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MARKET EFFICIENCY IN FINNISH HARNESS HORSE RACING*

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This paper analyzes the efficiency of betting markets in harness horse racing during the transition from on-track betting to Internet gambling. In order to test the market efficiency hypotheses, an alternative testing approach to other grouping methods is introduced. The betting market efficiency is tested by using a database accumulated from the Finnish harness horse racing. The results imply that the markets are weakly efficient but characterised by the favourite-longshot bias. However, convincing evidence for other gambling market anomalies such as the end of the day effect or the gambler's fallacy is not found.

1. Introduction

In this paper, we test the efficiency of gambling markets in Finland by searching for inefficiencies in horse race betting. The well-known inefficiencies, reported in the previous literature, are the favourite-longshot bias and the end of day effect (e.g., Ali 1977, and Asch, Malkiel and Quandt 1982). We also test the gambler's fallacy assumption, usually reported in lotteries and Casino games (Clotfelter and Cook 1993, and Croson and Sundali 2005). Although most horse racing studies are based on on-track betting information, our data also contains information that coincides with the transition from on-track gambling to Internet (off-track) betting.[1] It is possible that Internet gambling affects information efficiency in gambling markets because it provides easier access to casual gambling. In order to test the market efficiency hypotheses, we introduce a testing procedure which is based on the actual winning odds rather than commonly used probability estimates.

The paper is organized as follows. In section 2, we discuss definitions of market efficiency, and well-known inefficiencies. Next, we present the methods used to test betting market efficien-

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[1] *In fact, Internet betting in horse races has increased sharply from the early 2000s. For instance, during the years 2004 and 2005, Internet gambling increased over 46% (Yearbook of Finnish Gambling 2009).*

cy. In Section 4, we introduce our testing procedure. Section 5 describes our dataset. The empirical results are presented in Section 6. The last section concludes the paper.

2. Market efficiency in betting markets

2.1. *Pari-mutuel betting and market efficiency*

In a pari-mutuel betting system (or totalizator), gamblers' winning bets share the prize pool from all bets. Thus, under the assumption of a risk-neutral representative bettor the pool shares represent the subjective probabilities for every possible outcome, and these probabilities determine the odds (payoffs) for the gambler. The operator takes a share of the pool to cover the costs, taxes and profits. This is the so-called *take-out rate*, and it decreases the odds. Therefore, the established pari-mutuel system is affected only by the demand side, and it is risk-free for the operator. In essence, bettors gamble against each other.

As the odds are inverse winning probabilities, adjusted by the take-out rate, the probabilities reflect market information. Odds in the pari-mutuel system directly reflect gamblers' subjective probabilities. If all available information is used efficiently, this 'market price' will be close to the true odds, i.e., the market is expected to operate efficiently. Now, as we have historical information concerning the past race outcomes and the odds related to particular horses, we can test ex-post how accurate these market estimates are. In other words, this test shows how efficient or unbiased the horse race betting markets are.

There are several definitions of market efficiency. We follow the definitions of Thaler and Ziemba (1988):

1. *Weak market efficiency (ME1)*: Do some systematic bets have positive expected value?
2. *Strong market efficiency (ME2)*: Does every bet have the same expected value?

The first condition (ME1) means that no bet should have a positive expected value. The second condition (ME2) says that all bets should have expected values equal to the take-out rate.

2.2. *Well-known inefficiencies*

The most documented inefficiency in gambling markets is the *favourite-longshot bias* (FLB), where favourites are underbet while longshots are overbet.[2] As a result, the gamblers who bet systematically on the favourites do not lose as much as the gamblers who bet on the longshots (see e.g., Weizman 1965; Ali 1977; Kanto, Rosenqvist and Suvas 1992[3]; Golek and Tamarkin 1998; and Snowberg and Wolfers 2010). Two main theoretical explanations for FLB are that bettors have (1) a risk-loving utility function, and/or (2) a biased view of probabilities. For a survey of explanations of FLB, see; for instance, Thaler and Ziemba (1988), Sauer (1998), and Jullien and Salanié (2008).

A less documented inefficiency is *the end of the day effect* (EDE). In EDE, gamblers' behaviour becomes more aggressive in the final races of the day. This means that FLB is especially strong in the last races (see McGlothlin 1956, Ali 1977, and Asch et al. 1982). This is consistent with the assumption that bettors are loss-averse, and risk-loving, below the reference point, as in Prospect Theory (Kahneman and Tversky 1979). Most bettors have lost during the day, and the final races give an opportunity to win back the lost money. However, Snowberg and Wolfers (2010) find no evidence of EDE in their large data set.

Another inefficiency which has been detected in experiments and real life gambling markets is the gambler's fallacy (GF). GF is an incorrect belief concerning the probability of an independent event when the event has recently occurred. For instance, Clotfelter and Cook (1993) note that, in lottery gambling, gamblers rarely chose the number which occurred in the previous round. Croson and Sundali (2005) conducted field experiments in casinos (roulette) and

[2] *The bias was first noted by Griffith (1949).*

[3] *Note that Kanto et al. (1992) have previously studied Finnish horse race betting. However, they used a double betting data set instead of a win betting data to analyze FLB.*

found evidence that supports the assumption of GF. In the case of pari-mutuel horse race betting, the GF hypothesis can be stated as follows: bettors underestimate the probability of the favourite horse if it has won the previous race. Metzger (1985) finds some support for the gambler's fallacy: betting on the favourites decreases with the length of their run of success.

3. Methods of testing efficiency

3.1. Basic definitions and notations

The following definitions are employed. The odds (decimal), O_i, are derived from the gamblers' bets in each race. Thus, for horse can be written as

$$(1) \qquad O_i = \left(\frac{b_i}{\sum_{i=1}^{n} b_i} \right)^{-1} (1 - \tau_0),$$

where b_i denotes all bets for horse i, $\sum_{i=1}^{n} b_i$ is the sum of bets for all n horses, and τ_0 is the take-out rate. The average, or representative risk-neutral probability for the horse i is

$$\rho_i = \left(\frac{1}{O_i} \right) (1 - \tau_0).$$

3.2. Different methods of estimating efficiency

Grouping by favourite positions. First, horses are ranked into groups *(h)* by the favourite position in every race such that the favourite horse is group one, and so on. Second, suppose that π_h is an objective winning probability for a horse which was included in group h. The objective probability for group h is calculated by dividing all winning cases of group h with all races. Furthermore, subjective probabilities can be calculated by taking the average of subjective probabilities in each group h. The test for gambling biases is $H_0: \rho_h - \pi_h = 0$ for all $h = 1, ..., H$, i.e., are subjective and objective probabilities equal in different groups.[4]

Grouping by the pari-mutuel odds.[5] The basic structure of the method is close to the favourite position analysis, however, more information on the odds is used. We divide the betting data (horses) into 'nearby' even-sized groups by the odds levels (e.g., 1.0–2.0), and the objective probability is the proportion of the horses that won their races in an odds group. The benefit of this method is that the variation of the odds is reduced. However, there are many traditions in classifying horses, e.g., even-sized odds category, even-number of horses in each odds category. For further discussion of the classification problem, see Ali (1977), Busche and Hall (1988), and Woodland and Woodland (1994).[6]

We think that while these techniques are very simple, their use is also problematic. They all assume that the favourite positions in all races are Bernoulli variables. That is, races are considered independent binomial trials, which have their own statistical properties for the objective probability estimates. There are high variations in circumstances (e.g., jockey, contenders, weather etc.) that influence the race. Therefore, the nature of probability estimation for a horse is somewhat different from, for instance, estimating the objective probability of heads in an experimental coin toss trial. The violation of the random experiment assumption may bias the objective probability estimate and its standard error. Despite this, we will show that grouping methods are still appropriate when using an alternative approach.

4. Alternative approach to examine efficiency

The previous aggregation methods were based on probability estimates. Our approach instead

[4] *This method was first used by Ali (1977).*

[5] *This is the approach first used by Griffith (1949), and followed by, for instance, Snyder (1978).*

[6] *Vaughan Williams and Paton (1998) responded to the critique of the grouping methods by regressing the net return on the odds. In this analysis, the actual return for a unit stake on each horse is calculated (see also, e.g., Gandar, Zuber and Johnson 2001).*

focuses on the returns of bettors. We maintain the rank position (favourite) method suggested by Ali (1977) but instead of estimating objective probabilities, we use information on win odds which are actually observed and affected by bettors.

To understand the procedure, consider the win odds average, $\overline{WO}_h$, in every rank category h. Rank categories are based on favourite positions as suggested by Ali (1977). More precisely, the win odds are a subset of odds distribution on each rank such that the observed win odds are the odds that have actually won the race. Thus, we have a vector of win odds for each rank, which have their own means and standard errors. Consequently, in terms of market efficiency, the rate of net return on a one euro bet for rank h can be written as

(2) $$E(R_h) = \pi_h \overline{WO}_h - 1,$$

where π_h is an objective winning probability which for rank h is calculated by dividing all winning cases of group h with all races. To see that Equation (2) gives the actual rate of net return, see Appendix.[7] The objective probability is constant by nature because bettors cannot influence it and, therefore the probability does not affect the actual win odds. Contrary to this, the actual win odds are directly affected by bettors (the pari-mutual rule).

In practice, we directly calculate the rate of return in each rank category by using information about win odds, and we assume that the objective probability is constant. Therefore, we do not need to separately estimate the probability of winning. This means that we consider only one source of variance, which is based on the observed win odds of each category. This variation is driven by bettors' expectations.

This approach leads to a question: are the expected rates of net return in line with the definitions of market efficiency? It depends on which definition is used. First, if the expected rate of net returns is smaller than zero, the condition ME1 is established ($E(R) < 0$). Second, the condition ME2 implies that all bets should have an expected rate of net return equal to $-\tau_0$, and this should be valid in every rank category. That is, $E(R_1) = E(R_2) = ... = E(R_H) = -\tau_0$.

Therefore, we test whether the efficient rate of net return (the take-out rate) is equal to the actual rates of net return in each rank category. We do so by using information on the actual win odds' means and standard errors. In practice, we calculate confidence intervals on the actual rate of returns which are based on the actual win odds' information: the lower interval is $E(R_h^{low}) = \pi_h WO_h^{low} - 1$ and the upper interval is $E(R_h^{high}) = \pi_h WO_h^{high} - 1$, respectively. Finally, if the take-out rate is between confidence intervals, that is, $E(R_h^{low}) < -\tau_0 < E(R_h^{high})$, the condition ME2 is established.

Our approach has one main advantage compared to previous grouping methods. It does not assume that every race is an identical Bernoulli experiment. Instead, it takes into account only information in observed win odds. This may affect the statistical interference because the confidence intervals are calculated with a different method than in previous grouping approaches. On the other hand, the potential disadvantage is that we may lose information because we do not take into account the odds of losing horses in each category.

5. Data

Our data set is from the Suomen Hippos (the Finnish Trotting and Breeding Association) website, and it was obtained with a computer programme. In Finland, Suomen Hippos has a legal monopoly to organize pari-mutuel betting in harness horse racing. Off-track betting is offered and betting on the Internet is possible. In 2004, the share of Internet gaming was about 13% of total bets and it increased to 35% of total bets in 2007. Overall, on-track betting contributed only13% of Hippos's turnover of 198.1 million euros in 2006. Our data applies to gambling after off-track betting, and especially Internet gambling, became widely popular. Hippos's take-out rate is about 21% on average, as calculated from the data set.

[7] *Note that the expected rate of net return calculated by odds information can lead to biased results if win odds distribution has a different mean than the odds distribution. In fact, this is the case if FLB is present.*

Table 1. Win odds, actual rate of net returns, and confidence intervals

Rank	Win odds	Lower 99% conf. interval	Upper 99% conf. interval	Actual RR	RR lower 99% conf. interval	RR upper 99% conf. interval
1	2.41	2.38	2.43	–0.151*	–0.159	–0.143
2	4.52	4.47	4.57	–0.203	–0.211	–0.194
3	6.56	6.48	6.64	–0.202	–0.212	–0.192
4	8.82	8.68	8.96	–0.214	–0.226	–0.202
5	11.17	10.97	11.37	–0.246*	–0.259	–0.232
6	13.90	13.60	14.20	–0.285*	–0.301	–0.270
7	17.35	16.89	17.81	–0.346*	–0.363	–0.329
8	21.69	20.96	22.41	–0.292*	–0.316	–0.268
9	26.68	25.64	27.73	–0.332*	–0.358	–0.306
10	32.71	31.00	34.42	–0.431*	–0.461	–0.401
11	41.35	38.84	43.85	–0.376*	–0.413	–0.338
12	46.91	43.26	50.56	–0.449*	–0.492	–0.407
13	50.44	45.60	55.28	–0.421*	–0.476	–0.365
14	62.49	55.95	69.04	–0.440*	–0.499	–0.381
15	74.98	66.51	83.45	–0.445*	–0.507	–0.382
16	79.55	66.46	92.65	–0.541*	–0.617	–0.466

Note: The confidence intervals for the rate of net return are calculated by using the win odds intervals as mentioned in Section 4.

The dataset includes win bet information and consists of horse races run in Finland from January 3, 2002 to July 19, 2007. The data include 27,595 harness races with a total of 345,308 runners. Thus, our data contains odds for the horses in every race and information on the exact finishing order of horses. We dropped races that had fewer than 10 horses to balance the data. Moreover, we also dropped races if the take-out rate was an obvious outlier (i.e., too high or low). The data does not contain any information about the characteristics of an individual bettor or the average amounts of the bets per race per person. Therefore we maintain the representative bettor assumption.

6. Results

Favourite-Longshot Bias. We first examine whether FLB exists in Finnish data using our alternative procedure. The basic information about estimates and confidence intervals is shown in Table 1.[8] First, the theoretical rate of net return, or take-out rate is –0.21, and it is within the confidence interval only for groups two, three, and four. Second, favourites are underbet while longshots are overbet. Thus, the results confirm the FLB and are in line with the previous studies. The strong efficiency condition ME2 is rejected. However, there is no opportunity to make any profits by applying results from the FLB observed in the past, which provides initial support for ME1

Figure 1 shows that confidence intervals obtained with our alternative procedure differ from Ali's (1977) favourite position method in which the confidence intervals are based on objective probabilities.[9] In Figure 1, the outer bands of the rate of net returns are computed with the favourite position method whereas the inner bands are calculated with the alternative procedure. Consequently, the intervals calculated by using the objective probabilities from the favourite position method are wider than the win odds ones. This is due to the fact that the alternative method uses information on win odds, whereas the objective probabilities in the favourite position method are estimated as an experimental coin toss binomial trial. However, it should be noted that we cannot determine which bands of the rate of net returns are correct ones. Therefore,

[8] *Note that the win odds increases monotonically with rank position. This is necessary for the method by assumption, and it indicates that there is not any systemic violation that prevents the use of the rank positions method.*

[9] *Note that sipport for the FLB is found regardless of the method employed. Detailed results of other metods are available from the author upon request.*

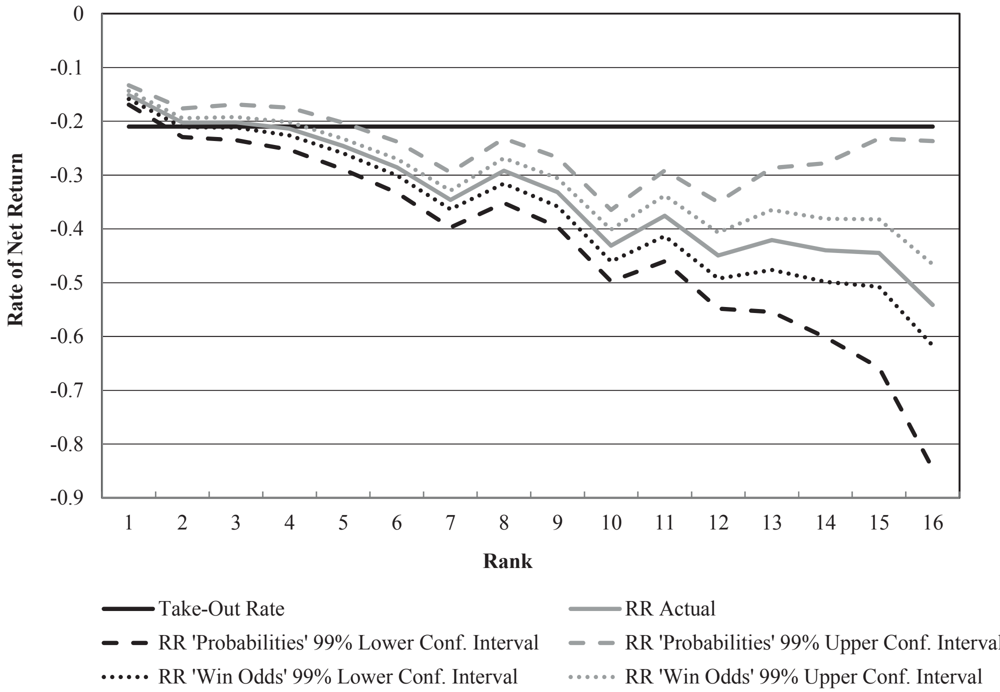

Figure 1. Confidence intervals of the rate of net returns

more theoretical research is needed about benefits and disadvantages of our procedure.

End of the Day Effect. The calculations for the end of the day effect are the same as above but only observations from the last race and from the last two races of the day were used. Compared to all races, the rate of net return should be higher for favourites and lower for long shots if the EDE is present. Table 2 displays the results. Confidence intervals for the rate of net return are calculated with the win odds intervals in subsamples.

In the last race of the day, the rate of net return is higher for the long shots (e.g., 6th and 7th rank) compared to the rate of net return of all the races. Thus, the returns of the last races are dispersed and there is no clear tendency. This might be due to the small number of observations and the heterogeneity of data. For this reason, let us consider the last two races. Again, the results indicate that the rates of net return are not higher for favourites than on average. Therefore, we conclude that there is no meaningful end of the day effect in the Finnish horse race betting markets, and we claim that the Prospect Theory's assumptions of loss-averse or risk-loving behaviour 'below the reference point' is not evident in our data. One possible explanation for the missing EDE could be the influence of off-track betting.[10] In particular, although Hippos offers betting in only one track per day, off-track bettors can continue gambling in other gambling choices.

Gambler's Fallacy. We tested for the influence of the favourite winner of the previous races in betting behaviour. Table 3 shows the main results.

The results are interesting. The favourite winner of the previous races increases the rate of net returns for the favourite bet. Recall that the rate of net return in all races was −0.151. This provides some support for the gambler's fallacy assumption. On the other hand, the favourite winner of two and three previous races decreases the returns for the favourite bet in comparison with the favourite winner of first race. Thus, this rejects the gambler's fallacy assumption that the rate of net returns systematically increases when favourites win consecutively.

[10] *I thank the anonymous referee who suggested this explanation.*

Table 2. The rate of net returns and confidence intervals for the day's last and last two races

Rank	RR Last Race	RR lower 99% conf. interval	RR upper 99% conf. interval	RR all races	RR two last race	RR lower 99% conf. interval	RR upper 99% conf. interval
1	–0.142	–0.164	–0.120	–0.151	–0.166	–0.182	–0.150
2	–0.251(L)	–0.275	–0.227	–0.203	–0.229(L)	–0.246	–0.211
3	–0.248(L)	–0.275	–0.222	–0.202	–0.247(L)	–0.266	–0.228
4	–0.220	–0.253	–0.186	–0.214	–0.194	–0.220	–0.167
5	–0.238	–0.276	–0.201	–0.246	–0.232	–0.259	–0.206
6	–0.194(H)	–0.236	–0.152	–0.285	–0.227(H)	–0.260	–0.193
7	–0.293(H)	–0.337	–0.249	–0.346	–0.287(H)	–0.321	–0.253
8	–0.188(H)	–0.259	–0.118	–0.292	–0.166(H)	–0.217	–0.115
9	–0.109(H)	–0.209	–0.008	–0.332	–0.246(H)	–0.307	–0.185
10	–0.474	–0.550	–0.398	–0.431	–0.380	–0.437	–0.323

Notes: (1) H (L) means that the rate of net returns for the last race is higher (lower) than on average. (2) The total number of last races was 3149 and the total number of the two last races was 6290.

Table 3. The rate of net returns for the favourite when the previous race won by the favourite

Win Horse	No. races	Win odds	RR	RR lower 99% conf. interval	RR upper 99% conf. interval	RR all races
Previous favourite	7519	2.40	–0.133(H)	–0.148	–0.118	–0.151
Two previous favourites	2052	2.35	–0.141	–0.169	–0.112	–0.151
Three previous favourites	560	2.40	–0.141	–0.197	–0.085	–0.151

Note: H (L) means that the rate of net returns for the last race is higher (lower) than on average.

7. Conclusions

We tested the efficiency of gambling markets in Finland using data from harness horse races during the period when internet gambling sharply increased. In order to test market efficiency hypotheses, we used a testing procedure which was based on the actual winning odds rather than commonly used probability estimates. Consequently, confidence intervals, which are used to test hypotheses, differ from the previous approaches.

Our results imply that markets are weakly efficient but characterised by the favourite-longshot bias. That is, there is no opportunity to make any profits using past data. We also conclude that the transition from on-track betting to off-track, and especially to the Internet, does not remove the FLB. However, meaningful evidence for other 'anomalies', namely the end of the day effect and the gambler's fallacy, was not found. This is a minor drawback for the Prospect Theory's assumption of loss-averse behaviour. In fact, consistent with the results in Snowberg and Wolfers (2010), if there was evidence of loss aversion in earlier data sets, it no longer appears in the more recent data. Thus, in our data, it is possible that this element has disappeared during the transition from on-track betting to off-track betting because gambling choices have no clear end point. Finally, the alternative procedure did not make any remarkable difference to the inferences made under standard methods because FLB is an evident phenomenon regardless of the testing method. However, the presented approach might be useful for smaller data sets or other areas of research.

The weakness of our testing approach is that we do not have information on individual betting behaviour (e.g., amounts of bets). Thus, we do not know whether observed biases are based on individual betting behaviour. Despite these shortcomings, aggregate level data gives us some interesting information. For instance, from the bookmaker's point of view, the information on the gambler's behaviour or on market inefficiencies can be used, e.g., in planning new gamble menus or setting up the rules of the gambles.

Appendix

The rate of net return is

(A1) $$E(R_h) = \frac{Wins_h - Bets_h}{Bets_h},$$

where $Wins_h$ measures the monetary value of the sum of winning bets on rank *h* and $Bets_h$ measures the monetary value of the sum of all bets on rank *h*.

Assume a one euro bet for each rank *h* in *N* rounds. Then Eq. (1) can be written as

(A2) $$E(R_h) = \frac{\sum_{i=1}^{n} w_{hi} - N_h}{N_h},$$

where N_h is the number of races, n_h the number of wins, and w_{hi} is the monetary value of a winning bet *h*. Furthermore, multiply the number of wins by n_h / n_h, i.e.,

(A3) $$E(R_h) = \frac{\frac{n_h \sum_{i=1}^{n} w_{hi}}{n_h} - N_h}{N_h} = \frac{n_h}{N_h} \frac{\sum_{i=1}^{n} w_{hi}}{n_h} - 1,$$

where $\frac{n_h}{N_h}$ is an objective winning probability π_h for rank *h* by definition, and $\frac{\sum_{i=1}^{n} w_{hi}}{n_h}$ is the average of win odds $\overline{WO}_h$ for rank *h*. Therefore, Equation (A2) gives exactly the same result as $E(R_h) = \pi_h \overline{WO}_h - 1$ presented in Section 4.

References

Ali, M.M. (1977). "Probability and Utility Estimates for Racetrack Bettors." *Journal of Political Economy* 85, 803–815.

Asch, P., B. Malkiel, and R.E. Quandt (1982). "Racetrack Betting and Informed Behavior." *Journal of Financial Economics* 10, 187–194.

Busche, K., and C.D. Hall (1988). "An Exception to the Risk Preference Anomaly." *Journal of Business* 61, 337–346.

Clotfelter, C.T., and P.J. Cook (1993). "The "Gambler's Fallacy" in Lottery Play." *Management Science* 39, 1521–1525.

Croson, R., and J. Sundali (2005). "The Gambler's Fallacy and Hot Hand: Empirical Data from Casinos." *The Journal of Risk and Uncertainty* 30, 195 – 209.

Gandar, J.M., R.A. Zuber, and R.S. Johnson (2001). "Searching for the Favourite-Longshot Bias Down Under: an Examination of the New Zealand Pari-Mutuel Betting Market." *Applied Economics* 33, 1621–1629.

Goleck, J., and M. Tamarkin (1998). "Bettors Love Skewness, Not Risk, at the Horse Track." *Journal of Political Economy* 106, 205–225.

Griffith, R.M. (1949). "Odds Adjustment by American Horse-Race Bettors." *American Journal of Psychology* 62, 290–294.

Kahneman, D, and A. Tversky (1979). "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47, 263–291.

Kanto, A.J., G. Rosenqvist, and A. Suvas (1992). "On Utility Function Estimation of Racetrack Bettors." *Journal of Economic Psychology* 13, 491–498.

Metzger, M. A. (1985). "Biases in Betting: An Application of Laboratory Findings." In *Efficiency of Racetrack Betting Markets* 2008 Edition, 31–36. Eds. D.B. Hausch, V.S.Y. Lo, and W.T. Ziemba. Singapore: World Scientific Publishing Co. Pte. Ltd.

McGlothlin, W.H. (1956). "Stability of choices among uncertain alternatives." *American Journal of Psychology* 69, 604–615.

Sauer, R.D. (1998). "The Economics of Wagering Markets." *Journal of Economic Literature* 36, 2021–2064.

Snowberg, E., and J. Wolfers (2010). "Explaining the Favorite-Longshot Bias: Is it Risk-Love or Misperceptions?" *Journal of Political Economy* 118, 723–746.

Jullien, B., and B. Salanié (2008). "Empirical Evidence on the Preferences of Racetrack Bettors." In *Handbook of Sports and Lottery Markets*, 27–49. Eds. D.B. Hausch, and W.T. Ziemba. Amsterdam: North-Holland.

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

Thaler, R.H., and W.T. Ziemba (1988). "Anomalies – Parimutuel Betting Markets, Racetracks and Lotteries." *Journal of Economic Perspectives* 2, 161–174.

Weiztman, M. (1965). "Utility Analysis and Group Behavior: An Empirical Study." *Journal of Political Economy* 73, 18–26.

Williams, L.V., and D. Paton (1998). "Why Are Some Favourite-Longshot Biases Positive and Other Negative?" *Applied Economics* 30, 1505–1112.

Woodland, L.M., and Woodland, B.M. (1994). "Market efficiency and the favourite-longshot bias: The baseball betting market." *Journal of Finance* 49, 269–279.

Yearbook of Finnish Gambling 2009 (2010). The National Institute for Health and Welfare, Helsinki (in Finnish).