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Risk Love and the Favorite-Longshot Bias: Evidence from German Harness Horse Racing

Abstract

Empirical studies of horse race betting in the U.S., the UK, and Australia have established the so called favorite-longshot bias. Studies find that on average, bets on longshots lose much more than do bets on favorites. This means that longshots are overbet and favorites are underbet. By using a large data set of pari-mutuel harness horse races, we show that the favorite-longshot bias exists in Germany as well. We provide evidence that there is bias not only for simple win bets, but also for other types of bets as well, and that the bias is a time- and track-invariant phenomenon. The bias is consistent with the assumption of the (local) love of risk of the betting audience.

JEL-Classification: L83, D58, D81.

Keywords: Betting; Favorite-Longshot-Bias; Horse Race; Market Equilibrium; Risk.

1 Introduction

One of the main findings of empirical racetrack research is the favorite-longshot bias (FLB). Empirically, studies find that bets on longshots on average lose much more money than do bets on favorites (e.g., Griffith (1949); Weitzman (1965); Ali (1977); Williams and Paton (1997); Jullien and Salanié (2000)). Although the probability that the longshot will win is well below that of the favorite, its payoff is of course higher. But as it turns out, it is not high enough to fully compensate for the lower probability of winning. Empirical studies show that the FLB exists in North America (e.g., Snyder (1978)), the UK (e.g., Bruce and Johnson (2000)) and Australia (e.g., Tuckwell (1983)). Busche and Hall (1988) find an exception to the FLB for a Hong Kong racetrack, Busche (1994) for Japanese tracks, and Swidler and Shaw (1988) for one Texas track.

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The most prominent explanation for the FLB suggested in theoretical papers is the assumption of bettors with a preference for risk. If the population of bettors is homogeneous across races and types of bets, then the FLB should be a ubiquitous phenomenon. Therefore, the aim of this paper is to test the generality of the FLB hypothesis in Germany.

Based on a dataset of about 35,000 pari-mutuel harness horse races with more than 300,000 horses, we analyze the win bet market and find strong evidence for the bias, thus corroborating the results of the studies mentioned above. We find no evidence for track or sequential effects such as "Gluck's Second Law", which proposes that the FLB will be most pronounced for the last race of a racing day. Nor do we find that total betting volume has any effect.

Although so far, the FLB has been mainly documented in the market only for win bets, we provide additional evidence that the FLB exists for other types of bets as well. We conclude that our findings are consistent with the assumption of a homogeneous population of risk-loving bettors in all markets under consideration.

The paper is organized as follows. In section 2 we briefly sketch the idea of the theoretical love of risk explanation, and also some other possible explanations. Section 3 reviews the available empirical evidence. In section 4 we present our data and results. Section 5 concludes.

2 Explanations of the FLB

Studies offer a variety of arguments to explain the FLB. Although it is beyond the scope of this paper to provide an exhaustive discussion, we briefly review some of the most prominent explanations. The explanations offered differ with respect to the assumed homogeneity of bettors, their goals, and capabilities.

Some researchers suggest that bettors may primarily play for fun and that it is more fun to bet on longshots (Thaler and Ziemba (1988)). Thaler and Ziemba suggest that "bragging rights" can only be earned by picking a longshot correctly. Thaler and Ziemba also offer another explanation, which is that bettors simply overestimate the probability that longshots will win. This overestimation could be considered a Kahneman-Tversky type error (Hurley and McDonough (1995)). However, this explanation is not very convincing, since races are frequent and data availability is good, thus offering a sound opportunity to update beliefs and arrive at correct estimates (Sauer (1998)).

Still another assumption is that the population of bettors may be heterogeneous. Thus, some bettors may be informed insiders while others are more or less ignorant (Sobel and Raines (2003)). The uninformed bet too evenly but the insiders bet correctly, resulting in too much money being spent on longshots. These arguments are based on demand-side factors in pari-mutuel markets, where bettors ultimately play against each other. The track acts only as an administrator, collecting the bets and paying out winners from the betting pool after subtracting the track's so-called "take".

Bookmakers typically offer bets at fixed odds, making them vulnerable to insider trading. Shin ((1991); (1992)) argues that bookmakers will set odds in a way that reduces their risk of being exploited by insiders. Since insider information on longshots is extremely valuable and winning longshots will result in high payouts for the bookie, bookies lower the odds on longshots when they fear insider activity. Indeed, the FLB has been found in bookmaker markets as well.

Still, the most prominent explanation for the FLB is that bettors (locally) love risk. We follow this idea in the remainder of this paper. By choosing this narrow focus we do not neglect the validity of any of the above explanations. We concentrate on this explanation for the following reasons. First of all, it gives us a simple and purely economic model that does not require any other ad hoc assumptions. Second, we have no information on the composition of the betting audience. Therefore, we are not able to test for composition effects like the informed/uninformed dichotomy. Last but not least, assuming that a homogeneous group of bettors loves risk yields a simple, testable hypothesis, which states that we should expect to observe the same pattern of the FLB in all markets under consideration.

Based on ideas on the curvature of utility functions suggested by Friedman and Savage (1948) and later amended by Markowitz (1952), researchers have used racing data to estimate utility functions of an artificially constructed "average bettor". Ali (1977) uses this "average bettor" to estimate an implied utility function of the type $u(w) = aw^x$. He finds $u(w) = 1.91w^{1.1784}$. Without explicitly specifying the functional form, Weitzman (1965) obtains similar results. These results show that both authors found that their data were consistent with marginally increasing utility of wealth.

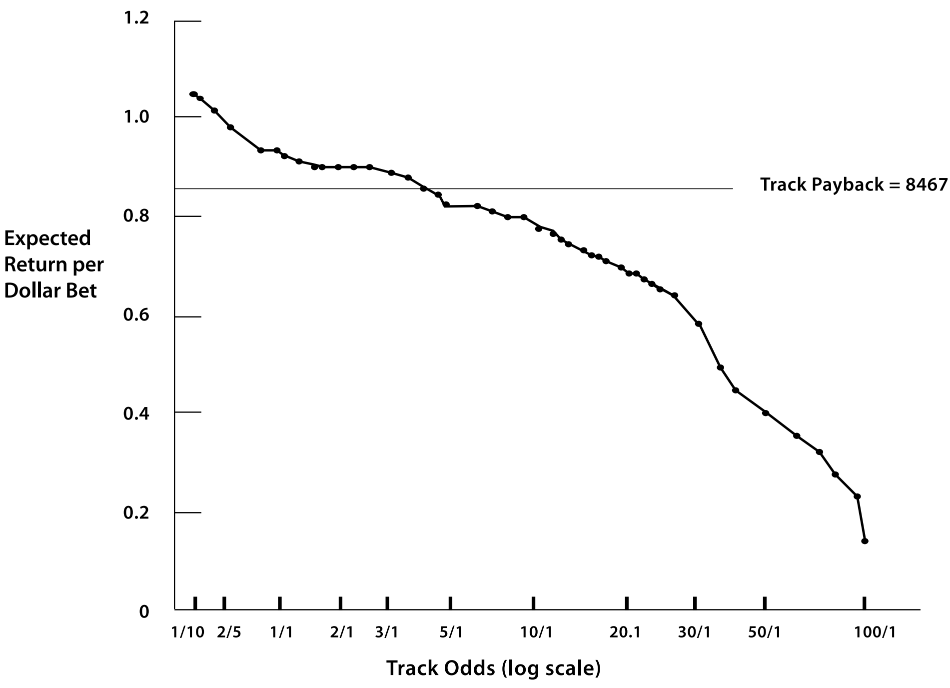
Assuming mean-variance expected utility functions of identical bettors, the FLB has even been shown to be the equilibrium outcome of a pari-mutuel betting market in which all bettors love risk (Quandt (1986)). The basic idea of this result is straightforward. If all bets have the same expected returns, then risk-loving bettors would prefer high-variance bets. If all bettors prefer high levels of risk, then no one would prefer low-variance bets. Declining demand would drive the expected returns of the low-variance bets up to a point at which bettors became indifferent. So in equilibrium, the high-probability/low-variance bets (i.e., the bets on favorites) must have higher expected returns than the low probability/high variance bets (i.e., bets on the longshots).

Taken together, the assumption of a love of risk is compatible to the FLB, whether we define love of risk within a mean-variance framework or some other concept of bettor utility with a positive utility of risk. Therefore, if we assume only that bettors prefer risk and that the population of bettors is homogeneous, we would expect some form of the FLB in all the markets under consideration.

3. The favorite-longshot bias

The FLB hypothesis states that from an expected return perspective, it is better to concentrate on betting on favorites. Empirical research so far has mostly backed this hypothesis. Researchers do indeed find that the expected returns on bets on favorites are higher than are bets on longshots. Griffith (1949) was the first to report this result. McGlothlin (1956) later reaffirmed Griffith's findings. Snyder (1978) reviews early studies covering about 30,000 races from 1947 to 1975. The FLB is highly visible in these studies, average returns declining from around -6% for odds about 0.75 to 1 to -40% for odds about 33 to 1. The effect of declining expected returns as odds increase seems to follow an accelerating pattern. Hausch and Ziemba (1995) present a meta-analysis of more than 50,000 races with more than 300,000 horses. They find that at odds of about 50 to 1 the expected return is -45% while at odds of 100 to 1 it is already -90% (See *Figure 1* below). As a line of reference the Californian track payback line is displayed. If there were no FLB, the effective payback line in *Figure 1* would have coincided with the constant track payback line 0.8467. The payback ratio is less than one because the track takes money out of the betting pool to cover costs and taxes. For extremely short odds, research finds that the average expected return has even be been positive.

Figure 1: Effective track payback for various odds levels (Source: Hausch and Ziemba (1995), 552)



For odds even longer than those covered in *Figure 1*, Jullien and Salanié (2000) find a return of -100%. Other studies that mainly back the FLB include Ali (1977), who finds evidence of the FLB in 20,247 harness horse races. Although earlier studies deal mainly with pari-mutuel markets, studies by Dowie (1976), Tuckwell (1983), Henery (1985), Williams and Paton (1997), Jullien and Salanié (2000), Bruce and Johnson (2000), and Law and Peel (2002) find that the FLB affects bookmakers' odds as well. All studies mentioned above concentrate only on win bets.

Many studies document the FLB, but some papers do not corroborate this finding. In fact, they may even present evidence pointing in the opposite direction. For example, Swidler and Shaw (1995) find a statistically significant positive rank correlation between winning odds and the levels of return. The longshot category in their sample with odds over 25 to 1 generated a return of -8.8%, while the favorites with odds below 2 to 1 earned -23.3%, which is a clear reversal of the FLB. Busche and Hall (1988) also find more of a longshort- favorite bias for Hong Kong racetracks. This finding is reconfirmed by Busche (1994), who presents additional evidence for Japan. But since those studies comprise only about 7,000 races, up to this point we view them as an anomaly to an anomaly.

4. Data and results

We obtain our data from TROT-ONLINE, an Internet-based information broker for German pari-mutuel harness horse races. The data set covers all 35,608 races run at 13 different German tracks between January 2000 and March 2004. The win odds at the start of the race are available for each of the 301,780 horses. Additionally, for each race we have odds for show bets, exactas, and trifectas, but only for those horses or horse combinations whose bets paid off. A show bet pays off when the horse that is bet on finishes first (wins), second (places), or third (shows). The payoff does not depend on whether the horse wins, places, or shows. For an exacta to pay off, the bettor must pick the winner and the second horse of the race in the correct order. The trifecta wins if the first, the second, and the third horses of a race are bet on in the correct order.

The track take at German tracks ranges between 20% and 30%, depending on the track and the type of bet offered. It is higher than in most other countries, where the take is typically less than 20%. This difference is due in part to the high German federal tax on horse bets, which alone is already 16.67%. Straight win bets typically trigger the lowest take, while the take for combined bets is typically highest. We have no specific information on the take for the individual races and types of bets.

The first question we address is how to classify favorites and longshots. Older studies classified favorites and longshots by defining odds categories and classifying each horse according to its odds (see, e.g., Griffith (1949)). But doing so could lead to selecting more than one horse in the favorite category – but only one can win. Therefore, as Ali (1977) suggests, a better procedure is to order the horses in each race according to their odds and define the favorite as the horse with the lowest odds. In that case, any horse that is ranked first in the odds is the favorite by definition, and no two horses in a race can be in the same category. One can break eventual ties in the odds by randomly assigning the respective ranks to the horses. We can then calculate the average odds across races for each rank and then can use these rankings to calculate the implied winning probabilities, which we can compare to the average empirical win probability of that specific rank.

We follow this ranking procedure. For 20 races we only have information on the win odds for those horses that had won. For these races we apply the following procedure: We calculate the average odds rank for the given odds of these winners. For example, if a horse has odds of, say, 3 to 1 and that corresponds to an average odds rank of 4, then we classify the horse in odds rank 4. We then award the other horses in those races the remaining ranks simply by their order of appearance in the data set. For some races data is missing for only one, or perhaps a few, horses. One plausible reason is that there were no bets on these horses. Therefore, we treat those horses as longshots, awarding the highest ranks not assigned so far. We check whether deleting horses with missing data has any effect on the win bets results. There is none. And since some horses with missing win odds still have odds available for show bets, dropping them totally would forgo information.

We first turn to the markets for win and show bets. A win bet pays off whenever the horse that has been bet on actually wins the race. For show bets the horse can finish first, second, or third. Only when the number of competing horses is less than seven must a horse come in first or second to make the show bet pay off.

Each type of bet constitutes a different market. Win bets have no effect on the odds for show bets, and vice versa. The odds for win bets in pari-mutuel settings are calculated as follows. Let b_i be the total amount of money bet on horse i, let N be the number of horses in the race and let t be the percentage of the track's take. Then the odds for horse k are given by (e.g., Sauer (1998))

$$O_k = \frac{(1-t)\sum_{i=1}^{N} b_i}{b_k} - 1$$

where odds O_k is the profit per unit spent on horse k if k wins the race.

However, these odds are only preliminary, in that they are subject to a rounding-down procedure called "breakage." In Germany, odds are rounded down to one decimal place, so odds of 1.49 become 1.4. These rounded odds for all horses are continuously displayed at the tracks, typically updated every minute. They change over time and any single bet changes the odds of all the horses in the race. For our analysis we use the final odds calculated after all betting activity stops, usually one to three minutes before the race starts. These are the odds that apply to all bets, no matter when the bets were placed. The odds for other types of bets are calculated in a similar fashion, although the calculations are somewhat more complicated for show bets. *Table 1* presents the results for win and show bets.

Table 1: Probabilities and returns for win and show bets

Odds category i[1]	Average Odds[2]	# Races[3]		# Winners[4]	Probability of Winning Empirical[5]	Probability of Winning Implied[6]	Return (%) Win bet[7]	Return (%) Show bet[8]
1	0.99	0	(35608)	16231	0.456*	† 0.409*	-16.56*	-5.03*
2	2.85	0	(35608)	7828	0.220*	‡ 0.215*	-23.98*	-11.54*
3	5.29	1	(35608)	4574	0.128*	† 0.135*	-29.23*	-18.66*
4	8.86	34	(35607)	2789	0.078*	† 0.090*	-36.46^{+}	-27.75*
5	14.34	328	(35573)	1826	0.051*	† 0.060*	-39.10^{+}	-32.08*
6	23.56	2019	(35245)	1156	0.033*	† 0.041*	-43.07^{+}	-38.23*
7	39.01	5998	(33226)	704	0.021*	† 0.028*	-47.37	-42.91^{+}
8	61.43	10012	(27228)	349	0.013*	† 0.019*	-50.41	-44.59*
9	87.58	8882	(17216)	146	0.008	† 0.015*	-53.54	-48.18*
10	123.92	7210	(8334)	67	0.008	† 0.011*	-42.56	-58.08
11	146.88	627	(1124)	7	0.006	‡ 0.011+	-34.56	-51.13
12	126.29	252	(497)	4	0.008	0.010*	13.74	-49.35^{+}
13	151.92	55	(245)	1	0.004	0.009*	-72.45	-63.70
14	194.55	32	(190)	2	0.011^{+}	0.007*	-36.11^{+}	-40.74*
15	218.16	23	(158)	0	0.000	0.006*	-100.00	-81.78
16	880.92	26	(135)	0	0.000	0.002^{+}	-100.00	-100.00
17	926.46	42	(109)	0	0.000	0.001	-100.00	-100.00
18	922.30	65	(67)	0	0.000	0.001	-100.00	-100.00
19	169.05	2	(2)	0	0.000	0.005	-100.00	-100.00

Notes

1. Odds rank; favorites ranked lowest. We break ties in the odds by order of appearance in data set. Alternative random selection does not change results.
2. Average odds of all horses in category *i*. The average odds of category 19 are lower than those in category 18. This result is not an error. In the 65 races with exactly 18 horses, most of the horses ranked 18th had extremely high odds.
3. Number of races with exactly *i* horses. Numbers in parentheses indicate the number of races with at least *i* horses.
4. Number of winners in odds rank *i*. The sum of the numbers of all winners exceeds the number of races due to 76 races with deadheads (ties).
5. Actual winning probability of horses of odds rank *i*. * (+) indicates that the difference in winning probabilities between category *i* and *i*+1 is significant at the 1% (10%) level. (one sided two-sample *t*-test, unequal variances).
6. Average winning probability implied by the odds for horses of odds rank *i*. * (+) defined as in column 5. † (‡) indicates that the difference between implied and empirical winning probabilities within category *i* is significant at the 1% (10%) level. (Two sided two-sample *t*-test, unequal variances).
7. Average return of win bets on all horses in category *i*. The positive return in category 12 is due to a single outlier that paid 433.4 to 1. * (+) indicates that the return difference between category *i* and *i*+1 is significant at the 1% (10%) level. (One sided two-sample *t*-test, unequal variances).
8. Average return of show bets on all horses in category *i*. * (+) defined as in column 7.

As it turns out, the FLB is strongly present in German harness racing. The average return for win bets on the favorites is about -16.6%, while the extreme longshots ranked 15 or higher never won a race, implying an average return of -100%. This decline in returns is strictly monotonic up to category 9. Given the small number of winners in categories 10 to 14, the erratic movements of average returns in these categories can be explained by outliers.

An interesting result is the FLB in show bets documented in column 8. The FLB is present in show bets and the bias is stronger compared to win bets. The favorites in the win bet market yield only marginally negative returns of about -5.03% in the show market. We calculate the return figures for show bets in *Table 1* based on 35,413 races. There are no show odds available for the remaining 195 races. In 42 races there are no bets on one of the horses that showed. For that case we substitute missing odds according to the respective averages of that category. The average show odds are 0.7 for the winners, 1.1 for place, and 1.3 for show. Whenever there is no bet on a winner, we award odds of 0.7 and so on. Dropping these 42 races altogether makes no difference whatsoever.

We now restrict our analysis to the market for win bets and turn to possible sources of variation in the FLB. There are several hypotheses in various papers about what may affect the FLB. One example is Gluck's Second Law (e.g., Johnson and Bruce (1993)), which states that the FLB is especially strong in the last race, or last few races, of a racing day. Thaler (1985) and Thaler and Johnson (1990) argue that bettors may base their decisions on a model of mental accounting. Bettors may then be inclined to try to break even at the end of the day by focusing even more on longshots. So far, the empirical evidence on this effect is mixed. Kopelman and Minkin (1991) and Asch et al. (1982), among others, do find some evidence for this effect, but Johnson and Bruce (1993) do not. If there is heavier betting on longshots in late races, the odds of favorites in the last races should be higher compared to early races. Kopelman and Minkin (1991) find mean odds of 2.37 for the favorites of the last race and mean odds of 1.75 for all other races. But this result may be driven by selection effects, i.e., that in the last races there is less diversity in horses' capabilities. From the investment point of view, it is more interesting whether the returns of bets on favorites differ across the racing day. For the favorites with odds of 2 or below, Asch et al. (1982) find average returns of -4.28% for the last race, but find -13.66% for all races. So their favorites are indeed better picks in the last races.

We analyze our harness-racing data for the last, the two last, and the three last races as compared to all other races, respectively. *Table 2* gives the results.

Table 2: Returns (%) across odds ranks by order of races

Odds rank of horse	Last race compared to all others		Last two races compared to all others		Last three races compared to all others	
	Last	All others	Last two	All others	Last three	All others
1	-15.10	-16.70	-17.09	-16.45	-16.28	-16.66
2	-22.33	-24.13	-21.09	-24.58	-22.52	-24.49
3	-31.55	-29.01	-31.15	-28.84	-30.11	-28.93
4	-37.68	-36.34	-31.73	-37.44	-33.20	-37.58
5	-34.29	-39.56	-34.37	-40.08	-36.27	-40.08
6	-46.28	-42.76	-49.13	-41.81	-46.93	-41.73
7	-57.15	-46.43	-59.85	-44.74	-55.54	-44.49
8	-58.59	-49.60	-54.56	-49.53	-42.11	-53.36
9	-64.25	-52.46	-66.75	-50.70	-72.69	-46.72
10	-54.72	-41.31	-36.41	-43.88	-41.43	-42.97

The table shows that the magnitude and pattern of returns across odds ranks is independent of the races included in the analysis. There are no meaningful differences related to the ordering of races over the racing day. The results of German harness racing refute Gluck's Second Law.

In their studies, Swidler and Shaw (1995), Busche and Hall (1988), and Busche (1994) find a reversal of the FLB. Each study concentrates only on one or a few tracks. While Busche and Hall use a Hong Kong racetrack, Swidler and Shaw use data from a Texas track. Busche (1994) uses both Hong Kong and Japanese data. Therefore, as compared to other studies focusing on the U.S., we cannot attribute Swidler and Shaw's different result to cross-country variations. So it may be that there is cross-track variation in the FLB. This effect could be because some tracks keep and publish more detailed information on past races than do others, so that bettors have better knowledge of past performances and thus a more educated average betting behavior. We checked that explanation for the 13 German tracks covered by our data. However, we do not find any meaningful cross-track variation. *Tables 6a* and *6b* in the Appendix present the full results.

Another possible source of variation is the "size" of the race. "Bigger" events that are heavily advertised attract a larger audience. It is very likely that for those events, people who are only occasional bettors are present, and these people are much less experienced in betting than is the core audience. Although we have no data directly indicating those events, we can rely on proxies that are very likely to identify the events correctly. One such proxy is the pool of prize money available for the race. A big pool is likely to indicate heavy sponsoring, and sponsors typically advertise these events themselves beyond the usual media coverage. When we divide the data set into three distinct groups at cut points of €10,000 and € 20.000, we find the following results.

Table 3: The FLB by pool of prize money

Odds rank of horse	Pool of prizes in €		
	< 10,000	10,000 - < 20,000	> 20,000
1	-16.71	-15.64	-15.76
2	-24.31	-21.77	-23.43
3	-29.48	-28.31	-24.76
4	-37.08	-31.43	-40.20
5	-40.40	-31.59	-30.95
6	-46.35	-22.75	-29.95
7	-48.95	-40.26	-28.94
8	-49.53	-59.43	-31.02
9	-49.89	-71.66	-50.30
10	-40.81	-40.50	-72.45
#Races	30442	4365	801

We can infer from *Table 3* that the FLB is present in all groups. We obtain similar results for other cut points.

Another idea is to divide the data set by total betting volume. As Busche and Hall (1988) point out, the average total betting volume at the Hong Kong tracks was US$5.6 million per race for 1985 and 1986, and US$152,000 for all thoroughbred racing in the U.S. in 1983. While a higher total volume does not necessarily imply higher average bets, high betting volume implies a lower impact of a given bet on the odds. If bettors recognize a betting opportunity with positive expected returns at given odds, they can more easily exploit this opportunity at higher volume, since the effect of this bet on the odds is likely to be negligible. In a sense, the larger the betting pool, the more promising is looking out for those opportunities. Therefore, it may be true that besides more amateur betting, there is also much more educated betting at high-volume races compared to low betting volume. This composition effect may result in a shift of market outcome.

However, we do not find any such effect. We have to admit that for our data set, this result is hardly surprising, given that the highest volume is €167,000 and about 60% of all races had handles of €10,000 or below. It could be that this degree of variation is simply too small. Without giving any more details here, we do not find any effects of the year, quarter, or month of the race. Neither do we find that the distance of the race has any effect.

We now examine the combined exacta and trifecta bets. An exacta wins when the first two horses of the race are bet on in the correct order. Trifectas are the three-horse equivalent of exactas. When analyzing the combined bets, we confront a situation in which we have only odds for those bets that had actually won. Therefore, we cannot rank the different exactas and trifectas in a race in the same way as for the win bets. There, we have odds for all possible bets in the race and can rank the bets by their implied probability of winning.

To rank the combined bets, obviously we needed to develop an alternative approach. We use a purely empirical approach that does not depend on any assumptions on the winning probabilities of those combined bets for which we had no odds.

The empirical approach works as follows. Let (A, B) be two horses in a race and let (i, j) be the ranks of these horses according to their odds in the win bet market. For example, if $(i, j) = (4, 1)$, then horse A is ranked fourth in the win bet market, and horse B is ranked first (the favourite). Then for each race we observe whether the rank combination (4, 1) ends up with the horses coming in in the order A-B, followed by all the other horses. In that case, an exacta on the rank combination (4, 1) wins. Now we can observe how often in a given set of races the combination (4, 1) wins. If in 20 out of 1,000 races the combination (4, 1) wins, then the empirical winning probability for this combination is 2%. We do these calculations for every possible rank combination.

The last step is to rank all the (i, j) combinations according to their winning probabilities. *Table 4* presents the results of this procedure. We can infer from *Table 4* that the combination (1, 2) has a winning probability of 15.17% and the combination (4, 1) wins in 2.4% of all races. We limit our analysis to the first ten ranks *k* because for lower winning probabilities, results on returns could already be severely affected by single outliers.

Table 4: Probabilities and returns for exactas

Rank *k* of	**Odds rank of**		# of winning	Probability of	
exacta	Winner	Second horse	exactas of rank *k*	winning (%)	Return (%)
1	1	2	5429	15.17	-14.42
2	1	3	3636	10.16	-18.50
3	2	1	2984	8.34	-19.75
4	1	4	2548	7.12	-24.33
5	1	5	1850	5.18	-21.76
6	2	3	1684	4.71	-26.98
7	3	1	1525	4.26	-25.36
8	1	6	1262	3.56	-27.33
9	3	2	1167	3.26	-29.98
10	4	1	858	2.40	-30.57

Table 5: Probabilities and returns for trifectas

Rank *k* of trifecta	Odds rank of Winner	Second horse	Third horse	# of winning trifectas of rank *k*	Probability of winning (%)	Return (%)
1	1	2	3	1675	4.68	-23.13
2	1	2	4	1328	3.71	-21.34
3	1	3	2	1195	3.34	-25.16
4	2	1	3	960	2.68	-11.83
5	1	2	5	940	2.63	-21.60
6	1	4	2	746	2.08	-27.37
7	2	1	4	674	1.88	-20.34
8	2	3	1	530	1.48	-23.88
9	3	1	2	506	1.41	-19.21
10	3	2	1	366	1.02	-28.41

We see from *Table 4* that the FLB is present in the exacta market. However, in *Table 5,* for the trifecta market we see that no such effect exists within the first ten ranks of bets included in our analysis. Of course, that finding does not imply that there is no FLB at all in the trifecta market. Indeed, even without detailed analysis of more unlikely trifectas, we already know from *Table 1* that no horse ranked 15 or below in the win odds has ever won a race. This observation implies that any bettor who put one of these horses in the front position in a trifecta would have lost, implying a return of -100%. So the gross picture would indicate the FLB in the trifecta market as well.

5. Conclusion

In this paper we seek to establish whether or not the favorite-longshot bias documented in studies of the U.S., Great Britain, and some other countries also exists in German harness racing.

Using a large-scale data set of approximately 36,000 races with more than 300,000 horses, we find this bias to exist in Germany. Concentrating on win bets, we do not find evidence for Gluck's Second Law, neither are we able to detect other sources of variation in the occurrence of the FLB. Although earlier papers have concentrated on simple win bets, we document the FLB for both show bets and combined bets. To the best of our knowledge, our paper is the first that documents the FLB for the combined bets. Our findings are consistent with the assumption that bettors with a positive preference for risk prevail in all markets analyzed here.

An interesting field of future research would be to test for differences across types of bets. As pointed out in Section 4, we did not find the FLB for the first ten ranks of trifectas, but did find it for all of the other bets (see also *Figure 2* in the Appendix). This finding is somewhat surprising, given the nearly monotone decline in returns for the other types of bets. So far, we have no clear explanation for this result. But, as a track manager suggested, the characteristics of the typical trifecta player may very well differ from the other types of bettors. The track manager described the trifecta player in terms of being better informed, more devoted to betting, and playing for higher stakes. This description supports the assumption of a heterogeneous population of bettors, an assumption that has become more prominent in recent research (e.g., Coleman (2004)). We feel that it would be worthwhile to follow this line of reasoning.

Appendix

Table 6a: Returns (%) of odds categories across tracks

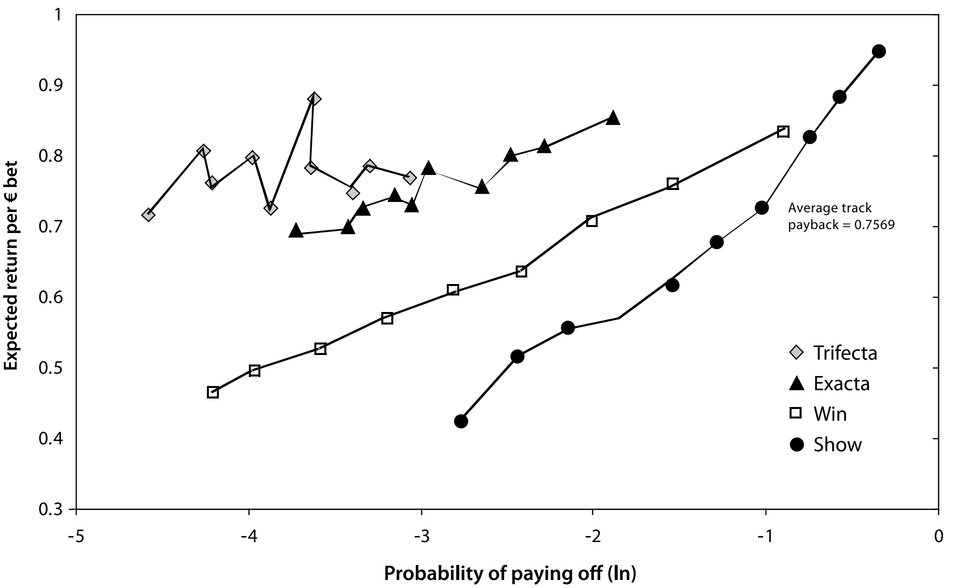
Odds rank	# Track 1	2	3	4	5	6	7
1	-23.87	-17.67	-16.68	-21.61	-15.38	-16.59	-13.10
2	-25.34	-27.98	-21.95	-24.19	-18.68	-24.88	-24.26
3	-26.87	-31.98	-28.37	-22.25	-30.86	-26.65	-30.36
4	-39.91	-43.01	-31.39	-33.84	-34.89	-41.75	-35.10
5	-42.18	-49.53	-25.53	-23.45	-43.16	-44.66	-36.28
6	-45.48	-54.96	-32.31	-36.57	-25.09	-39.86	-50.07
7	-46.24	-53.77	-32.57	-32.11	-38.37	-55.88	-48.40
8	-61.84	-67.68	-48.87	-19.48	-53.27	-57.02	-53.67
9	-53.44	-72.22	-68.46	75.67 [b]	-56.78	-58.25	-84.20
10	-45.53	-72.35	-28.10	-30.54	-59.02	-78.36	-26.34
Take[a]	27.78%	27.62%	22.76%	23.98%	22.19%	25.01%	22.06%

Table 6b: Returns (%) of odds categories across tracks (cont.)

Odds rank	# Track 8	9	10	11	12	13
1	-15.73	-14.58	-15.69	-12.12	-10.92	-23.22
2	-17.23	-21.24	-19.11	-40.59	-30.16	-30.45
3	-25.88	-24.69	-26.98	-51.76	-32.08	-43.99
4	-30.37	-37.51	-25.88	-40.24	-33.11	-50.37
5	-31.90	-39.24	-40.34	-23.53	-38.00	-59.48
6	-41.88	-60.71	-54.49	-89.65	-52.52	-54.68
7	-62.00	-24.85	-58.34	-52.31	-48.94	-48.94
8	-48.23	33.51 [d]	9.10 [f]	-100.00	-64.12	-49.06
9	-48.30	14.01 [e]	-11.45	-100.00	-67.42	-83.66
10	184.17 [c]	-100.00	-87.04	-100.00	-82.34	-100.00
Take[a]	21.27%	22.87%	21.45%	32.75%	22.77%	33.26%

Notes
[a] Average take of the respective track as implied by the odds of the win bets averaged over all races at that track.
[b] Based on 15 winners in that category
[c] Based on 8 winners in that category
[d] Based on 4 winners in that category
[e] Based on 3 winners in that category
[f] Based on 11 winners in that category

Figure 2: Expected returns as a function of winning probabilities (natural logarithm)



References

Ali, Mukhtar M. (1977), Probability and utility estimates for racetrack bettors, *Journal of Political Economy* 85, 803-815.

Asch, Peter, Burton G. Malkiel, and Richard E. Quandt (1982), Racetrack Betting and Informed Behaviour, *Journal of Financial Economics* 10, 187-194.

Bruce, Alistair C. and Johnnie E.V. Johnson (2000), Investigating the Roots of the Favorite-Longshot Bias: An analysis of decision-making by supply- and demand-side agents in parallel betting markets, *Journal of Behavioral Decision Making* 13, 413-430.

Busche, Kelly (1994), Efficient Market Results in an Asian Setting, in Hausch, Donald B., Victor S.Y. Lo, and William T. Ziemba (eds.), *Efficiency of Racetrack Betting Markets*, New York: Academic Press, 615-616.

Busche, Kelly and Cristopher D. Hall (1988), An exception to the risk preference anomaly, *Journal of Business* 61, 337-346.

Coleman, Les (2004), New light on the longshot bias, *Applied Economics* 36, 315-326.

Dowie, Jack A. (1976), On the Efficiency and Equity of Betting Markets, *Economica* 43, 139-150.

Friedman, Milton and Leonhard Savage (1948), The Utility Analysis of Choices Involving Risk, *Journal of Political Economy* 56, 279-304.

Griffith, Richard M. (1949), Odds Adjustments by American Horse Race Bettors, *American Journal of Psychology* 62, 290-294.

Hausch, Donald B. and William T. Ziemba, (1990), Arbitrage Strategies for Cross-Track Betting on Major Horse Races, *Journal of Business* 63, 61-78.

Hausch, Donald B. and William T. Ziemba (1995), Efficiency in Sports and Lottery Markets, in Robert A. Jarrow Vojislav Maksimovic, and William T. Ziemba (eds.), *Finance – Handbooks in Operations Research and Management Science* 9, Amsterdam: North Holland, 545-580.

Henery, Robert J. (1985), On the average Probability of losing Bets on Horses with given Starting Price Odds, *Journal of the Royal Statistical Society* 148, 342-349.

Johnson, Johnnie E. and Alistair C. Bruce (1993), Gluck's Second Law: An empirical investigation of horserace betting in early and late races, *Psychological Reports* 72, 1251-1258.

Jullien, Bruno and Bernard Salanié (2000), Estimating Preferences under Risk: The Case of Racetrack Bettors, *Journal of Political Economy* 108, 503-530.

Kopelman, Richard E. and Betsy L. Minkin, (1991), Toward a psychology of parimutuel behavior: test of Gluck's Law's, *Psychological Reports* 68, 701-702.

Law, David and David A. Peel (2002), Insider Trading, Herding Behaviour and Market Plungers in the British Horse-race Betting Market, *Economica* 69, 327-338.

Markowitz, Harry (1952), The Utility of Wealth, *Journal of Political Economy* 56, 151-158.

McGlothlin, William H. (1956), Stability of Choices among Uncertain Alternatives, *American Journal of Psychology* 69, 604-616.

Quandt, Richard E. (1986), Betting and Equilibrium, *Quarterly Journal of Economics* 101, 201-207.

Sauer, Raymond D. (1998), The economics of wagering markets, *Journal of Economic Literature* 36, 2021-2064.

Shin, Hyun Song (1991), Optimal betting odds against insider traders, *Economic Journal* 101, 1179-1185.

Shin, Hyun Song (1992), Prices of state contingent claims with insider traders, and the favourite-longshot bias, *Economic Journal* 102, 426-435.

Snyder, Wayne W. (1978), Horse Racing: Testing the Efficient Markets Model, *Journal of Finance* 33, 1109-1118.

Sobel, Russel S. and Travis Raines (2003), An examination of the empirical derivatives of the favourite-longshot bias in racetrack betting, *Applied Economics* 35, 371-385.

Swidler, Steve and Ron Shaw (1995), Racetrack Wagering and the "Uninformed" Bettor: A Study of Market Efficiency, *Quarterly Review of Economics and Finance* 35, 305-314.

Thaler, Richard H. (1985), Mental accounting and consumer choice, *Marketing Science* 4, 199-214.

Thaler, Richard H. and Eric J. Johnson (1990), Gambling with the house money and trying to break even: the effects of prior outcomes on risky choice, *Management Science* 36, 643-660.

Thaler, Richard H. and William T. Ziemba (1988), Parimutuel Betting Markets: Racetracks and Lotteries, *Journal of Economic Perspectives* 2, 161-174.

Tuckwell, R.H. (1983), The thoroughbred gambling market: efficiency, equity and related issues, *Australian Economic Papers*, June, 106-118.

Weitzman, Martin (1965), Utility Analysis and Group Behavior: An Empirical Study, *Journal of Political Economy* 73, 18-26.

Williams, Leighton Vaughan and David Paton (1997), Why is there a favourite-longshot bias in British racetrack betting markets?, *Economic Journal* 107, 150-158.