali model is the unbiased link between belief and empirical reality. Ottaviani and Sorensen (2010) show that if the posterior belief were precisely equal to the prior then the realized portion of bets on the favorite would be given by:

$$\pi^* = \frac{Ln\left(\frac{1-\Pr(Bet\ on\ F \mid L\ Wins)}{1-\Pr(Bet\ on\ F \mid F\ Wins)}\right)}{Ln\left(\frac{1-\Pr(Bet\ on\ F \mid L\ Wins)}{1-\Pr(Bet\ on\ F \mid F\ Wins)}\right) + Ln\left(\frac{\Pr(Bet\ on\ F \mid F\ Wins)}{1-\Pr(Bet\ on\ F \mid L\ Wins)}\right)} \tag{6}$$

In the Ottaviani-Sorensen (2010) model this quantity plays the role that "½" plays in the Ali model. It is the "neutral" probability from which no bias is manifest. In theory this probability would be observed when the flow of information confirms priors and updating does not cause posterior beliefs to be different from the priors. When the flow of information during the betting process causes priors to be updated then bias results.

The size and direction of the bias depends on the quality of the signals that the bettors receive. The quality of the signals can be measured by the ratio,

$$\frac{\Pr(Bet\ on\ F \mid F\ Wins)}{\Pr(Bet\ on\ F \mid L\ Wins)} \tag{7}$$

Ottaviani and Sorensen show that when this ratio exceeds a certain cut-off quantity then both the favorite's market probability and the posterior probability will exceed the neutral probability but the posterior probability will exceed the market probability:

$$\beta_F > m_F > \pi^*, \tag{8a}$$

thus FLB is observed. In the case of the longshot the market probability and the posterior probability is less than both the neutral probability and the posterior probability is less than the market probability:

$$\beta_L < m_L < \pi*, \tag{8b}$$

If the ratio is small then the opposite result holds. A small ratio can result if the number of bettors (the sample size of the signals) is small or if there is a lot of noise in the signals. Ottaviani and Sorensen's process is in contrast with the one conjectured by McDonald, Sung, and Johnson (2012) where all bias is eliminated as the information set improves.

Ottaviani and Sorensen give numerical examples to show that (1) the greater the number of bettors, the greater the FLB and (2) the smaller the Pr(Bet on $F|F$ wins), the smaller the FLB or larger the RFLB. The first of these conjectures is consistent with the observations of Gramm and Owens (2005) whose study pre-dates the work of Ottaviani and Sorensen (2010). While Gramm and Owens (2005) observe FLB across their entire sample, they find that the extent of FLB was inversely related to the size of the betting pool.

Of the key variables in the Ottaviani and Sorensen (2010) model only m_i, the market probability and the empirical probability, can be observed. Ottaviani and Sorensen (2010) assume that the distribution of posterior beliefs equates to the distribution of possible outcomes. Unfortunately the quality of the signals cannot be observed in a real pari-mutuel setting so no rigorous test of their model can be carried out. One implication that is unique to their model is that one would expect to observe FLB only in pari-mutuel settings where the quality of the signals is high. In other pari-mutuel settings where the quality of the signals is lower one would expect a less pronounced FLB or even RFLB.

3. Hypotheses Formation

The greyhound pari-mutuel betting market is similar to the horse pari-mutuel betting market in that the track management attempts to run homogenous races so that no entrant is an obvious winner. The betting procedure in both entails a period where wagers are made and bettors are informed of changing odds. In both cases wagers can not be revised, sold, or rescinded so that it becomes necessary for bettors to conjecture the final odds. For these reasons we would expect the same empirical results regarding FLB.

But there are differences. First, there are no jockies in greyhound racing so there is no "jockey effect" that can inform bettors. Second, greyhounds are not exercised or trained so pre-race observations are limited to pre-race inspection when the entries are weighed in. Greyhounds are kept in cages and are relatively unobserved except during the race. Third, unlike horse racing, the number of entrants in a greyhound race is always eight so that information generated is more standardized than in horse racing. Finally, greyhounds focus on a quarry while racing rather than on each other so that each entrant may tend to run more independently of the others. For all these reasons we conjecture that the quality of signals during the betting period for greyhounds is inferior to the quality of signals that transpire during the betting period for horses. Consistent with the work of Ottaviani and

Sorensen (2010) it is more likely that we would observe either weak or reverse FLB in greyhound racing than horse racing.

Hypothesis: In greyhound racing we would expect to observe either a smaller FLB relative to horse racing, no bias, or even RFLB.

4. Greyhound Racing: Data

The names of nine greyhound race tracks used in this study along with the respective time spans of data are presented in Table I. The number of races shown is all races held on the track during the time period, which includes all grades, all distances, and all sessions.

Table I. Track Names, and Data Used in the Present Study*

	Track Name	Racing results from	Number of races
1	Birmingham Race Course	Apr 2002 - Dec 2010	36,186
2	Bluffs Run	Jan 1997 - Dec 2010	65,147
3	Derby Lane	Mar 2008 - Dec 2010	17,137
4	Gulf Greyhound Park	Jan 2004 - Dec 2010	26,189
5	Jacksonville Kennel Club	May 2002 - Apr 2009	40,762
6	Palm Beach Kennel club	Jan 2004 - Apr 2009	29,118
7	Phoenix Greyhound Park	Jan 2006 - Apr 2009	16,649
8	Southland Park	Aug 2006 - May 2009	11,623
9	Victoryland	Jul 2008 - Dec 2010	13,130
		Total	255,941

* Table I enumerates the universe of data to which we apply filters to drill down to the final sample.

Filters are applied to enhance consistency in the data. First, we limit our dataset to the top four grades on each race track. Because each track generally holds races in at least two distances with significantly more races held in the shorter distance (typically 1650 feet/550 yards), we limit our study to the shortest distance on each track. Table II shows the number of races that met the conditions set in the first two filters.

Table II. Number of Races in Top Four Grades for Shorter Distance*

	Track	Number of races	Distance - yards
1	Birmingham	29,506	550
2	Bluffs	44,726	550
3	Derby	12,908	550
4	Gulf	19,147	550
5	Jacksonville	30,002	550
6	Palm Beach	20,452	545
7	Phoenix	12,380	550
8	Southland	7,038	583
9	VictoryLand	10,806	550
	Total	186,965	

* Table II shows the number of races that were held in the shorter of the two distances to both standardize the observations and maximize the sample size. The races in Table II are for the fastest grades which evoke the largest betting pool.

All greyhounds start their racing careers in the lowest grade. Tracks classify greyhounds in several grades. Each race held is for a specific grade and all entries in that race hold the same grade at that point in time in order to provide a competitive field to the bettors. Based on recent performance, greyhounds move up or down in grade following rules set by the gaming commission overseeing the track. So we further limit our dataset to greyhounds that have reached the highest grade on their respective tracks at some point. Table III shows the number of greyhounds that meet this filter.

Table III. Number of Greyhounds Which have Competed in All Four Top Grades*		
	Track	Number of greyhounds
1	Birmingham	3,000
2	Bluffs	4,437
3	Derby	986
4	Gulf	1,442
5	Jacksonville	2,277
6	Palm Beach	1,717
7	Phoenix	754
8	Southland	763
9	VictoryLand	1,106

* Table III gives the final sample size which includes only the greyhounds that have reached the highest grade at some point during their career.

A greyhound is considered when it meets our selection criteria and ignored otherwise. For example, at the Birmingham racetrack, our dataset contains 3,000 individual greyhounds that have reached the highest grade at some point during their racing careers.

Some of these greyhounds are currently active while others are past their racing careers. Depending on the time span of the racing career, each greyhound competes in a different number of races with a varying number of those in each grade. Since greyhounds can move up and down in the grades, a greyhound may have competed in the same grade at several points during the racing career. Additionally, the proportion of the betting pool a greyhound attracts varies from one race to the next. In other words, a greyhound may be the favorite in one race, a longshot in the next, or any of the other six ranks in between. In keeping up with the theme of our study, we limit our results to favorites and longshots.

For each race track we segregate performance results of favorites in all four grades. We use Birmingham race track information from Table III to illustrate this filtering process.

The 3,000 greyhounds (our pool) which meet all criteria set by the filters, competed in a total of 29,506 races. A particular race may include a number of greyhounds from our pool ranging from zero to all eight (very unlikely event). Races with no greyhounds from our pool receive no further consideration in our analysis while races with one or more greyhounds from our pool remain in the database only when the entries are the favorite or the longshot. The favorite was a member of our pool in 15,374 races and the longshot was a member in 12,675 races.

We place a hypothetical two dollar bet on the favorite to win in 15,374 races. If our entry wins we collect the payoff and forfeit our bet otherwise. We calculate the percent return comparing the total winnings we realize with the total $30,748 bet. The same process is repeated for 12,675 races for the longshots.

5. Methodology and Results

Our hypothesis is that because the greyhound racing market differs from horse racing in the quality of signals that are distributed during the betting period and therefore we expect small to negative FLB. We assume that bettors have access to recent win histories of the greyhounds and other relevant information from which they are able to form expectations based on these histories. It is a standard practice to provide bettors with each greyhound's performance results from a handful of recent races via racing programs which are freely available on track websites or from other intermediaries. We assume that bettors consider a number of factors, including the recent performance, to estimate the probability of winning (their subjective probability) for greyhounds in a race and they compare that subjective probability to the posted odds (market probability) in making their betting decisions. In a pari-mutuel setting opportunities to earn economic profit are available when empirical probability and market probability are far apart. These gaps, when favorable, must be sufficiently large to overcome the track take. Errors in processing signals and/or poor quality signals, if sufficiently large, will lead bettors to adjust their expectations so that subjective probabilities will differ from market probabilities to produce RFLB That is, the resulting market probability will exceed the empirical probability for favorites, and vice versa for the longshots.

Table IV. Performance of Favorites in the Top Four Grades*

	Races contested	Races won	Percent won	Median odds	Percent return on a two dollar win bet - all races contested
Birmingham	15,374	3,938	25.61%	1.70	-11.52%
Bluffs	31,406	9,320	29.68%	1.90	-13.73%
Derby	8,491	3,094	36.44%	2.10	35.65%
Gulf	10,925	3,318	30.37%	2.00	-9.27%
Jacksonville	22,053	6,647	30.14%	1.90	-12.40%
Palm Beach	14,554	4,269	29.33%	1.40	-19.66%
Phoenix	7,295	2,224	30.49%	1.80	-13.27%
Southland	1,399	442	31.59%	1.80	-10.51%
Victoryland	6,830	1,859	27.22%	1.80	-23.66%

*Table IV shows performance results and returns for a hypothetical $2 bet to win wagered on each greyhound whenever the favorite was from our pool. The returns generated on the bets on the favorites bets are always negative with only one exception.

Table IV shows

the performance results and the returns for a hypothetical $2 bet to win wagered on each greyhound whenever the favorite was from our pool.

The returns generated on these bets are always negative with only one exception. Table V shows results for similar bets on longshots.

Table V. Performance of Longshots in the Top Four Grades*

	Races contested	Races won	Percent won	Median odds	Percent return on a two dollar win bet - all races contested
Birmingham	12,675	979	7.72%	15.00	54.38%
Bluffs	23,807	1534	6.44%	16.40	29.15%
Derby	5,131	282	5.50%	14.45	-4.40%
Gulf	7,250	507	6.99%	13.90	15.23%
Jacksonville	13,805	864	6.26%	14.40	5.55%
Palm Beach	8,802	603	6.85%	17.24	11.13%
Phoenix	4,000	238	5.95%	13.85	-2.46%
Southland	719	59	8.21%	15.30	46.69%
Victoryland	4,467	383	8.57%	14.70	64.07%

*Table V shows performance results, and returns for a hypothetical $2 bet to win wagered on the longshots.The right hand column shows that the returns generated by bets on the longshots are always positive with two exceptions. In four of the tracks the positive returns were economically significant, large enough to overcome the track take which averages about 20%.

The right hand column shows that the returns generated by these bets are always positive with two exceptions. In four of the tracks the positive returns are economically significant, large enough to overcome the track take which averages about 20%. In order toto measure the statistical significance of the reverse FLB bias we compare the market probability implied by the averaged odds to the empirical probability in Table VI.

A two sample paired *t*-test shows that the differences between the market probability and empirical probability is not significant at 5% level implying that the market is fairly accurate in processing the signals correctly. In contrast, a similar calculation for the longshots indicates a significant bias. The paired *t*-test shown in Table VII results in a *p*-value of 0.0009 giving the appearance that bettors significantly underestimate the market probability to win consistent with Ottaviani and Sorensen (2010).

Table VI. Empirical, and Market Probabilities to Win for Favorites in Top Four Grades		
	Empirical probability – win bets	Market probability to win as implied by median odds
Birmingham	25.61%	29.63%
Bluffs	29.68%	27.59%
Derby	36.44%	25.81%
Gulf	30.37%	26.67%
Jacksonville	30.14%	27.59%
Palm Beach	29.33%	33.33%
Phoenix	30.49%	28.57%
Southland	31.59%	28.57%
VictoryLand	27.22%	28.57%
Average	30.10%	28.48%
t value = 1.0813 p value = 0.3110		

*Table VI compares the market probability implied by the average odds to the empirical probability of a favorite winning. A two sample paired t-test shows that for favorites the differences between the market probability, and empirical probability are not significant at 5% level implying that the market is fairly accurate in processing the signals correctly.

6. Discussion of Results

The theoretical work of Ottaviani and Sorensen (2010) implies that the noisier the pre-race signals the less pronounced the FLB. Their model predicts a continuum of observed inefficiency ranging from RFLB to very pronounced FLB depending on the quality of information bettors receive. Their work is consistent with the observations of Gramm and Owens (2005) whose study pre-dates the work of Ottaviani and Sorensen (2010). While Gramm and Owens (2005) observe FLB across their entire sample, they find that the extent of FLB was inversely related to the number of horses in the race. If more horses add to the noise of the signals then one would expect FLB to be less pronounced. The present study adds to the evidence supporting the Bayes-Nash paradigm of Ottaviani and Sorensen (2010). In the case of Greyhound racing, where pre-race observations are even less informative, we observe reverse FLB. In seven out of nine tracks longshot greyhounds out-perform the market odds, and the difference between market odds and empirical odds is statistically significant. In four out of the eight tracks the difference between the market probability and the historical probability is economically significant.

Table VII. Empirical, and Market Probabilities to Win for Longshots in Top Four Grades*		
	Empirical probability – win bets	Market probability to win as implied by median odds
Birmingham	7.72%	5.00%
Bluffs	6.44%	4.60%
Derby	5.50%	5.18%
Gulf	6.99%	5.37%
Jacksonville	6.26%	5.19%
Palm Beach	6.85%	4.39%
Phoenix	5.95%	5.39%
Southland	8.21%	4.91%
VictoryLand	8.57%	5.10%
Average	6.94%	5.01%
t value = 5.0557 *p* value = 0.0009		

*Table VII compares the market probability implied by the average odds to the empirical probability of a longshot winning. In contrast to Table VI concerning favorites, Table VII, concerning longshots, indicates a significant bias. The paired *t*-test shown in Table VII results in a *p*-value of 0.0009 giving rise to the appearance that bettors significantly underestimate the market probability to win.

7. Conclusion

Theoretical work by Ottaviani and Sorensen (2010) predicts that in betting situations where information is noisy and/or of poor quality one would observe systematic under-betting of favorites and over-betting of longshots. This observation is in contrast to betting situations where information is of better quality. We maintain that because the quality of information at greyhound racing tracks is inferior to the quality of information at horse racing tracks we would observe under-betting of longshots in the former and over-betting in the latter. This study focused only on greyhound racing tracks and found that under-betting of longshots is both economically and statistically significant, consistent with both our information assumptions and Ottaviani and Sorensen's (2010) work.

Studies of horse track racing consistently find that longshot horses are over-bet, and favorites are under-bet. This study contributes to the literature by showing that this phenomenon does not transcend all pari-mutuel racing situations. More importantly, this study gives support to a model in which all bettors are rational, symmetrically informed, and risk neutral.

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