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Do Bettors Prefer Long Shots Because They Are Risk-Lovers, or Are They Just Overconfident?

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Abstract

This study examines whether bettors' risk preferences or overconfidence in choosing winners better explains their well documented preference for low-probability wagers. Although previous studies using racetrack data often suggest that risk-loving behavior explains long-shot preference, such data cannot distinguish between the alternative explanations. We use football betting data to make the comparison and find that overconfidence more closely fits the data. This result complements evidence of overconfidence from behavioral studies as well as stock-market models of overconfident noise traders.

Key words: overconfidence, risk-lovers, long shots, football gambling

Betting markets should exhibit equal nonpositive returns across all bets if bettors are risk-neutral, expected-value maximizers with rational expectations.[1] Nevertheless, numerous studies have documented the anomalous regularity that expected returns to racetrack wagers decrease monotonically with win probability (the long-shot anomaly).[2] The common explanation of this phenomenon assumes that bettors are risk-loving, i.e., that they give up some expected return in exchange for the additional risk of low-probability wagers. An alternative explanation is that bettors are overconfident. In betting and financial markets, bettors may be willing to accept low returns along with additional risk, because their "expertise" reduces their perceived risk. Such expert bettors will often see greater risk reduction potential in high-risk bets.[3] We attempt to empirically discriminate between these two alternatives (of course, other alternatives may exist).[4]

It is important to distinguish between the alternative theories because each has different implications for behavior in other risk markets. For instance, globally risk-loving bettors should not purchase insurance. Since bettors often buy insurance, some explain this behavior by assuming that they are locally risk-loving, but globally risk-averse.[5] An alternative explanation is that bettors are overconfident at the track (where they have readily available information), but not in graver matters such as estimating their life expectancy or the probability of a house fire. According to De Long, Shleifer, Summers, and Waldmann (1991), a similar story holds for the stock market, where overconfident investors trade on their perceived expertise and add volatility to the market.

Academic interest in betting markets springs primarily from their similarity to other risk markets, such as securities markets, where individuals make investment decisions under uncertain conditions. Indeed, much like other risk markets, gambling markets involve economically significant trading with numerous participants, including professional gamblers (traders) and bookies (brokers). Thaler and Ziemba (1988) note that a major advantage of studying bettors' risk-taking behavior is that betting market expectations and outcomes are clearly and repetitively observable. In contrast, the uncertainty of long-lived securities is not periodically resolved, since today's values depend upon unobservable expectations of many future events.

Earlier gambling studies have not been able to discriminate between overconfidence and risk-loving behavior. We are able to do this because certain football bets have similar win probabilities (risk), but are differently affected by overconfidence with respect to expectation error variance. The data are largely consistent with overconfident behavior (although risk-loving behavior is not entirely dismissed). We suggest that individuals are sometimes overconfident, because they believe that they are well-informed, i.e., their actions only appear to be risk-loving. We speculate that in cases in which individuals believe that they are relatively uninformed, they act in a risk-averse manner.

The article is organized as follows. Section 1 gives some institutional details of football betting. Here, we motivate the two explanations of the long-shot anomaly. Section 2 presents a simple model of probabilities and expected returns for football bets. Section 3 describes the data along with empirical support for overconfident bettors. Section 4 contains conclusions.

1. Institutional details of football bets

A simple football bet is a bet on either the favorite or the underdog team against the point spread. The point spread or spread is the football betting market's expectation of the game outcome, i.e., an expectation of the favored team's margin of victory. Licensed sports books in Las Vegas purchase opening point spreads from professional point-spread makers on Sundays and immediately offer betting to the public for the following weekend's games. Illegal bookies in other parts of the country typically adopt these spreads as well. Announcements during the week, such as those concerning player injury, may cause bookies to adjust the spread of the affected games. Bets made at the preadjusted spread are not affected, but new wagers are made at the new spread. By implication of market rationality, the spread is an up-to-date aggregation of information on the relative scoring strengths of opposing teams, much as a stock's price reflects up-to-date information about a firm's future cash flows.

The list of the point spreads offered by a bookie or sports book for a week's wagering is called "the line." An example of "the line" for December 27, 1987, appears in table 1. A winning simple bet is one placed on a team that "beats the spread." In table 1, favorites beat the spread in eight of fourteen games, i.e., the favorite's margin of victory (the outcome) is larger than the spread. Conversely, a bet on the underdog wins in the other six games, i.e., the underdog's margin of loss is less than the point spread, or the underdog

Table 1. An example of "the line" or list of NFL games and respective point spreads for December 27, 1987[a]

Favored team	Underdog team	Point spread	Outcome
Detroit[b]	Atlanta	1	17
Philadelphia[b]	Buffalo	2	10
Chicago[b]	L.A. Raiders[c]	2.5	3
Houston	Cincinnati[b]	6	4
Cleveland[b]	Pittsburgh[c]	4	6
Denver[b]	San Diego	11	24
New Orleans[c]	Green Bay[b]	10	9
Indianapolis[b]	Tampa Bay	11	18
Seattle	Kansas City[b]	6	−21
San Francisco[b]	L.A. Rams	9	48
Miami	New England[b]	5	−14
Minnesota[c]	Washington[b]	3	−3
N.Y. Giants[b]	N.Y. Jets[c]	8	13
Phoenix	Dallas[b]	2.5	−5

[a]The point spread is the betting market's expectation of the number of points by which the favored (underdog) team is expected to win (lose) the game. The outcome is the actual difference between the favored and underdog team's scores.
[b]Denotes that this team "beat the spread," i.e., won by more than expected or lost by less than expected. Bets placed on teams that beat the spread win.
[c]Denotes that this team did not beat the spread, but could be part of a winning teaser bet.

wins the game. Winners win $10.00 for each $11.00 that they bet, losers lose the amount that they bet. If the favorite's (underdog's) margin of victory (loss) equals the spread, then the bet is canceled (a push).[6]

Lower probability, higher payoff bets, called *exotic bets*,[7] depend upon the outcomes of more than one game. One exotic football bet, an n team parlay, refers to a combination of n simple bets. Here, the bettor must choose correctly the team that beats the spread in each of n games in order to win the bet. For example, the bettor would have won a three-team parlay if he or she had chosen three of the teams with "b" superscripts in table 1.

A second exotic bet, a *teaser*, is a combination of n adjusted simple bets. Let S denote the spread (a positive number for favorites and a negative number for underdogs) and T denote the number of adjustment (teaser) points. To win an n team teaser, all n chosen teams must beat their adjusted spreads, $S - T$. Most sports books offer choices of six, six and one-half, and seven teaser points.

Consider a seven-point teaser for the line in table 1. There are 19 teams that beat the adjusted spread, i.e., the original 14 teams that beat the spread outright, plus five more teams (denoted with "c") that beat the smaller adjusted spread. For instance, the L.A. Raiders were two-and-one-half-point underdogs and lost by three; they did not beat the spread. The adjusted spread makes them nine-and-one-half-point underdogs; they beat the adjusted spread. Obviously, the probability of winning an n team teaser is greater than the probability of winning an n team parlay; hence, bookies' teaser payoffs are smaller.

Tversky and Kahneman (1974) and Tversky, Slovic, and Kahneman (1990) discuss and formalize results from their own and other behavioral studies that show individuals systematically misperceive probabilities because they underestimate error variance. De Long, Schleifer, Summers, and Waldmann (1991) maintain a similar argument to support their model of noise traders in the stock market. Following this line of reasoning, we will show how bettors may overestimate the increase in win probability afforded by teaser points. Indeed, bookies reportedly believe that this overestimation causes bettors to be "teased" into accepting smaller payoffs than are warranted for the teaser points—hence, the name "teaser."

Teaser bets provide a unique opportunity to distinguish between risk-loving and overconfidence explanations of the long-shot anomaly because teaser points impact the risk-lover and the overconfident in different ways. Teaser points increase a bet's win probability and reduce its risk (return variance); risk-loving bettors view the decrease in risk negatively. By contrast, overconfident bettors overvalue the teaser points. Intuitively, they believe that it is unlikely that they will make large errors, and teasers allow the bettor to be in error by up to a certain number of teaser points. Teaser bets attract those who worry that they will lose bets on "fluke" plays (Gilovich, 1983). We show more formally in the next section how error variance has a greater impact on teasers' win probabilities than on the win probabilities of parlays or simple bets.

2. Expected rates of return and probabilities for football bets

Consider the objective expected rate of return on a \$1.00 bet, R_O. Let B be the bookie's payoff to a winner of a \$1.00 bet (losers lose \$1.00), and P_o be the objective probability of winning the bet. (The objective probability refers to the win probability which one expects by randomly betting on a game or games.) The return is

$$R_o = P_oB - 1. \tag{1}$$

An individual's subjective expected rate of return is the rate of return expected from choosing bets based upon the individual's information, e.g., betting the team whose quarterback the individual perceives to be superior. Adjusting (1) for the subjective win probability, P_s, to obtain the subjective expected return, R_s, yields

$$R_s = P_sB - 1. \tag{2}$$

Assuming that the difference between the spread and the margin of victory is normally distributed, the objective win probability of a simple bet can be estimated by

$$P_{oM} = P(M - S > 0) = \Phi(E[M - S]/\sigma), \tag{3}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, E is expectation, M is the margin of victory or the outcome (positive for the game winner and negative for the loser), S is the spread (positive for the favorite and negative for the underdog), and σ is the standard deviation of $[M - S]$. Since S can be thought of as the market's expectation of the margin of victory, $[M - S]$, the point-spread error, is the error in market expectations, and σ is the standard deviation of the error. Efficiency of the football betting market implies unbiasedness, i.e., $E[M - S] = 0$, and minimum errors (σ is minimized). Hence, a random simple bet should have an objective win probability of 50% ($\Phi(0) = 0.5$).

The objective probability of winning a single part of a teaser can be calculated by adjusting (3) as follows:

$$P_{oT} = P(M - S > 0) = \Phi(E[M - S + T]/\sigma), \tag{4}$$

where T is the number of teaser points. Clearly, P_{oT} is a positive function of T and a negative function of σ.

The subjective probabilities, P_{sM} and P_{sT}, depend upon the perceived distribution of $[M - S]$ for an individual, given his or her information. A bettor wagers on games when his or her subjective win probability exceeds the objective win probability. A necessary condition for a bettor's subjective win probability for a simple bet to exceed the objective win probability is that he/she perceive $E[M - S] > 0$. This betting advantage is enhanced if his/her subjective error variance is smaller than the market's. For a teaser, either $E[M - S] > 0$ or a smaller subjective error variance implies that a bettor's subjective win probability exceeds the objective win probability.

In a small survey of football bettors, we found that bettors expected to beat the spread by 4.4 points on average, i.e., $E[M - S] = 4.4$ on average. In addition, they estimated that six teaser points increased win probability by 23 percentage points (when the objective effect is 17) and estimated their chance of winning a four-team six-point teaser at 45% when the objective probability is actually 20%. This indicates that they believed that their subjective error variance was smaller than the market's.[9]

Win probabilities for exotic bets can be calculated using (3) and (4). Assuming that observations of $[M - S]$ for different games are independent, the objective probabilities of winning an n game parlay and an n game teaser are $(P_{oM})^n$ and $(P_{oT})^n$, respectively. For ease of comparison, assume that bettors wager on games that have the same subjective probability. Then, the subjective probabilities of winning an n game parlay and an n-game teaser are $(P_{sM})^n$ and $(P_{sT})^n$, respectively. Hence, the bettor's perceived advantage (overconfidence) will compound as more games are added to a parlay or teaser.

Risk-loving and overconfidence explanations of the long-shot anomaly have observationally equivalent empirical implications when only the simple bet and parlays are considered (racetrack bets are similarly flawed). The risk-loving explanation predicts that expected returns decline with their win probability because bettors give up some return for the added risk of low-probability bets. The overconfidence explanation predicts that expected returns and objective win probability decline together because bettors act on subjective (not objective) win probability, which happens to increase as expected returns fall for the simple bet and parlays. Both explanations imply the same order for bets ranked from high to low expected returns: simple bet, two-team parlay, three-team parlay, four-team parlay and so forth—hence, those bets do not help distinguish between the two explanations.

Teaser bets help distinguish between the two explanations. Consider an overconfident bettor who perceives that his or her subjective σ is smaller than that of the market's. Unlike the case for parlays or simple bets, even if the bettor perceives $E[M - S] = 0$, he or she expects a better-than-market win probability from a teaser, since $P_T = \Phi(E[M - S + T]/\sigma) = \Phi(E[T]/\sigma)$ increases as subjective σ decreases. Therefore, overconfident bettors will be willing to give up some return to exploit their advantage in teasers. Conversely, risk-loving bettors will require additional return to bet teasers, because teaser points increase objective win probability and reduce risk. If the bettor perceives $E[M - S] > 0$, subjective win probabilities for all bet types increase as σ decreases; however, the effect for teasers is larger than the effect for other bets. This differential effect of error overconfidence on teasers is used to empirically distinguish between overconfidence and risk-loving behavior in the next section.

3. The data and the empirical investigation

The *Handicapper's Pointspread Notebook*, published by Nation-Wide Sports Publications, Inc., compiles data on all regular season and play-off games played by teams in the National Football League (NFL). The 1989 edition used in this study covers 3,473 NFL games from 1973 to 1988, and includes the Las Vegas closing spreads, the final scores (used to calculate the margin of victory or loss), favorite and home team designations, and game dates.

Equations (1) and (2) can be used to calculate expected returns to simple and exotic bets, given a menu of bookie payoffs and estimates of win probabilities for particular bets. The standard payoff menu for simple and exotic bets is obtained directly from the Las Vegas sports books. The payoffs are set by market forces, as opposed to regulation, although only a few payoffs have changed over the last ten years. Win probabilities are estimated from past betting results, assuming that the point-spread error, $[M - S]$, is normally distributed. Stern (1986) shows that normality is supported for data taken from 1981, 1983, and 1984. Table 2 reconsiders this issue and summarizes the distributions of the margin of victory and point spread as well as the point-spread error. Overall, normality is rejected for the full sample of 16 years. The degree of nonnormality, however, appears slight, since in only four of 16 years can normality be rejected (none of these are included in Stern's sample).

Normality may be rejected for two reasons. First, the average skewness and kurtosis of the distributions differ slightly from the normal values of zero and three, respectively. Second, figure 1 illustrates that certain values of $[M - S]$ have more probability mass because points usually are scored in three- and seven-point increments.[10] Hence, the distribution is bumpy around the points three, four, six, seven, etc. The large number of observations in the full samples causes even these small deviations to be picked up as significant by the Kolmogorov–Smirnov D-statistic. Nevertheless, for any particular year, the normal appears to be a reasonable approximation and allows easy estimation of win probabilities. Thus we assume normality for tractability, but note the slight discrepancies.[11]

Table 2. Testing for the normality of the distribution of the point-spread error for NFL games[a]

				Statistics used to judge normality			
	Mean	Median	Standard deviation	Skewness	Kurtosis	Kolmogorov–Smirnov D-Stat	Observations
			Panel A. Full sample: 1973—1988				
NFL Games							
Margin of victory	0.331	1.0	15.210	0.042	3.169	0.046[b]	3473
Point spread	0.245	1.0	7.124	−0.041	2.808	0.071[b]	3473
$[M - S]$	0.086	0.0	13.566	−0.003	3.271	0.024[b]	3473
			Panel B. $[M - S]$ by year				
1973	−1.070	−1.0	14.144	−0.401	3.297	0.045	191
1974	0.207	0.0	12.516	0.206	2.833	0.064[b]	217
1975	−0.547	1.0	13.419	−0.314	3.480	0.076[b]	190
1976	0.159	−1.25	13.557	0.379	3.118	0.058	204
1977	−1.044	−0.5	12.532	0.272	4.681	0.085[b]	203
1978	−0.565	−0.25	12.768	0.121	3.165	0.035	236
1979	−0.110	0.0	13.342	−0.263	3.381	0.054	235
1980	−1.364	−1.0	13.237	−0.151	3.431	0.056	233
1981	0.493	1.0	14.085	0.003	2.889	0.039	236
1982	1.971	2.0	12.927	0.121	2.957	0.046	141
1983	1.228	0.5	14.044	−0.062	3.236	0.046	232
1984	0.429	0.0	13.643	0.117	2.810	0.035	234
1985	0.631	0.5	13.887	0.001	2.964	0.042	235
1986	0.822	1.0	13.984	−0.181	3.342	0.041	237
1987	0.809	0.5	14.439	0.032	3.337	0.044	220
1988	−0.353	0.0	14.067	0.242	3.725	0.075[b]	229

[a]Summary statistics are reported for NFL games during the 1973-1988 period for the margin of victory, the point spread, and the point-spread error, $[M - S]$. Statistics are also reported for $[M - S]$ for individual years of NFL data. The Kolmogorov-Smirnov D-statistic tests for normality.
[b]Denotes a rejection of normality according to the Kolmogorov-Smirnov D-statistic at least at the 5% significance level.

3.1. Empirical methods and evidence

Table 3 lists the standard menu of simple and exotic football bets offered by most Las Vegas sports books. While books will accept almost any bet at their own odds, standard payoff schedules are offered only for these bets. They include parlays of two through five teams, and six-, six-and-one-half, and seven-point teasers of two through six teams. Single-game teasers are seldom bet, so their payoffs vary among sports books. Nonetheless, table 3 reports win probabilities for hypothetical single-game teasers, because they are used to generate win probabilities for multiple-game teasers.

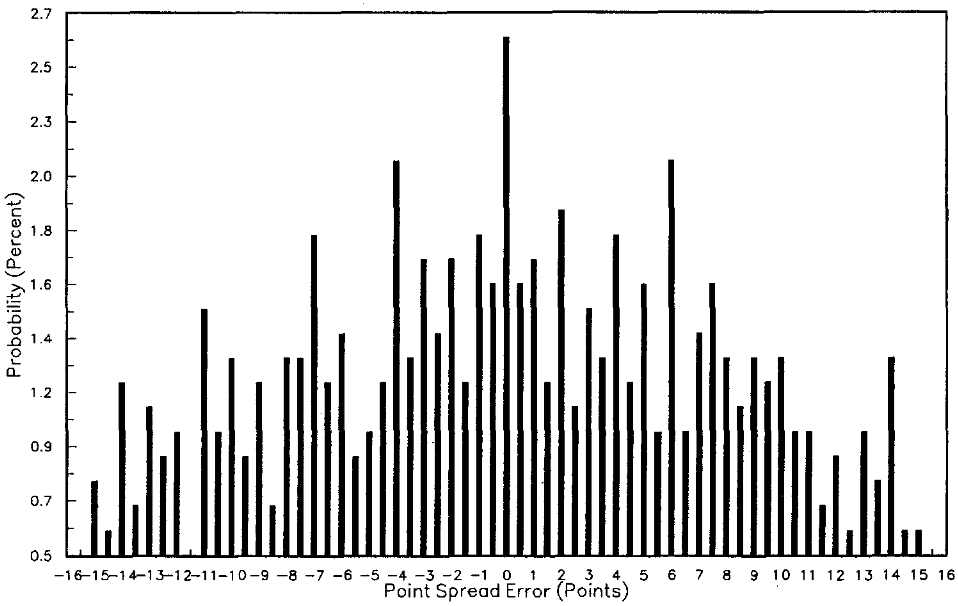

Figure 1. Probability distribution for the point-spread error ($M - S$) for NFL games during 1973–1987.

The statistics for the full sample in table 2 are calculated objectively by assuming that for each game, one chooses randomly between the favorite (positive point spreads) and the underdog (negative point spreads). Hence, means for M, S, and $[M - S]$ of approximately zero (the median of $[M - S]$ is also zero) imply that random selection of teams for simple point-spread bets offers a 50% win probability. This probability and the objective win probabilities of other bets described in section 2 appears in the second column of table 3. Yearly means and standard deviations vary, however, differences among years are not statistically significant (using common tests for mean and variance differences assuming normality).

Consider the objective probability of winning a single portion of a six-point teaser. This probability is calculated as $\Phi(6/13.566) = 0.67$, an improvement in win probability of 0.17 over the win probability of the simple point-spread bet.[12] The standard deviation of the point-spread error (nearly 14 points) is surprisingly large, making the advantage of teaser points relatively small. Such a flat error distribution (see figure 1) makes more plausible the claim that bettors underestimate error variance and overestimate the increase in win probability afforded by teaser points.

All of the expected returns listed in table 3 are negative, reflecting the bookie's commission or "take." The simple point-spread bet offers the highest return (smallest expected loss), and the five-team parlay offers the lowest return (largest expected loss). Recall that the long-shot anomaly supported by risk-loving behavior refers to a positive monotonic relationship between bet returns and win probability. Clearly, objective returns in table 3 do not decline monotonically with win probability.

Table 3. Objective betting results[a]

Bets	Bookie payoff on $1 bet	Win probability	Expected return
	Panel A. Simple bets		
Point spread	1.909	0.5000	−0.0455
Hypothetical			
Single-game teasers			
Six-point	—	0.6710	—
Six-and-one-half point	—	0.6840	—
Seven-point	—	0.6980	—
	Panel B. Exotic bets		
Parlays			
Two-team	3.600	0.2500	−0.1000
Three-team	7.000	0.1250	−0.1250
Four-team	11.000	0.0625	−0.3125
Five-team	21.000	0.0313	−0.3427
Six-point teasers			
Two-team	1.909	0.4502	−0.1405
Three-team	2.800	0.3021	−0.1542
Four-team	4.000	0.2027	−0.1892
Five-team	5.500	0.1360	−0.2520
Six-team	8.000	0.0912	−0.2704
Six-and-one-half-point teasers			
Two-team	1.833	0.4678	−0.1425
Three-team	2.600	0.3200	−0.1680
Four-team	3.500	0.2188	−0.2342
Five-team	5.000	0.1497	−0.2515
Six-team	7.000	0.1024	−0.2832
Seven-point teasers			
Two-team	1.769	0.4872	−0.1382
Three-team	2.500	0.3400	−0.1500
Four-team	3.000	0.2373	−0.2881
Five-team	4.500	0.1656	−0.2548
Six-team	6.000	0.1156	−0.3064

[a]Las Vegas bookie payoffs on $1.00 bets, objective win probabilities, and expected returns for simple single-game bets and exotic multiple-game bets, when bets are placed on randomly selected teams. Probabilities are estimated using the point-spread error distribution of 3,473 NFL games played between 1973 and 1988.

Our empirical approach compares a given teaser's expected return to the expected returns of other bets (simple bets, parlays, and other teasers) that have similar or greater objective win probabilities. According to the risk-loving explanation, the chosen teaser should have a smaller expected return, because it is as risky or riskier than the comparison bets. It is easy to see that this will not be the case, because similar probability bets have different returns. These differences can often be explained by overconfident bettors overestimating the value of teaser points.

For example, compare the simple point-spread bet with the two-team teasers. The bets have comparable win probabilities, but the teaser returns are much smaller.[13] Compare two-team parlays with two- and three-team teasers. The teasers have larger win probabilities but considerably smaller returns. Compare three-team parlays with two-, three-, and four-team teasers. In each instance, the teasers have greater win probabilities, but smaller returns. Finally, compare teasers, while holding the number of teams constant. In all but three cases, an increase in teaser points (which increases win probability) leads to a decrease in expected return. All of this evidence is consistent with overconfident bettors and inconsistent with risk-loving bettors.

There is, however, some evidence consistent with risk-loving behavior. Win probability and bet returns decline monotonically in the number of teams within each bet category (except for the four-team, seven-point teaser). Also, four- and five-team parlays have the smallest win probabilities and the smallest returns. Of course, these results are consistent with overconfidence as well.

The overconfidence explanation of the data appears to be superior to the risk-loving explanation because it is more inclusive; i.e., the set of data consistent with the risk-loving explanation is a proper subset of the set of data consistent with the overconfidence explanation. Nevertheless, a potential problem in our presentation is that we used all the games to calculate a point-spread error variance. Perhaps teaser bettors select games with relatively small error variance. Error variance heterogeneity across games presents a problem. One cannot fully guard against this possibility, because there is no clear rule for judging which games might have small error variance, although there are many possibilities.

We will consider three possibilities that readily come to mind. First, teams have different styles of play; scoring for some may be more predictable. One popular belief is that the more conservative (and perhaps predictable) teams employ offenses that contain relatively more running plays as opposed to passing plays. Thus, we might expect point-spread error variance to differ significantly across teams. Second, there may be a "learning" effect, wherein spreads become better predictors of outcomes as the season progresses, and bettors learn about new players, coaches, etc. Finally, Vergin and Scriabin (1978) suggest that outcomes for games involving a very weak team and a very strong team will be less predictable, although they provide no evidence or tests. We consider each of these in turn.

Table 4 investigates whether conservative style of play, learning over the season, or games involving mismatched opponents produce relatively small σ. First consider style of play. Panel A of table 4 shows that Cleveland, the New York Giants, Philadelphia, and Tampa Bay each have a small σ relative to the full sample σ, with the differences marginally significant at the 5% level (using an F-test). While Cleveland, the New York Giants, and Philadelphia are known for conservative play, Tampa Bay is not. In addition, others with similar reputations, such as Minnesota and Chicago, do not have small σ's. Indeed, considering the degree of variation in σ across 28 teams, four such outliers are not surprising.

Further analysis shows that conservative play does not help to explain error variance. We measure conservative play by the ratio of a team's passing plays to total plays during each season for the 1973–1987 period. The correlation between point-spread error standard deviation and the passing ratio for the 28 teams is a statistically insignificant 0.01. Of

Table 4. Evidence of the effects on the point-spread error variance of style of play, learning, and the degree of opponent mismatch[a]

	Mean	Standard Deviation	Observations		Mean	Standard Deviation	Observations
Panel A. Style of play: $[M - S]$ by team							
Atlanta	−0.601	14.934	246	Miami	1.652	12.874	259
Buffalo	−0.487	13.242	245	Minnesota	−1.072	13.535	263
Chicago	1.038	14.946	249	New England	−0.070	14.107	250
Cincinnati	0.613	13.808	247	New Orleans	−0.193	13.873	243
Cleveland	1.128	12.468	252	N. Y. Giants	−0.831	12.420	250
Dallas	−1.018	13.122	265	N. Y. Jets	0.445	15.451	250
Denver	0.308	13.300	256	Philadelphia	−1.218	12.180	245
Detroit	−0.590	13.257	242	Pittsburgh	0.419	13.555	241
Green Bay	−0.761	13.957	243	Phoenix	−0.384	13.649	265
Houston	0.675	13.239	251	San Diego	0.699	14.515	250
Indianapolis	1.520	13.394	244	San Francisco	0.369	13.229	252
Kansas City	0.285	13.639	242	Seattle	0.198	15.389	202
L. A. Raiders	−1.318	13.111	264	Tampa Bay	−1.123	12.213	202
L. A. Rams	1.158	13.839	265	Washington	1.374	13.366	259
Panel B. Learning: $[M - S]$ by month of the season							
September	−0.284	13.216	765				
October	−0.043	13.773	904				
November	0.328	13.315	949				
December	0.305	13.658	754				
January	0.120	16.541	91				
Panel C. Opponent mismatch: $[M - S]$ by point-spread magnitude (S)							
$S < 3$	−0.560	13.870	666				
$3 \leq S < 4$	0.881	13.602	623				
$4 \leq S \leq 6$	−0.016	13.942	762				
$6 < S \leq 10$	0.045	13.457	938				
$S > 10$	0.194	12.751	484				

[a]Analysis of the distribution of the point-spread error for NFL games by team, month, and magnitude of the point spread for games played during the 1973–88 period.

course, proportion of passing plays may not be a good proxy for style of play. For example, better teams often find themselves ahead late in a game and, consequently, employ running plays (which use up more time), even though their preferred style of play is more aggressive.

Panel B investigates the possibility that spreads become more accurate predictors of the margin of victory as bettors learn about teams over the season. There is, however, little evidence of a "learning" effect, and, in fact, σ is larger in January. Perhaps playoff games, which make up the January sample, are less predictable than regular season games. Of course, random variation and the small sample size for January could account for the result as well.

Finally, Panel C shows that games involving mismatched teams (point spread greater than ten) may be more predictable than those involving evenly matched teams. This conflicts with what Vergin and Scriabin (1978) predicted. Again, the sample of games involving mismatched teams is relatively small, and random variation may explain the result.

This simple analysis of point-spread error variance is not meant to be exhaustive; a more comprehensive analysis is beyond this study. Nonetheless, the three possibilities which we have examined offer little support for heteroscedasticity. Except for Vergin and Scriabin (1978), previous football betting studies provide no guidance about the factors that might generate heteroscedastic error variance.

4. Conclusions

We have considered two explanations of the long-shot anomaly: the commonly held, risk-loving explanation and the overconfidence explanation. The former supports the assumption of rational bettors, while the latter does not. We find that overconfidence better explains our data.

It might be argued that bettors' behavior is rational, because their information is limited. In particular, accurate estimates of the win probabilities of teasers require accurate estimates of the distribution of point-spread (expectations) errors. Using data from a 16-year period, we show that the distribution is quite flat; its standard deviation is about two touchdowns (14 points). Such large expectations errors imply that betting results are subject to much noise; consequently, bettors may not be able to learn much from their own limited betting experience.

Of course, unusual behavioral tendencies have a better chance of survival under noisy conditions. Overconfidence might be eliminated if bettors could clearly reject the hypothesis that their subjective error variances are smaller than that of the market. Noisy conditions and small samples, however, will often thwart such rejection. Hence, overconfidence is probably not obvious to many bettors. Similar potential may exist in other risk markets, and we look forward to future studies of them.

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Notes

1. Bettors are expected to act in a risk-neutral manner, either because they are well diversified and bets have no systematic risk, or because they wager very small portions of their wealth. Expected returns are negative when there is a cost to bet such as a track take or a bookie fee. See Thaler and Ziemba (1988) for more.

2. These include Weitzman (1965), Rosett (1971), Ali (1977), Snyder (1988), Asch, Malkiel, and Quandt (1982) for racetracks in the United States, and Dowie (1976), Tuckwell (1981, 1983), Crafts (1985), and Gabriel and Marsden (1990) for the British and Australian bookie systems, which are closer to the football betting system that we examine in this article.
3. Heath and Tversky (1991) show that subjects prefer to gamble in areas where they perceive that they have expertise. March and Shapira (1987) report that managers believe that they can control the odds of the risks which they take. They take risks that may look large to others, but, because of their expertise, look manageable to them. In other words, expertise or confidence increases subjective probability of success.
4. Both hypotheses require some betting market imperfection, since, otherwise, competition among suppliers would eliminate the differences in expected returns.
5. See Rosett (1965) and Quandt (1986).
6. Legal bookies in Nevada and illegal bookies in most cities follow this convention, although illegal bookies in some small towns may require gamblers to accept a loss if a tie results.
7. We borrow the term "exotic bet" from Ali (1979) and Asch and Quandt (1987), who study exotic racetrack bets, such as exactas and daily doubles. To our knowledge, exotic football bets have not been previously studied.
8. Other biases in the football betting market have been empirically documented by Vergin and Scriabin (1978), Gandar, Zuber, O'Brien, and Russo (1988), and Golec and Tamarkin (1991). Winkler documents biased football betting behavior by subjects in a controlled experiment.
9. Our local bookie agreed to offer our survey to his regular bettors. Particularly unsuccessful bettors were not interested in filling out the survey; hence, the sample is small (26) and probably biased. Nevertheless, it gives some evidence that some bettors are overconfident.
10. The tails of the distribution in figure 1 are cropped below -15 and above 15, approximately one standard deviation above and below the mean. None of the points in these tails has probability greater than 1%.
11. In addition to ease of calculation and exposition, using a continuous distribution means that the probability of a tie is zero, which is particularly helpful in calculating returns for parlays and teasers. The issue is moot for all games in which the spread or spread plus teaser points is not an integer, since ties are not possible; however, for integer spreads, the probability of a tie exists, although it is only 2.6% (figure 1). Nevertheless, this means that the probability of winning integer-spread games is slightly less than 50%. On the other hand, for simple bets that tie, bookies return all bets. Thus, even though the probability of an outright win is less for integer bets, the expected returns to integer-spread bets and half-point-spread bets are approximately equal after the expected return from a tie is included. A 2.6% probability of ties means that only six ties on average occur over a 230-game season. Given a sixteen-week season, there is less than a 40% chance of even one tie in a given week. For simplicity, we ignore the probability of ties, but acknowledge that expected returns are slightly different if ties are allowed.
12. The win probability of a two-team, six-point teaser is $(0.67)^2$, for a three-team, six-point teaser $(0.67)^3$, and so forth.
13. One may argue that since parlays and teasers are compound bets, one avoids the compound transaction costs of placing multiple simple bets. Nevertheless, the differences in returns are too large to be fully explained by transactions costs.

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