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The favorite-longshot bias and the impact of experience

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Abstract With a unique data set from New Zealand which allows us to assign each bet to individual bettors, we analyze the impact of experience on behavior and success in non-parimutuel (fixed odds) sports betting markets. We find that experienced bettors bet more on favorites than inexperienced bettors do. Average returns, which we use as success measure, increase with experience even after controlling for odds. This means that the higher return of experienced bettors cannot only be attributed to betting more on favorites. To get a more detailed picture, we divide the data set into ten equally large subgroups, sorted by experience. We find that odds decrease from subgroup to subgroup, while success consistently increases. This shows that the positive impact of experience is not mainly driven by professional bettors.

Keywords Behavioral economics · Behavioral finance · Favorite-longshot bias · Betting markets · Learning in financial markets

JEL classification D14 · D81 · G11

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1 Introduction

In this paper, we analyze the impact of experience on behavior and success in sports betting markets. Our data set contains all 5,136,660 non-parimutuel bets placed at the monopolistic New Zealand betting agency, the New Zealand Racing Board (NZRB) between August 2006 and April 2009. In the non-parimutuel betting mode, bettors get the odds they bet on; irrespectively of the development of these odds over time.

As the data set allows us to assign each bet to a single bettor, we can measure the experience of bettors. We approximate experience by the total amount invested and by the number of bets placed up to each bet considered. We find that experience has two positive effects: first, the odds of bets placed are decreasing in experience. As our data set reveals a strong FLB, this is a first reason why experienced bettors are more successful. The FLB expresses the largely robust phenomenon that average returns on favorites are higher than those on longshots (Ottaviani and Soerensen 2008 for an overview on different explanations of the phenomenon). Second, experience leads to higher success, defined as the average of returns, even after controlling for odds. Thus, the positive effect of experience cannot exclusively be explained by the lower susceptibility to the overweighting of small probabilities. To the best of our knowledge, such an analysis has never been carried out before as the data sets utilized so far did not allow tracking the wagering record of individual bettors over time.

Recent empirical literature has demonstrated that a plausible explanation for the FLB might be seen in the interplay of casual bettors and (semi-)professionals who benefit from the fact that favorites are underbet (Gandhi and Serrano-Padial 2012). To investigate if the impact of experience on odds and success is exclusively driven by large investors, we divide the population into ten equally large subgroups, sorted by experience. This leads to a surprisingly consistent picture, showing that odds are decreasing from subgroup to subgroup. Accordingly, success is constantly increasing between subgroups. We hence conclude that the positive effect of experience cannot exclusively be attributed to large investors but rather holds for any degree of experience. This indicates that there are strong learning effects with respect to the overweighting of small probabilities.

Another point we are interested in is the relationship between odds and bet sizes. Due to a lack of data, the overwhelming majority of the literature estimating preferences from odds and outcomes has assumed that bet sizes are independent of odds (e.g., the seminal paper by Jullien and Salanié 2000). This assumption, however, is implausible as few bettors are willing to invest high amounts on outcomes with a success probability of 5 %, for instance. For our data set, we indeed find that bet sizes are, for all levels of experience, consistently decreasing in odds. Although this result is perfectly intuitive, it seems to be important as it implies that all models estimating preferences from the data by assuming equal bet sizes are likely to be biased (Kopriva 2009).

As a side step of this analysis, we investigate the relationship between odds and the variance of returns. We are interested in this as it seems reasonable to view the variance as a (though clearly imperfect) proxy for the risk of bets. For purely arithmetical reasons, the variance of the return for a bet on longshots is higher when bet sizes are independent of odds. If there are just two possible outcomes and bet sizes on favorites and longshots are proportional to win probabilities (that is, inversely proportional to fair odds), then the variance of return is the same for both bets. As bet sizes decrease in odds, the relation between the variance and odds per bet is an open empirical question. When we do not control for experience, we find that the variance per bet is, on average, decreasing in odds. Controlling for experience, however, shows that this result is driven by large investors who bet high amounts on favorites. This finding is reinforced by our separation into subgroups: the variance is significantly increasing in odds for the first nine subgroups, but significantly decreasing in odds for the subgroup with the highest experience.

We now relate to the literature. Most fundamentally, our data set confirms the FLB. When we define favorites as the bottom fifty percent lowest odds placed and longshots as the other fifty percent, losses with longshots are on average almost 90 % higher than those with favorites. The FLB has proven to be largely robust with respect to sports, countries and the estimation method (Ottaviani and Soerensen 2008; Forrest and McHale 2007; Winter and Kukuk 2006), and only a few papers find a reversed FLB (Woodland and Woodland 1994, Sobel and Travis Raines 2003). The main focus of the existing empirical literature on wagering is to investigate the explanatory power of different theories on behavior under risk for the FLB. Most of the literature is based on the representative bettor approach which assumes that risk preferences of all bettors are identical, and that bet sizes are independent of odds. Based on these assumptions, most of the literature has found that prospect theory fits the data much better than expected utility theory (Jullien and Salanié 2000, 2008; Ottaviani and Soerensen 2008). Snowberg and Wolfers (2010) provide additional evidence that the FLB can better be explained by an overweighting of small probabilities in the framework of prospect theory compared to risk-seeking behavior based on the expected utility theory.

We are aware of three other papers accounting for different bet sizes. While Bradley (2003) provides a theoretical model based on prospect theory, Kopriva (2009) and Andrikogiannopoulou (2010) seem to be the only other empirical papers having data on bet sizes. Kopriva's data set is from betfair.com which differs significantly from the usual betting platforms. On betfair.com, bettors can post limit orders where they stipulate at which odds they would be willing to trade. As on share markets, it then depends on the clearing price whether bets are put through or not. Kopriva shows that the estimation results for risk preferences change considerably when controlling for bet sizes. Our paper simply demonstrates that the negative correlation between odds and bet sizes is an important empirical fact which holds for all levels of experience. Andrikogiannopoulou (2010) has randomly picked data on hundred bettors from a large betting company which she uses to estimate individual risk preferences.

A vastly growing literature emphasizes the importance to take the heterogeneity of bettors into account. In an early theoretical contribution, Shin (1991) explains the FLB as an equilibrium phenomenon in a non-parimutuel betting market with sophisticated and unsophisticated bettors. Hurley and McDonough (1995) explain the FLB for parimutuel betting with a dichotomy of informed and uninformed bettors who are both assumed to be risk neutral. In fact, Andrikogiannopoulou (2010) finds a large heterogeneity in the risk preferences of the hundred bettors considered in her data set. Andrikogiannopoulou and Papakonstantinou (2011) argue that the FLB is exploited by about 2 % of all bettors earning positive returns. Recently, Gandhi and Serrano-Padial (2012) challenge the predominant view on the superiority of prospect theory by emphasizing that previous results were driven by the assumption of homogenous bettors. An innovative approach is taken by Chiappori et al. (2012) who estimate the heterogeneity in risk preferences not from individual betting behavior, but from aggregated data on a large data set with different horse races. They also confirm a large heterogeneity and that expected utility theory performs rather poorly in explaining the data. Our data set reveals that the overweighting of small probabilities, which plays an important role in estimating preferences based on prospect theory, is largely connected to experience. In this sense, the heterogeneity of preferences is related to experience. Our analysis, however, does not support the view that betting behavior can be well explained by assuming just two types of bettors.

Finally, while there are no other papers with experience data, some observations in the literature are in line with our results. Gandar et al. (2001) use data for parimutuel betting in New Zealand and show that a large part of the FLB is eliminated by late bettors. As one might presume that late bets are more likely to be placed by experienced bettors, this is consistent with our finding that experienced bettors are far less prone to the FLB. Finally, Gramm, McKinney and Owens (2012) also find an FLB in their data set from the horse race market in the US, but show that the results are not pronounced enough for identifying profitable betting strategies. This corresponds to our result that, even though experienced bettors are far more successful than inexperienced bettors, their average gains are slightly negative, so that there seem to be no systematically profitable betting strategies.

The remainder of the paper is organized as follows: Sect. 2 presents the data. In Sect. 3, we explain betting behavior, and in Sect. 4, we turn to betting success. Sect. 5 concludes and points to further research.

2 Data

In close cooperation with the ‘New Zealand Racing Board’ (NZRB) which is the only licensed betting agency in New Zealand, we have compiled a data set consisting of all 5,136,660 non-parimutuel bets placed at the agency between August 2006 and April 2009. Non-parimutuel betting (fixed-odds betting) means that bettors get exactly the current quota (the odds) they bet on. If odds change over time, then different bettors get different odds, and we use the last available odds in all of our tables and regressions.

The first row in Table 1 provides descriptive statistics for all bets. Odds are relatively high with an arithmetic mean of 8.42 which is due to the fact that there are many sports with a large number of possible outcomes. Consequently, average odds are low for sports with just two outcomes such as tennis and baseball. Average losses amount to around 14.4 % which shows that the monopolistic agency NZRB

Table 1 Descriptive statistics on bets and returns

	Obs.	Odds	Bet sizes	Return (%)	Return on favorites (50 %-threshold.) (%)	Return on longshots (50 %-threshold.) (%)	Return on favorites (50 %-prob.) (%)	Return on longshots (50 %-prob.) (%)
All bets	5,136,660	8.42	50.50	−14.39	−9.78	−19.00	−6.75	−15.90
Baseball	126,920	3.64	101.62	−11.14	−9.13	−13.14	−9.37	−12.55
Basketball	235,482	4.39	86.87	−10.21	−6.33	−14.10	−5.91	−12.67
Cricket	266,476	5.89	46.51	−14.42	−7.32	−21.52	−7.22	−16.55
Football	355,400	8.05	42.02	−14.43	−8.45	−20.41	−6.50	−16.46
Golf	131,529	19.69	29.24	−18.50	−9.57	−27.44	−3.48	−20.06
Greyhounds	177,107	8.07	46.21	−15.98	−9.67	−22.29	−4.99	−17.55
Harness	325,155	9.86	49.53	−10.96	−6.34	−15.59	−5.17	−11.53
Others	221,681	6.54	57.30	−11.25	−7.47	−15.02	−8.02	−12.66
Rugby League	713,056	7.73	42.19	−17.20	−13.20	−21.19	−6.22	−19.12
Rugby union	884,109	8.03	46.93	−16.43	−10.34	−22.52	−6.41	−18.48
Tennis	173,959	4.77	92.61	−14.07	−9.17	−18.97	−9.34	−18.30
Thoroughbred	1,525,786	9.98	46.02	−13.48	−10.36	−16.60	−5.30	−14.07

Table 2 Descriptive statistics on bettors

	Number of bettors	Number of bets				Total amount invested				Return
		Average	Median	Min	Max	Average	Median	Min	Max	
Bettors	70,400	72.96	10	1	14,538	3,685	175	5	24,900,000	−22.72 %

charges high take-out-rates. Average bet sizes are slightly above 50NZ$. The exchange rate of the NZ$ to the Euro fluctuated over the observation period, but on average, 1NZ$ was about 45 Cent.

To illustrate the impact of odds on the return of bets, we next distinguish between favorites defined as the bottom fifty percent lowest odds placed and longshots defined by the other fifty percent. As shown in Table 1, the return on favorites is −9.78 % compared to −19.00 % for longshots, so that the descriptive statistics already reveals a large FLB (columns five and six). As a robustness check, we next define favorites as outcomes with a probability of winning above 50 % (columns seven and eight). This reduces the percentage of bets on favorites from 50 to 21.5 % as many sports allow for more than two possible outcomes. Consequently, average losses on favorites are now only around 6.75 %. Disaggregating by sports shows that the FLB is robust.

Recall that all averages in Table 1 are taken over bets. When taking instead averages over bettors, then each bettor enters with the same weight, and bets of infrequent bettors are hence overrepresented. Table 2 gives descriptive statistics for bettors and shows that each bettor has, on average, placed around 73 bets with a maximum of more than 14,500 bets, though. Average amounts invested were 3,685NZ$, but this high average is partly driven by some large investors. In particular, there are 386 bettors who invested more than 100,000NZ$ during the observation period. Due to the fact that averages are now taken over bettors instead of bets, and since frequent bettors are more successful, average losses are now 22.72 % instead of 14.39 %.

As mentioned in the introduction, we use two proxies for experience. ExpAmount measures for each bet the total amount invested so far in 1,000NZ$. ExpNumber is the number of bets already placed by a bettor.

3 Betting behavior

We now start the analysis by investigating betting behavior. All regressions in the paper are OLS with sports-fixed effects. Dummies for the different sports are needed as we know from the descriptive statistics that average odds vary largely among sports.

Model 1 in Table 3 shows that odds and bet sizes are negatively correlated as expected. This result is robust with respect to the experience measures added in the next Models. The size of the bet-size coefficient basically does not change when adding the experience measures. The coefficient in the first specification means that

Table 3 Odds

	Odds model 1	Odds model 2	Odds model 3	Odds model 4
Bet size	−0.**0004***	−0.**0003***	−0.**0004***	−0.**0003***
	(0.00001)	(0.00002)	(0.00001)	(0.00002)
ExpAmount		**−0.0004***		**−0.0003***
		(0.00005)		(0.00005)
ExpNumber			−0.**00008***	−0.**00007***
			(0.00007)	(0.00007)
Baseball	**−5.663***	**−5.655***	**−5.613***	**−5.612***
	(0.068)	(0.068)	(0.069)	(0.069)
Basketball	**−5.444***	**−5.438***	**−5.414***	**−5.413***
	(0.059)	(0.059)	(0.059)	(0.059)
Cricket	**−3.663***	**−3.664***	**−3.654***	**−3.656***
	(0.057)	(0.057)	(0.057)	(0.057)
Football	−0.**077**	−0.**079**	−0.**073**	−0.**075**
	(0.054)	(0.054)	(0.054)	(0.054)
Golf	**17.46***	**17.46***	**17.48***	**17.48***
	(0.068)	(0.068)	(0.068)	(0.068)
Harness	**2.832***	**2.835***	**2.832***	**2.834***
	(0.055)	(0.055)	(0.055)	(0.055)
Others	**−2.439***	**−2.437***	**−2.420***	**−2.420***
	(0.059)	(0.059)	(0.059)	(0.059)
Rugby League	−0.**343***	−0.**344***	−0.**341***	−0.**342***
	(0.049)	(0.049)	(0.049)	(0.049)
Rugby Union	−0.**0994**	−0.**102**	−0.**105**	−0.**106**
	(0.048)	(0.048)	(0.048)	(0.048)
Tennis	**−5.064***	**−5.063***	**−5.043***	**−5.045***
	(0.063)	(0.063)	(0.063)	(0.063)
Thoroughbred	**2.774***	**2.778***	**2.776***	**2.778***
	(0.047)	(0.047)	(0.047)	(0.047)
Constant	**7.920***	**7.924***	**7.958***	**7.957***
	(0.044)	(0.0442094)	(0.044)	(0.0443)
Number of observations	5,136,660	5,136,660	5,136,660	5,136,660
R^2	0.04	0.04	0.04	0.04

OLS regression. Bet size is the amount for the respective bet in NZ$. Greyhounds are the reference categories for sports. Coefficients are bold and standard errors are in brackets. *, **, and *** denote significance at the 10, 5 and 1 % level, respectively. ExpAmount is the amount so far betted by an individual in 1,000NZ$ and ExpNumber is the number of bets so far placed by an individual bettor. The Models differ only with respect to the control variables for experience: In model 1, we do not control for experience. Model 2 adds ExpAmount, and model 3 ExpNumber. Model 4 controls for both experience measures

a 1,000NZ$ increase in bet size results in a decrease of odds by 0.3955. As the two experience measures are correlated at 0.16, we consider them first separately.

In model 2, we add ExpAmount which measures for each bet the total amount invested so far in 1,000NZ$. ExpAmount has a highly significant negative impact on odds, that is, the exposure to the FLB decreases with experience. A higher betting experience of 1,000NZ$ leads, on average, to a decrease in odds by 0.0004. We will argue below, however, that the coefficient underestimates the impact of experience on the behavior of average bettors; see the discussion after Table 5.

In model 3, we substitute ExpAmount by ExpNumber which measures the number of bets already placed by a bettor. This experience proxy also has a highly significant negative sign. If the number of bets placed so far increases by 1,000, odds decrease on average by 0.08. Finally, we add both experience measures in model 4. Due to their correlation, both coefficients are now slightly smaller than before.

Given that bet sizes are decreasing in odds, it is interesting to see how the final odds set by the monopolistic betting agency differ from odds which would be realized at the totalisator (parimutuel-betting market), and which would just be given by the ratio of the amount bet on the correct outcome and the overall amount.

Figure 1 shows two alternatives for calculating the subjective probabilities: The dotted line just calculates the inverse of odds, while the straight line uses the quota which would have occurred from a parimutuel-betting market (totalisator) and thus divides the money bet on the correct outcome by the overall money invested in the event. Both subjective probabilities are displayed as functions of the objective probabilities that are the percentages of successful bets on the respective odds. While the inverse of odds reflects (partly) the behavior of bookmakers, the probabilities calculated according to the totalisator reflect exclusively the behavior of bettors. Figure 1 shows that bets with low objective winning probabilities

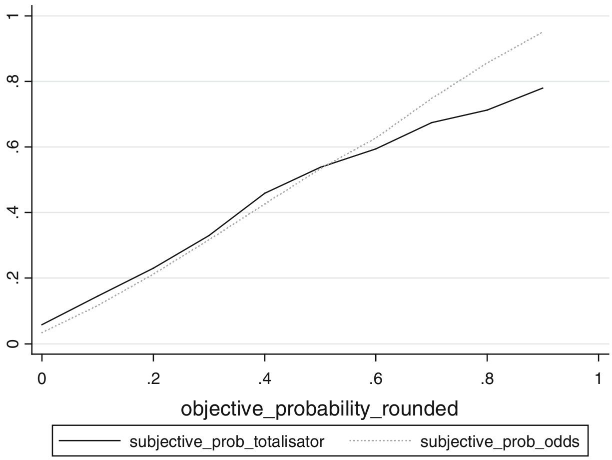

Fig. 1 Probabilities (odds in the data vs. totalisator calculation)

(longshots) have lower odds than it would be the case in a parimutuel-betting market.

Our result that odds are decreasing in both experience measures can be interpreted in different ways. A first interpretation suggested in the literature discussed in the introduction could be that some large and sophisticated investors take advantage of the FLB caused by non-professional bettors (Andrikogiannopoulou and Papakonstantinou 2011). Second, it could be that there are learning effects with respect to the overweighting of small probabilities for all experience levels. As our data set contains a non-negligible number of large investors realizing higher average returns than casual bettors, we cannot exclude per se that our results are exclusively driven by a small group of large bettors. To account for this, we redo our four regressions on odds by excluding the 1 % of bettors who have invested the highest overall amounts in the period covered by our data set, as well as by excluding the 1 % of bettors who placed the highest overall number of bets. The 1 % threshold is arbitrary, but we have duplicated all regressions with 3 and 5 % limits and results are qualitatively the same. Table 4 provides descriptive statistics for the two subgroups.

Table 4 reveals that, in the New Zealand betting market, there are some bettors who have invested surprisingly large amounts. When considering only bettors who have invested the 1 % highest amounts during our observation period (second row in Table 4), then the average amount invested is more than 240,000NZ$. Recall that this is not the average amount invested over the whole observation period, but the average amount invested so far when considering each bet in the data set, so that average amounts over the whole observation period are even higher. Average losses for these large investors are very close to zero (−0.89 %), and for some betting accounts, we observe considerable positive gains. This confirms that the positive effect of experience found in our data set is indeed particularly pronounced for highly experienced bettors.

The marginal investor defining the 1 % threshold has spent 52,712NZ$, so that arguing that individuals below this threshold are non-professional bettors seems sensible. Note that those who have placed the highest number of bets are only slightly more successful than average bettors with a return of −12 %. This confirms the prior that those investing high amounts may be considered as professionals, rather than those betting with a high frequency. Consequently, we restrict our presentation to the case where we take out those bettors who have invested the highest amounts. Neglecting instead the bettors with the highest numbers of bets leads to results which are basically identical to our original results derived with the entire data set. Table 5 presents our regression results.

Comparing the results in Table 5 to those in Table 3 where large investors are included shows that bet sizes and experience have qualitatively the same impacts, but the coefficients are now much higher. For instance, the coefficient for ExpAmount is now around two hundred times higher compared to the regression results displayed in Table 3. To see the reason, consider a simple example where we have just two bettors, a relatively inexperienced bettor with ExpAmount = 100 betting on a longshot with odds of 12, and a somewhat more experienced bettor with ExpAmount = 1,000 betting on a longshot with odds of 10. Now, add a very

Table 4 Large investors and high-frequency bettors

	Number of bettors	Number of bets	Amount (average)	Amount (median)	Odds (over bets)	Bet size (over bets)	Return (over bets)
All bettors	70,400	73.0	3684.9	50	8.42	50.50	−0.144
Highest amounts (1 %)	704	1,135.1	241,535.8	109,230	6.41	212.80	−0.009
Highest number of bets (1 %)	702	2,044.8	87,951.5	29,784	7.60	43.01	−0.120

experienced bettor with ExpAmount = 10,000,000 who bets on a favorite with odds of 1.5. Due to the fact that even the most experienced bettors cannot bet on odds below one, including these bettors reduce the coefficient to a large extent. Thus, the results shown in Table 5 are more appropriate for assessing the quantitative impact of experience on average bettors than those displayed in Table 3.

So far, the analysis shows that our results on the positive impact of experience hold without the largest investors. To get a more detailed picture, our next step is to divide the population into ten equally large subgroups, sorted by experience. We use ExpAmount as proxy for experience, and the results are again robust when ExpNumber is used instead.

Figure 2 shows that odds are consistently decreasing from subgroup to subgroup. This indicates that the positive impact of experience is not (at least not exclusively) driven by a dichotomy of professional and recreational gamblers, but holds also for casual bettors. In this sense, our findings contradict arguments that the FLB can be explained by the interplay of casual bettors and (semi-)professionals who are not prone to the FLB (Gandhi and Serrano-Padial 2012). Learning seems to be important at any experience level, and it helps to reduce the overweighting of small probabilities. This is something Gandhi and Serrano-Padial (2012) cannot account for as they do not have experience measures in their data set.

Note that Fig. 2 also shows that experience is largely unequally distributed between bettors. For instance, the first 30 % of all bettors (see the upper limit for this centile) have invested <40NZ$, and experience increases only slowly from centile to centile. Only in the last two centiles, we observe a large difference between the lower and the upper bound. Note, however, that we nevertheless observe a significant and quantitatively non-negligible difference in the behavior between the lower centiles. In other words, bettors who rarely ever bet are in fact more prone to the FLB than those who bet regularly, even if the latter group invests relatively low amounts.

The same disaggregation into subgroups shows that bet sizes are consistently increasing from subgroup to subgroup. We do not need to report the figures here. Average bet sizes increase from 6.11 in the subgroup with the lowest experience level to 70.73 in the group with the highest experience level. Finally, if we run separate regressions of odds on bet sizes, we find that odds are decreasing in bet sizes in all subgroups. This is significant at the 1 % level in all subgroups. The coefficients of bet sizes range from a minimum of −0.0003 (subgroup 10) to a

Table 5 Odds without large investors

	Odds model 5	Odds model 6	Odds model 7	Odds model 8
Bet size	−0.**011*****	−0.**010*****	−0.**011*****	−0.**009*****
	0.0001	0.0001	0.0001	0.0001
ExpAmount		−0.**081*****		−0.**112*****
		0.000001		0.000002
ExpNumber			−0.**0005*****	**0.0006*****
			0.00002	0.0000243
Baseball	**−5.892*****	**−5.787*****	**−5.823*****	**−5.839*****
	0.087	0.087	0.087	0.087
Basketball	**−5.599*****	**−5.513*****	**−5.543*****	**−5.553*****
	0.070	0.070	0.070	0.070
Cricket	**−3.972*****	**−4.044*****	**−3.939*****	**−4.115*****
	0.065	0.065	0.065	0.065
Football	−0.**119***	−0.**196*****	−0.**099**	−0.**252*****
	0.062	0.062	0.062	0.062
Golf	**17.13*****	**17.06*****	**17.17*****	**16.98*****
	0.077	0.077	0.077	0.077
Harness	**2.882*****	**2.872*****	**2.883*****	**2.867*****
	0.063	0.063	0.063	0.063
Others	**−2.272*****	**−2.325*****	**−2.244*****	**−2.383*****
	0.069	0.069	0.069	0.069
Rugby League	−0.**672*****	−0.**786*****	−0.**664*****	−0.**842*****
	0.057	0.057	0.057	0.057
Rugby Union	−0.**315*****	−0.**483*****	−0.**333*****	−0.**526*****
	0.056	0.056	0.056	0.056
Tennis	**−5.284*****	**−5.266*****	**−5.218*****	**−5.346*****
	0.074	0.074	0.074	0.074
Thoroughbred	**2.830*****	**2.799*****	**2.827*****	**2.792*****
	0.054	0.054	0.054	0.054
Constant	**8.506*****	**8.935*****	**8.652*****	**8.912*****
	0.051	0.052	0.051	0.052
Number of observations	4,337,575	4,337,575	4,337,575	4,337,575
R^2	0.04	0.04	0.04	0.04

OLS regression. Bet size is the amount for the respective bet in NZ$. Greyhounds are the reference categories for sports. Coefficients are bold and standard errors are in brackets. *, **, and *** denote significance at the 10, 5 and 1 % level, respectively. ExpAmount is the amount so far betted by an individual in 1,000NZ$ and ExpNumber is the number of bets so far placed by an individual bettor. The models differ only with respect to the control variables for experience: In model 5, we do not control for experience. Model 6 adds ExpAmount, and model 7 ExpNumber. Model 8 controls for both experience measures

maximum of 0.53 (subgroup 1) when we define the highest experienced group as group ten.

In the following, we consider the impact of odds on the variance of returns of bets. This is interesting because the literature based on expected utility theory has associated betting on longshots with higher risk preferences than betting on favorites. This follows immediately when assuming that bet sizes are independent of odds. However, in the simplest case with only two possible outcomes, the variance of the return per bet is independent of odds if bet sizes are proportional to win probabilities (we are grateful to an anonymous referee who has pointed this out). It hence depends on the degree of the negative correlation of odds and bet sizes whether the variance increases or decreases in odds. Table 6 presents our results.

Model 9 in Table 6 presents the results when we control only for the different sports. We then find that the variance decreases in odds. This means that bet sizes are so largely shrinking in odds that this overcompensates the direct effect of odds on the variance. The result is significant with a p value below 0.001, but given the huge data set with more than five million observations, this does not necessarily mean that the effect is notable. The coefficient shown in Model 9 expresses that increasing the odds by 1 leads to a lower variance of about 1,442. The average variance over all bets is around 209,000. In any case, the variance does not increase in odds. Thus, if one accepts the variance of the return as a reasonable proxy for the risk associated with a bet, there seems so far no reason for assuming that the risk of the average bet actually placed increases in odds.

However, the coefficient of odds changes sign as soon as we add ExpAmount as a control variable (models 10 and 12). The reason is that large investors do not only invest large overall amounts, but also high amounts per bet. And as these amounts are placed on favorites, the favorite bets placed by these bettors exhibit a particularly large variance. This effect is very pronounced, and is responsible for the results in Table 6. Therefore, part of the high variance of favorite bets is now absorbed by ExpAmount. Consequently, odds have a positive sign when controlling for the amounts invested. By contrast, the coefficient for odds does basically not change compared to model 9 when we add ExpNumber instead of ExpAmount. ExpNumber itself has a negative sign which is not surprising as high-frequency bettors often invest low amounts per bet. In other words, bet sizes are ceteris paribus decreasing in the number of bets when controlling for the overall amount.

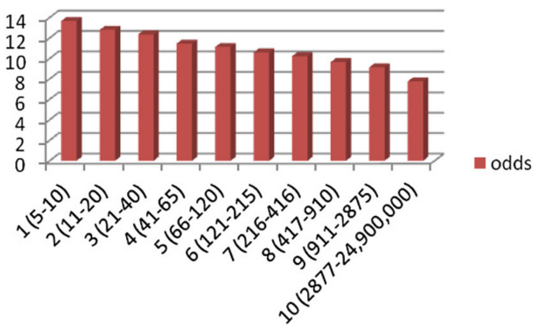

Fig. 2 Odds, sorted by experience. *Horizontal axis* centiles for ExpAmount. The *numbers in brackets* show the lowerand upper bounds for the respective centiles. *Vertical axis* average odds of betsplaced for the respective centiles

Table 6 Variance of returns of bets

	Variance model 9	Variance model 10	Variance model 11	Variance model 12
Odds	**−1,442*****	**2,956*****	**−1,4534*****	**2,751*****
	(448)	(410)	(448)	(409)
ExpAmount		**37.8*****		**38,815*****
		(0.038)		(38.)
ExpNumber			**−39.1*****	**−1,126*****
			(7.41)	(6.85)
Baseball	**1,574,153*****	**238,707*****	**1,598,911*****	**916,447*****
	(69,576)	(63,661)	(69,734)	(63,628)
Basketball	**539,745*****	**−416,507*****	**554,315*****	**−22,069**
	(59,515)	(54,452)	(59,578)	(54,362)
Cricket	**52,911**	**124,306****	**57,144**	**247,949*****
	(57,984)	(5,304)	(57,989)	(52,909)
Football	**46,828**	**213,718*****	**49,027**	**281,312*****
	(54,989)	(50,304)	(54,991)	(50,174)
Golf	**123,550***	**307,202*****	**132,079***	**557,361*****
	(69,260)	(63,359)	(69,279)	(63,211)
Harness	**55,814**	**−286,481*****	**56,040**	**−288,833*****
	(55,848)	(51,090)	(55,848)	(50,956)
Others	**384,832*****	**37,753**	**394,400*****	**304,027*****
	(60,263)	(55,129)	(60,291)	(55,009)
Rugby League	**86,648***	**156,922*****	**87,715***	**189,433*****
	(50,194)	(45,917)	(50,194)	(45,797)
Rugby Union	**171,197*****	**34,5015*****	**168,499*****	**271,880*****
	(49,218)	(45,024)	(49,221)	(44,909)
Tennis	**256,635*****	**−160,591*****	**267,102*****	**129,759****
	(63,859)	(58,419)	(63,890)	(58,293)
Thoroughbred	**94,630****	**−275,832*****	**95,327****	**−265,351*****
	(47,476)	(43,432)	(47,476)	(43,318)
Constant	**49,572**	**−733,839*****	**68,478**	**−210,201*****
	(45,063)	(41,231)	(45,205)	(41,246)
Number of observations	5,136,660	5,136,660	5,136,660	5,136,660
R^2	0.0002	0.17	0.0002	0.17

OLS regression. Bet size is the amount for the respective bet in NZ$. Greyhounds are the reference categories for sports. Coefficients are bold and standard errors are in brackets. *, **, and *** denote significance at the 10, 5 and 1 % level, respectively. ExpAmount is the amount so far betted by an individual in 1,000NZ$ and ExpNumber is the number of bets so far placed by an individual bettor. The models differ only with respect to the control variables for experience: In model 9, we do not control for experience. Model 10 adds ExpAmount, and Model 11 ExpNumber. Model 12 controls for both experience measures

Table 7 Success

	Return model 13	Return model 14	Return model 15	Return model 16
Odds	**−0.003*****	**−0.003*****	**−0.003*****	**−0.003*****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ExpAmount		**0.00004*****		**0.00003*****
		(0.00001)		(0.00001)
ExpNumber			**0.000005*****	**0.000004*****
			(0.000001)	(0.000001)
Baseball	**0.063*****	**0.062*****	**0.06*****	**0.06*****
	(0.009)	(0.009)	(0.009)	(0.009)
Basketball	**0.08*****	**0.079*****	**0.078*****	**0.078*****
	(0.007)	(0.007)	(0.007)	(0.007)
Cricket	**0.021*****	**0.022*****	**0.021*****	**0.021*****
	(0.007)	(0.007)	(0.007)	(0.007)
Football	**0.028*****	**0.028*****	**0.028*****	**0.028*****
	(0.007)	(0.007)	(0.007)	(0.007)
Golf	**0.003**	**0.003**	**0.002**	**0.002**
	(0.009)	(0.009)	(0.009)	(0.009)
Harness	**0.108*****	**0.108*****	**0.108*****	**0.108*****
	(0.007)	(0.007)	(0.007)	(0.007)
Others	**0.044*****	**0.044*****	**0.043*****	**0.043*****
	(0.007)	(0.007)	(0.007)	(0.007)
Rugby League	**−0.001**	**−0.0005**	**−0.001**	**−0.001**
	(0.006)	(0.006)	(0.006)	(0.006)
Rugby Union	**−0.005**	**−0.005**	**−0.005**	**−0.005**
	(0.006)	(0.006)	(0.006)	(0.006)
Tennis	**0.029*****	**0.029*****	**0.028*****	**0.028*****
	(0.008)	(0.008)	(0.008)	(0.008)
Thoroughbred	**0.043*****	**0.042*****	**0.043*****	**0.042*****
	(0.006)	(0.006)	(0.006)	(0.006)
Constant	**−0.154*****	**−0.154*****	**−0.156*****	**−0.156*****
	(0.006)	(0.006)	(0.006)	(0.006)
Number of observations	5,136,660	5,136,660	5,136,660	5,136,660
R^2	0.0007	0.0007	0.0007	0.0007

OLS regression. Bet size is the amount for the respective bet in NZ$. Greyhounds are the reference categories for sports. Coefficients are bold and standard errors are in brackets. *, **, and *** denote significance at the 10, 5 and 1 % level, respectively. ExpAmount is the amount so far betted by an individual in 1,000NZ$ and ExpNumber is the number of bets so far placed by an individual bettor. The models differ only with respect to the control variables for experience: In model 13, we do not control for experience. Model 14 adds ExpAmount, and model 15 ExpNumber. Model 16 controls for both experience measures

Table 8 Success without large investors

	Return model 17	Return model 18	Return model 19	Return model 20
Odds	**−0.003*****	**−0.003*****	**−0.003*****	**−0.003*****
	0.0001	0.0001	0.0001	0.0001
ExpAmount		**0.001*****		**0.002*****
		0.0002		0.0002
ExpNumber			**0.00001*****	**−0.00001*****
			0.000002	0.000003
Baseball	**0.074*****	**0.072*****	**0.073*****	**0.073*****
	0.011	0.011	0.011	0.011
Basketball	**0.086*****	**0.084*****	**0.085*****	**0.085*****
	0.009	0.009	0.009	0.009
Cricket	**0.03*****	**0.032*****	**0.03*****	**0.033*****
	0.008	0.008	0.008	0.008
Football	**0.035*****	**0.036*****	**0.034*****	**0.037*****
	0.008	0.008	0.008	0.008
Golf	**0.01**	**0.011**	**0.009**	**0.012**
	0.009	0.009	0.009	0.009
Harness	**0.11*****	**0.111*****	**0.11*****	**0.111*****
	0.008	0.008	0.008	0.008
Others	**0.049*****	**0.05*****	**0.049*****	**0.051*****
	0.008	0.008	0.008	0.008
Rugby league	**0.01**	**0.012***	**0.01**	**0.013***
	0.007	0.007	0.007	0.007
Rugby union	**−0.0003**	**0.003**	**0.000002**	**0.004**
	0.007	0.007	0.007	0.007
Tennis	**0.039*****	**0.038*****	**0.037*****	**0.04*****
	0.009	0.009	0.009	0.009
Thoroughbred	**0.041*****	**0.042*****	**0.041*****	**0.042*****
	0.007	0.007	0.007	0.007
Constant	**−0.167*****	**−0.175*****	**−0.169*****	**−0.175*****
	0.006	0.006	0.006	0.006
Number of observations	4,337,575	4,337,575	4,337,575	4,337,575
R^2	0.0007	0.0007	0.0007	0.0007

OLS regression. Bet size is the amount for the respective bet in NZ$. Greyhounds are the reference categories for sports. Coefficients are bold and standard errors are in brackets. *, **, and *** denote significance at the 10, 5 and 1 % level, respectively. ExpAmount is the amount so far betted by an individual in 1,000NZ$ and ExpNumber is the number of bets so far placed by an individual bettor. The models differ only with respect to the control variables for experience: In model 17, we do not control for experience. Model 18 adds ExpAmount, and model 19 ExpNumber. Model 20 controls for both experience measures

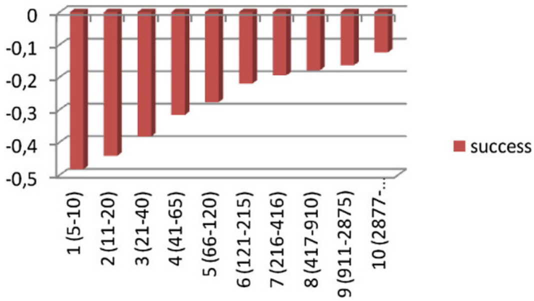

Fig. 3 Success, sorted by experience. *Horizontal axis* centiles for ExpAmount. The *numbers in brackets* show the lowerand upper bounds for the respective centiles. *Vertical axis* average odds of betsplaced for the respective centiles

Again, it is instructive to consider the ten subgroups, ordered by ExpAmount, separately. Not surprising, we find that the variance per bet increases from subgroup to subgroup. More interesting results are obtained when we run regressions on the variance of odds for each of the ten subgroups. We then find that the variance increases in odds for the first nine subgroups, but decreases in odds for the subgroup with the largest investors; all significant at the 1 %-level. Thus, for all subgroups but the one with the highest experience, bet sizes and odds are negatively correlated, but at a degree which does not overcompensate the direct effect of odds on variance.

4 Betting success

We now turn to the impact of experience on betting success.

Table 7 reveals that higher odds have a significantly negative impact on the return and hence confirm the existence of the FLB. In addition, our experience measures—ExpAmount and ExpNumber—display an impact on outcomes, too. We control for odds, taking into account that experienced bettors are less prone to the FLB and state that experience has a positive impact on the return. We conclude that experienced bettors are more successful due to two reasons: the play better odds and they choose a better selection within odds. Whether we use ExpNumber, ExpAmount or both to illustrate does not change the results qualitatively.

Not considering the 1 % largest bettors in Table 8 even intensifies the effect of experience measured by the amounts. The coefficient of ExpAmount is 25 times higher in model 18 and 67 times higher in model 20 compared to the respective models in Table 7.

Finally, we consider again the success in the ten different subgroups sorted by experience.

Figure 3 shows that success consistently increases with experience which reinforces the view that the positive effect of experience is not limited to (semi-)professional bettors. Running separate regressions show that success decreases in odds for all ten subgroups. This, however, does not provide new insights as this result is already implied by the FLB.

5 Conclusion

Our data set consisting of more than five million bets placed in the non-parimutuel betting mode New Zealand between August 2006 and April 2009 is unique as it allows assigning each bet to individual bettors. This enables us to analyze the impact of experience on betting behavior and success. We approximate experience by the amount invested and by the number of bets placed up to each bet considered. Experience increases success for two reasons: it reduces the susceptibility to the overweighting of small probabilities, and leads to higher success even after controlling for odds. To the best of our knowledge, such an analysis has never been carried out before as the data sets utilized so far did not allow tracking the wagering record of individual bettors over time.

An important question is whether the positive effect of experience can best be explained by a dichotomy of experienced and recreational bettors. As for this, we divide the population into ten equally large subgroups, sorted by experience. We show that odds are consistently decreasing from subgroup to subgroup. Thus, the positive effect of experience cannot exclusively be attributed to large investors but rather holds for any degree of experience. This indicates that there are strong learning effects with respect to the overweighting of small probabilities.

We acknowledge a limitation for our results on experience. We find a strong positive relationship between experience and success, but we did not so far separate between selection effects (heterogeneity of bettors) and learning effects. In other words, we have not disentangled yet if smarter individuals bet more or if betting more increases the knowledge about the probability distribution over outcomes. This requires an instrumental variable for the decision to leave the market, and we were not successful yet in searching for such an instrument. This must hence be left to further research.

As a side effect of our analysis, we show that bet sizes and odds are negatively correlated at all levels of experience. This supports two current empirical papers (Kopriva 2009 and Andrikogiannopoulou 2010) showing that accounting for different bet sizes is important when estimating preferences from the data.

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