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Sports Forecasting

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SPORTS FORECASTING

Predicting the outcome of sporting events certainly falls within the purview of the field of forecasting. Moreover, the large amount of data regarding the outcomes of sporting events makes it possible to undertake significant research about the forecasts of those events. Yet despite the 40,000 entries in JSTOR and 3700 in Econ Lit that refer to sports, there are few papers that have focused exclusively on the characteristics of sports forecasts. Rather, the data associated with sporting events have been used to examine a number of topics and test a number of hypotheses that are *related* to forecasting or to economic and financial behavior under uncertainty. These include the economic efficiency of betting markets and the use of information in responding to betting odds.[1]

Economic studies concerned with the efficiency of the betting market have sought to determine whether there were any betting strategies that could "beat the market", i.e be

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[1]Sports data have also been used to investigate topics such as: the strategies (minmax, risk taking) that competitive players and teams employ, the benefits of stadia and teams to cities, the business and management of professional team sports including the trading of players, the market structure and competitiveness of professional leagues with free agency and payroll caps, labor relations and the effects of strikes, the determinants of attendance at sporting events, and even the problems associated with adverse selection in the sale of thoroughbred race horses.

profitable. (See Sauer (1998) and Vaughan Williams (1999) for surveys of the efficient market literature). These betting markets are similar to financial markets, so it is possible to test behavioral hypotheses applicable to the financial markets and to the field of forecasting. If there were any inefficiencies, such as those produced by the forecasting process, it would be possible to determine the biases that produced those inefficiencies.[2] Even in the absence of inefficiencies, the betting data available from these markets would permit one to extract information about the betting market process and the way it attains efficiency. (Sauer, 2005).

Since, the majority of previous betting markets studies were concerned with economic efficiency, they did not evaluate the actual (or implied) forecasts associated with those markets. As it turns out, it is possible to derive considerable information about the forecasts and the forecasting process from the studies that tested the markets for economic efficiency.

Since the betting markets provide a huge number of observations, it is possible to obtain robust tests of various hypotheses concerning forecasting. It is not necessary to base findings on laboratory experiments with a small number of observations that may not replicate the conditions of the real world. For example, one study that compared the predictive accuracy of judgmental forecasters with statistical systems was based on 31,000 observations of real time predictions of the outcomes of American football games.

This paper is concerned with a number of forecasting topics. The first topic involves the type of forecast that is made. In some sports the forecast is intended to determine the winner of an event. In other betting markets, individuals predict whether/or not the favored team wins by x points (called the point spread). A second topic involves the procedures that are used to evaluate the forecasts. This paper will show that the evaluation procedures depend on the type of betting market that is associated with each sport. A third topic involves a comparison of alternative forecasting methods. For every sport, forecasts have been made by models (systems) and

[2]Moreover, since a sporting event has a definite outcome at a specific point in time, it is not necessary to make assumptions about expectations of the future as is necessary in other asset markets.

experts. In some sports, it is also possible to analyze a forecast that is made by the market. The final topic is to determine whether the forecasts are biased and, if they exist, the sources of the biases.

These topics will be discussed on a sport-by-sport basis in the next few sections. Then we will undertake a cross sport comparison to determine whether the results for individual sports yield valid generalizations about sports forecasting. Finally, we compare the findings from sports forecasts with the profession's generally accepted beliefs and see whether they are consistent.

I. The Sports Gambling Market and Forecast Evaluation Procedures

Given that the data are generally associated with and obtained from the gambling market, it is first necessary to discuss how the markets are structured. The gambling markets are constituted differently from sport to sport. In horse racing, baseball and soccer the bet involves picking a winner, and the market quotes odds that a particular horse or team will win.   As an example, if there were only two teams and there were no commissions, the odds on the underdog might be 2 to1 and the odds on the favored would then be 1 to 2. A winning bet on the underdog will pay $2 for every $1 that was bet and the payoff to the favorite would be 50 cents for every dollar bet. In either case, the winner would also have the original bet returned; in our example the payoffs would be $3 and $1.50, respectively for every dollar bet.

In markets where odds are quoted, it is not possible to determine whether forecasters correctly predicted the winners when there are more than two competitors.   Rather the forecasting evaluation is based on a comparison of the ex ante probabilities and the ex post ratio of outcomes. The betting odds must, therefore, be converted into probabilities by the formula, p = 1/(1+odds).[3] For each ex ante probability, p_i, the ex post proportion of winning horses, that went off at those odds, should be equal to p_i. Using statistical terminology, the ex ante probabilities and the ex post winning percentage should be calibrated, i.e. horses whose ex ante probability of winning was 0.30 should have won 30 percent of the time.

The evaluation procedure is different in those markets where bets are placed on the margin of victory. In American football and in basketball, bets are not made on which team will win nor are odds quoted in the market. Rather there is a bet on whether or not the favored team will win by more than the specified margin (point spread) that is set in the market.[4] Given the data from the betting markets of those two sports, it is possible to evaluate the accuracy of two types of forecasts: The accuracy of the forecasts in (a) selecting the winning team and (b) in predicting whether the favored team beat the spread?

The procedures for evaluating forecasts will differ from sport to sport depending upon the institutional structure of the betting market that is associated with that sport.

II. Types of forecasts

The forecasts that we examine come from three sources. First, there is the market forecast itself. Experts, be they bookmakers, handicappers or sports commentators, also issue forecasts about the likely outcomes of sporting events. Finally, forecasts can be derived from

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[3]If the sum of the betting odds exceeds one because of the bookmakers' commissions or the parimutuel take, they must be adjusted so that they sum to one.

[4]Although odds are not quoted, the bet is not even money because the bettor must commit $11 to win 10. Since bookmakers set the point spread in an attempt to receive an equal amount

statistical models that are based on the fundamentals of the sports or are based on variables that are proxies for these characteristics.

A. Market forecasts

For each sport, the largest number of forecasts come from the betting market. The market forecast is either the final odds that a team will win or the final point spread. As indicated above, these forecasts can be analyzed in several different ways, depending on whether odds or point spreads are quoted. Nevertheless, it is always possible to test for the existence of biases and to determine whether the market forecasts were more accurate than those of other forecasting methods.

B. Models[5]

In order to predict the outcome of sporting events, different types of models can be constructed. At the most disaggregated level, it is possible to predict the outcome of a game by modeling the effects of every play. (For baseball see Bukiet et al.,1997 and Sauer, 2005; for soccer see Carmichael et al., 2000). At a more aggregative level, production functions are used. These functions focus on the fundamental factors that determine the outcome of a game. On offense it is the *factors* that determine the number of points or runs scored; on defense the *factors* that determine the number of points or runs allowed. The model that is used to forecast the outcome of a game is then based on the differences in the fundamental characteristics of the two teams.

An alternative statistical procedure is to construct a power score or index that is a <u>proxy</u>

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of money on both sides of the bet, the deviation from the even money bet represents the bookmakers' commission.

for these fundamental characteristics or the latent skills and strengths of the teams. Such a model merely uses the difference in runs (points, goals) scored as a predictor. Then there are models that use power scores based on relative performance as the independent variables. The focus of these models is exclusively on the relative number (and margins) of victories of the competing teams and the time trend in this relationship. For example, the New York Times created power scores for every NFL team that summarized each team's relative performance in previous games. It was based on the winning percentage of each team, its margin of victory, and the quality of its opponents. Similar measures, that include the strength of schedule, have been constructed for other sports. These power scores can be transformed further into ordinal rankings. (Boulier and Stekler, 2003).

C. Experts

Finally, we have predictions made by individuals (experts) who may or may not reveal their methods. Some of these experts are sports writers, editors of newspapers or sports magazines, or sports commentators on the major television networks; others are tipsters . The odds makers in the betting markets and the track handicappers should also be considered experts.

III. What has been forecast?

The literature with which we are concerned has examined economic efficiency issues in virtually every sport, but the emphasis has been on the outcomes of horse races and of baseball, football, basketball, and soccer games. There are also forecasts about the winners of tournaments such as the NCAA basketball championships and the winners of the championship

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[5]It should be noted that many of the models that have been estimated and that are

of particular leagues. We present the methodologies and results for each sport separately and then provide a cross-sport summary in order to generalize the findings.

A. Horse Racing

Sauer (1998) and Vaughan Williams (1999) have surveyed the major studies that analyzed the outcomes of horse races. While the major emphasis of these studies was on the economic efficiency of the betting markets, these analyses provided insights that can have general applicability to all fields of forecasting. The observed inefficiencies provide information about the biases that exist. Moreover, the results suggest that it is even possible to model the outcome of horse races. These statistical models take into account the quality of the competition that occurs during a race.

1. Betting Market

The results indicate that the market can distinguish among horses of different quality. With a particular exception, the subjective probabilities obtained from the odds rank of the horses are well calibrated with the observed frequency of wins. (Sauer, 1998, pp. 2035 and 2044). This indicates the obvious presence of individuals who are informed forecasters and can predict the outcomes of horse races.

The exception to the aforementioned calibration occurs at the extremes of the odds distribution. Most studies of horse racing in the US yield a result that has been called " the favorite- long shot bias". This means that in the parimutuel market, an insufficient amount is bet upon the horses that are favored to win and an excessive amount is bet on the long shots, thus

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discussed in this paper have never been used in forecasting beyond the period of fit.

distorting the odds at the extremes.[6]

This bias can be explained either by individuals' underestimates (overestimates) of favorites (long shots) or by bettors' utility functions that are locally risk seeking. (Quandt, 1986). Golec and Tamarkin (1995) favored the hypothesis that bettors were overconfident in their abilities to predict rather than being risk seekers. This result is consistent with the findings from some laboratory experiments indicating that individuals generally underestimate the probability of likely events and overestimate the probability that an unlikely event will occur.[7]

The bias may also occur because the quality of information that is available to bettors is poor. (Vaughan Williams and Paton, 1998). When more information is available publicly and the bettors are better informed, the more likely it is that the consensus forecast (represented by the market odds) will converge to the true odds. Empirical evidence is consistent with this view, because the bias is diminished if either the betting pool or the number of horses in the race is increased. (Busche and Hall, 1988; Gramm and Owens, 2005).

2. Modeling

Bolton and Chapman (1986) construct a multinomial logit model of horse racing that includes characteristics of both the horse and the jockey.[8] While the final equation includes many variables that are not statistically significant, one characteristic, the speed of the horse contributes the most to explaining the variance of the horse races. The adjusted R^2 of the

[6]This bias does not exist in race horse betting in Hong Kong and Japan, for example. It also does not exist in most other sports.

[7]In fact, Vaughan Williams (1999, p.8) cites one study that finds that bettors are overconfident.

[8]The characteristics of the horse include the percentage of races won, winnings per race, an index measuring speed, weight and post position. The jockey characteristics include the number of races won and his winning percentage.

equation is .09 indicating that the equation explains 9% more than the null that each horse has an equal chance of winning.

Expanded versions of this multinomial logit model improve the explanatory power of the equations, with most of the new variables significant and the adjusted R^2 exceeding 12%. (Bentner, 1994;Chapman, 1994). While the final betting odds have even more explanatory power, a combination of the model and the market odds improves upon both.[9] This finding is consistent with the results obtained from the non-sports forecasting literature which indicates that combining forecasts usually improves accuracy.

3.Experts

Figlewski (1979) examined the forecasting record of a number of individuals who handicapped horse races. While the handicappers were successful 28.7% of the time in selecting the horse that would win the race, the favorite, as measured by the betting odds, won 29.4% of the time. Both the track-odds and the handicappers improved over the null that all horses had an equal probability of winning, but combining the handicappers' selections with the market odds did not significantly improve forecasting accuracy.[10] In Britain, the odds in the handicapper's morning line were also less accurate in predicting the probability of winning than were the final market odds.(Crafts, 1985).

The experts also displayed the favorite-longshot bias. Snyder (1978) found that the favorite-long shot bias of official race track handicappers and newspaper forecasters was greater than that of the general public. Lo (1994) showed that the favorite-longshot bias associated with

[9]However, in a real time situation an individual might not have the time and thus be in a position to use the final odds in combination with the model before placing a bet.

the handicappers' morning line odds was even larger than that of the final odds of the betting market.

4.**Summary**

a. The market odds and the frequency of wins are calibrated except for the favorite-longshot bias. However, this bias is not observed universally.

b. Models can explain some of the variance of horse races. Combining models with market odds improves accuracy.

c. The odds provided by experts are better than those obtained by chance but not as accurate as the betting market odds.

d. Experts displayed even more favorite-longshot bias than the final market odds.

B. Baseball

There is so much information about baseball, that it is surprising how few forecasts are available for analysis. There are a number of models that have estimated the importance of the offensive and defensive factors that determine the outcome of a game, but forecasts from these models have not been published in the open literature.11

1. The betting market

Bets in this market are made on the outcome of a game. Consequently, like the horse race betting market, the analysis is based on odds which can then be converted into probabilities, but the odds are not quoted directly. The bookmaker quotes, a line, +140, -150 for example. This

[10]Bird and McCrae (1987) found that the odds of Australian bookmakers, who could be considered experts, were fully incorporated into the racetrack odds.

means that the winner of a $100 bet on the underdog team would win $140, while someone betting on the favored team would bet $150 to win $1. The difference is the commission. From these odds it is possible to calculate the betting market's subjective probability that the underdog will win. The probability is calculated at the midpoint of the line, i.e. 1/(1.45 +1) = 0.41 . This subjective probability can then be compared with the percentage of times that the underdog won when those odds were quoted. If the subjective probabilities are calibrated with the observed probabilities, the forecasts would be considered rational.

Three studies examine the relationship between these subjective and observed probabilities. Woodland and Woodland (1994, p.275; 1999, p.339) and Gandar et al. (2002, p.1313) all indicate that the odds are related to the observed outcomes, but the relationship is not strictly monotonic.12 In order to test whether the forecasts were rational, Woodland and Woodland (1994) regressed the objective probabilities on the subjective odds. They obtained mixed results that were dependent on the method of estimation. They argued that betting in baseball yielded a reverse favorite-underdog bias, with underdogs underbet. Gandar et al. made a minor correction to the Woodland-Woodland methodology and found that rationality was not rejected, and if there were any bias, it was very slight.

2. Modeling

Many of the basic models of a baseball game consider either the characteristics of the offense to determine the number of runs scored or the qualities of the pitching staff in permitting runs to be scored. Thus Porter and Scully (1982) estimate a production function based on a

[11] Individuals may have used these models in deciding whether to place bets about the outcome of games, but these data are not readily available.

team's slugging average and its strike out to walk pitching ratio.[13] Other models provided more detail about baseball's offense and pitching; for example Bennett and Flueck (1983) examined various characteristics of offense[14] to determine the number of runs that would be scored but did not make explicit predictions with their model. The model was estimated using data from the 1969-1976 seasons. It was then reestimated by sequentially eliminating one year's data from the sample using the data of the remaining seven years. While the adjusted correlation coefficients of those eight regressions did not differ significantly, the coefficients of some of the variables did display considerable variation.

Rosner et al. (1996) estimated relationships that measured pitcher performance and determined the number of runs that would be scored in each inning. They were able to do this because play-by-play data have been available for all Major League Baseball games since 1984. An adjusted negative binomial distribution was fit to the data to explain the number of batters that a particular pitcher would face. The number of runs that will be scored is a complex function of two distributions: this negative binomial distribution and a conditional distribution of the number of runs that score given that the pitcher has faced a specified number of batters. (Rosner et al. 1996, p.352.) Other studies include Malios (2000) who listed the factors that determined offensive and pitching performance, and Turocy (2005) who added a speed variable to the conventional production function. None of these models produced forecasts that could be

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[12]The QPS statistic also known as the Brier score could have been calculated and decomposed to determine the degree of calibration.

[13]This model was not used as a predictor but rather was employed to measure the relative performance of baseball managers. Horowitz (1994) uses a power score variant of this production function (runs scored/ runs allowed) in a similar analysis of managerial performance. See Ruggiero et al. (1997) and Horowitz (1997) for a further discussion of this subject.

[14]These variables included the various types of hits, walks, types of outs, etc.

evaluated.

On the other hand, Bukiet et al. (1997) modeled each at-bat as a 25x25 transition matrix that explained all of the alternatives that might occur. Markov chains were then used to predict team performance based on the characteristics of each batter. This model was used to predict the actual number of games that all of the teams in the National League would win in 1989. While the model failed to predict one of the two divisional winners and the number of runs that were scored was underestimated, the Spearman Rank Correlation between the predicted and actual number of games that each team won was .77. (Authors' calculations).

There are two other models that were used to predict National League divisional winners. Barry and Hartigan (1993) used a binary choice model to calculate the probability that in 1991 a National League team would win its division. The model was based on the strength of the teams as the season progressed with greater weight placed on the most recent sequence of games as well as the teams' home field advantage. Using simulations, the model successfully showed that Atlanta's probability of winning its division was increasing as the season progressed. Finally, Smyth and Smyth (1994) based their predictions of division winners and relative standings on the payrolls of each of the teams in each division and league. They found that the rankings within a division were correlated with the teams' payrolls.[15]

3. Experts and Experts vs. Models

Despite all the predictions that are made every year by experts about the relative expected performance of the Major League teams, we found only one study that examined the quality of

[15]Szymanski (2003, p. 1154) presented similar results for soccer. He showed that, within each league, the winning performance of a team was associated with the relative size of the teams' payrolls. Forrest et al. (2005a) use payrolls as a measure of team quality.

those forecasts. Smyth and Smyth (1994) found that the experts' forecasts were better than random guesses. However, the predictions of those experts were not significantly different from those based on the rankings of teams' payrolls.

4. **Summary**

a. The market odds are calibrated with the observed ratios of outcomes, but there is some debate about the possibility of a reverse favorite-longshot bias.

b. Many models that explain various aspects of a baseball game have been estimated, but they have not been used to make forecasts.

c. There is one study that examined the forecasts of experts. The experts' predictions were better than random, but not different from models that used payrolls as the predictor.

C. Football

The forecasts about the outcomes of professional and college football games, like those from other sports, come from the betting market, statistical systems, and experts.   Unlike horse racing and baseball where odds are used in establishing the payoff to a bet that involves selecting a winning horse or team, football bets do not involve selecting the winning team. Rather the bet is whether or not the favored team beats the underdog by a margin (number of points) specified in the bet. This margin is called the point spread. If an individual bets that the favored team will beat the underdog by more than this spread, the bettor only wins if the favorite is victorious by more than this number of points. Someone betting on the underdog can win if there is an upset and the favored team loses <u>or</u> if the favorite wins by less than the specified number of points.

Every bettor pays $11 for a $10 payoff. The difference is the bookmaker's commission also known as the vigorish. Given this commission, a bettor must be right at least 52.4% of the time, just to break even. (Sauer, 1988, p. 211)

While the betting market is not concerned with selecting the winning team, it is possible to use the data about the spread to determine whether the market accurately predicts who will win. Thus, our analysis of the betting market examines two questions: (1) How frequently does the team that is favored to win actually win? and (2) Are there any observed biases in the spreads that were published just before the game was played?

1.Betting Market

a. Winners

The focus of the previous analyses have been whether the betting market involving NFL games was economically efficient. With a few exceptions, the studies have not considered the forecasting accuracy of the market in predicting the winners of games. Stern (1991) demonstrated the difference between the winning margin and the point spread was normally distributed with mean zero and a standard deviation equal to 14. He then used the observed spreads in simulations to determine how the teams would have done in the 1984 season. The results were mixed. While 5 of the 6 division winners were identified, only 1 of the 4 additional playoff teams was selected by the model.

Boulier and Stekler (2003) and Song et al. (2007) showed, that in every year from 1994-2001, the betting market correctly predicted the winner of NFL games at least 63% of the time. The average over this time period was about 65%. In fact, in selecting the winners of games, the betting market was the most accurate forecasting method in every year. We tabulated the relationship between the point spread and the ex post winning percentage of the home team. Table 1 indicates that the ex post winning percentage is positively related to the ex ante spread, but the increase is not monotonic.

b. Point spread

In analyzing the market's performance relative to the spread, the main question is: Are there any observed biases? The overwhelming majority of the evidence indicates that the betting market is efficient in the sense that, on average, there is no profitable betting strategy against the spread. The traditional method for determining whether a forecast is unbiased is to run the regression:

$$A = a + bF + e, \qquad (1)$$

where A is the actual value and F is the forecast. If the joint null hypothesis that a = 0 and b =1 is rejected, the forecasts are biased. In the football betting market, the equivalent equation is:

$$DP = a + bPS + e, \qquad (2)$$

where DP is the difference in the game score (actual points) and PS is the betting market point spread.[16] If the forecast is unbiased, on average, the difference in the point scores will not differ significantly from the point spreads. Most studies do not reject the null hypothesis that a = 0 and b =1, but the explanatory power of the equation is usually low indicating that there is considerable unexplained variation.

On the other hand, Gray and Gray (1997) use a different method to test the hypothesis that the forecasts are efficient. They estimate a probit where the dependent variable is whether the team beat the spread or not.[17] They find that two variables, whether a team plays at home and whether it is a favorite, are jointly significant. If the market had provided an efficient forecast, neither variable should have had any explanatory power.[18]

Since there is a considerable amount of unexplained variability, forecasting biases and profitable betting strategies may exist. We are concerned only with the forecast biases. Vergin (2001) argued that bettors (forecasters) were subject to an overreaction bias, i.e. they overreact to the most recent *positive* information and undervalue other data. "For example, if a team won a game by a very large margin in a given week, the betting public would tend to overrate the team in the following week." (Vergin, 2001, p. 499).[19] Vergin examined a number of ways that bettors (forecasters) could have reacted to recent information. He found that, in most cases, over 15 seasons, the bettors had displayed a bias in interpreting recent positive data. Gray and Gray (1997) also found that the market overreacted to the most recent information.[20]

The forecasting literature has also analyzed the way that individuals interpret information. Kahnemann and Tversky (1982) had argued that individuals place too much emphasis on new information, but some experimental data suggested the opposite: people anchor on a past observations and place too little emphasis on new information. (Andreassen, 1987, 1990) The data from the football betting market seem to favor the former view.

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[16]Both the scores and the point spreads are usually constructed on a home team minus away team basis.

[17] A probit places less weight on outliers than OLS does.

[18]There is, however, a controversy about the appropriate way to jointly test for home team bias and underdog bias. (Golec and Tamarkin, 1991; Dare and MacDonald, 1996; Dare and Holland, 2004).

[19]Vergin and Scriabin (1978) were also concerned with this issue.

2.Models

The many statistical systems that are designed to predict the margin of victory of NFL or college football games are estimated in different ways.[21] Zuber et al., (1985) and Sauer et al., (1988) derived models using the fundamental characteristics of a team's offense and defense to explain the margin of victory. Those models correctly predicted a margin of victory that would have been profitable 59% of the time for games played in 1983, but the success rate was only 39% in 1984.[22] Dana and Knetter (1994) developed a dynamic model using point score indices as a measure of the abilities of the teams but the accuracy ratio of the model was generally less than 50%.

Other models are based on power scores that summarize the latent abilities of the football teams. Variants of these power scores have been used in forecasting both the outcomes of football games and the margins of victory. Harville (1980) found that in the 1971-77 seasons the betting market, with a 72% success rate in selecting the winner, was more accurate than his statistical procedure, which was right 70% of the time.[23] Boulier and Stekler (2003) used the power scores published in the *New York Times* and analyzed the forecast: the team with the

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[20]In addition, Gray and Gray observed that the market had a slight overconfidence in the favorite's ability to cover the spread. In the 1976-94 seasons, that team won by slightly less than the market had expected.

[21]Song et al. (2007) used information from 32 systems that provided information on the Internet.

[22]The papers did not indicate the number of times that the model predicted the winners of each game, but the models explained 73-81% of the variance of the score differentials for the two NFL seasons.

[23]These success rates are higher than the accuracy that has been observed in more recent seasons. One explanation is that more ties occurred in the earlier seasons and Harville counted a tie as ½ of a successful forecast. Harville did not report the methods' record in betting against the spread.

higher power score would win. These forecasts had an accuracy ratio of 61%, less than that of the betting market which achieved 66% accuracy and only comparable to a naive forecast that the home team will win.

An intensive evaluation of the forecasting record of statistical systems indicated that they had a 62% average accuracy ratio in picking the winners of the games played in the 2000 and 2001 NFL seasons. (Song et al., 2007). This ratio was comparable to the record of experts but less than the 66% accuracy of the betting market. Every system had a success rate of at least 50% and the ratios for all but one system were significantly different from those that could have occurred by chance.[24] In forecasting against the betting spread, most systems, however, were not even as accurate as the naive forecast of flipping a coin.

3. Experts

We found information about two types of experts: bookmakers[25] and sports commentators (analysts). In NFL games the bookmakers ....AVERY AND CHEVALIER. In the college football betting market, the bookmakers set an opening line that was biased against the favorite team, but the closing spread was less biased. (Dare et al., 2005).

Song et al. (2007) undertook a comprehensive analysis of the other group of experts and examined the ability of sports commentators to predict either the outcome of NFL football games or the margin by which a team was expected to win. That study used the forecasts of 48 experts who predicted which team would win and an overlapping (but not identical) set of 52 forecasters who made selections against the betting line. All told, the forecasts of 70 experts were analyzed.

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[24] The test was based on the binomial distribution and a 5% level of significance.

Based on this sample of nearly 18,000 forecasts for the 2000 and 2001 seasons, Song et al. concluded that experts predicted the game winner approximately 62% of the time; this was the same accuracy ratio as the statistical systems achieved, but was less than the betting market's 66%. Similarly, the accuracy ratios of both the experts and systems in forecasting against the betting line was 50%. On average the experts did worse than using the naive model of flipping a coin.

Less comprehensive studies yield similar findings. Boulier and Stekler (2003) report that the sports editor of the New York Times selected the winner of the games during the 1994-2000 seasons 60% of the time. Even earlier, Pankoff (1968) showed that experts' accuracy in forecasting whether a team would beat the spread ranged from 48% to 56%.

4. **Summary**

a. The market correctly picks the winner of a game about 2/3 of the time. This record is better than that of the experts and systems.

b. The null that the point spread is an unbiased predictor of the margin of victory is generally not rejected.

c. Models are successful in predicting winners but they are not as accurate as the betting market.

d. Models and experts are equally good both in forecasting winners and in predicting against the spread. The predictions against the spread are not significantly better than chance.

D. Basketball

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[25]For information about the process of setting the opening line (spread) on football

1. Betting Market

The studies that have analyzed the basketball betting market have not found any *significant* biases. There is a slight but insignificant underestimate of the home court advantage, (Brown and Sauer 1993a) and large favorites may be over bet. (Paul and Weinbach, 2005a, 2005b).

The major forecasting issues of interest in the basketball betting market are (1) the absence or presence of the "hot hand" phenomenon and (2) the use of information in this market. The "hot hand" is a belief that a team that wins a game is more likely to win the next game and indicates that forecasters believe that these events are not independent but rather are positively autocorrelated. Camerer (1989) argues that the hot hand is a myth and that bettors have a misunderstanding of random processes, especially with small samples. Brown and Sauer (1993b) build a model based on teams' abilities and streak dummies in order to test this hypothesis. They conclude that the hot hand belief is embodied in the point spread and is, therefore, an important effect.[26] However, they were not able to determine whether, in fact, a hot hand phenomenon existed or whether it was a myth and bettors were misperceiving the real process and thus displaying a cognitive bias.

Using changes in the betting line, it is possible to infer the role that information and informed bettors play in the betting market. Brown and Sauer (1993) and Gandar et al (1998, 2000) examine these questions from different perspectives. Brown and Sauer first estimate a model based on a proxy for fundamentals: the points scored by the two teams that play against each other. This model explains 89% of the variation in the point spread and also predicts well

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games, see Schoenfeld, (2003).

out of sample. Brown and Sauer thus conclude that the betting market adjusts for fundamental changes in the relative team abilities that may have occurred from one season to another.

Gandar et al. examine the differences between the opening and closing point lines for NBA games.[27] They show that frequently there are large changes between the opening and closing quotations. These changes reflect betting sentiment that is different from that of the bookmaker. They test a number of hypotheses, show that the opening line is not as accurate as the closing line in forecasting the margin of victory, and conclude that informed bettors have eliminated some of the bias in the opening line.

2. Models

Zak et al. (1979) developed a production function that represented the defensive and offensive elements of a basketball game. The model was designed to measure the relative contribution of each of those elements to the winning margin. Each team's productive efficiency was then calculated. The rank of each team in terms its productive efficiency was identical to the rank based on winning percentage in the 1976 NBA season. This method has not been subsequently used for making forecasts.

Berri (1999) used a similar model that was designed to measure the contribution of individual players to a team's wins. Rather than directly predicting a team's wins, each player's contribution towards his team's wins were summed. The ranking obtained by summing the

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[26] Also see Paul and Weinbach (2005b).

[27] Gandar et al. (1998) examine the winning margin (the difference in the scores of the two teams) while Gandar et al. (2000) analyze the totals betting market (the sum of the scores of the teams).

The opening line is set early in the day that the game is played and the closing line is established just before the game begins. Thus it is not likely that much *new* information about the teams will have become available during the course of the day.

contributions of each player to team victories was remarkably close to the ranking based on the teams' actual won-lost records in the 1997- 1998 season. The Spearman Rank Correlation was .986 (Authors' calculations).

Other modeling approaches did not construct production functions but rather used proxy variables that measured the latent skills or strengths of each team. The margin of victory in a contest between two teams was considered a measure of the comparative strengths of the two. (Brown and Sauer, 1993; Harville and Smith, 1994; Oorlog, 1995; Kaplan and Garstka, 2001; Harville, 2003). On the other hand, if two teams that had not played each other previously were to meet, it would be impossible to measure the comparative strengths of those opponents. This is a particular problem in trying to forecast the outcomes of college basketball (and football) games, because no team plays every other team.

Statistical scoring systems have been developed to overcome this problem. As an example, Sagarin has developed a system that can be used to predict the expected scoring by any two teams. This system is based on the number of victories of each team, the strength of the teams that were defeated, the margin of victory adjusted for blowouts, and an adjustment for the home court advantage.[28]

Alternatively, in a tournament, the seedings, which are obtained from a statistical scoring system, of the teams can be used as a predictor. Since 1985, the NCAA has selected 64 college basketball teams to participate in a tournament to select a national championship. The 64 teams

[28]The difference between two teams' Sagarin ratings is a good predictor of the margin of victory. (Carlin, 1996).

are divided into four regional tournaments of 16 teams that are ranked from 1 through 16.[29] Boulier and Stekler (1999), Caudill and Godwin (2002), Kaplan and Garstka (2001), and Harville (2003) all found that the difference in ranks predicted the winner around 70% of the time. However, their statistical models differed.

Boulier and Stekler (1999) used a probit based solely on the difference in ranks. Caudill and Godwin (2002) developed a heterogeneous skewness model that takes into account not only the difference in ranks but also the level of the seed. Thus the probability that a Number 1 seed beats a Number 5 seed is greater than the probability that a Number 5 seed beats a Number 9 ranked team. Finally, Harville (2003) constructed a modified least squares ranking procedure based by placing a limit on the margin of victory and then compared the forecasts of the model solely with the difference in ranks. (Also see Schwertman et al., 1991, 1996; Carlin, 1996).

The accuracy of forecasts based on ranks has been compared with that of other methods. Kaplan and Garstka (2001) found that forecasts based on picking the higher seeds was slightly more accurate than using the betting market and that forecasts based on the Sagarin system were superior to both. Harville (2003) then compared the forecasting accuracy of his statistical method with (1) forecasting that the higher seed will win and (2) the betting market. The statistical procedures were the most accurate in forecasting the winners of the 2000 NCAA tournament, but there was little difference between forecasts based on ranks and the betting market. *Kaplan and Garstka and Harville have been the only authors who have found that forecasts obtained from the market were not more accurate than those obtained from either*

[29] The seeds are determined from a statistical scoring system, the RPI, called the ratings percentage index. It gives weights of .25, .50, and .25 to the team's winning percentage, the

experts or statistical systems.[30]

3. Experts

While there are no studies that have directly examined the forecasts of experts in predicting the outcomes of basketball games, there is one piece of indirect evidence. The bookmakers who set the opening line or point spread can be considered experts. The evidence is that the opening line that is established by the bookmakers is somewhat less accurate than the closing line established by the betting market.[31] (Gandar, et al., 1998). This indicates that experts are not as accurate as the market in forecasting the winning margins. However, this result does not imply that the experts exhibit a bias, because the changes between the opening and closing lines seem to be normally distributed around zero (no change). (Gandar et al., 1998, Table IV, p. 395).

4. **Summary**

a. The basketball betting market does not have any observed biases; the market moves to eliminate the early biases of the bookmakers.

b. Many models of basketball games have been estimated, but except for games played in the NCAA tournaments there have been few forecasts.

c. The only evidence that we have about experts is that the bookmakers' opening line is less accurate than the final spread.

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winning percentage of its opponents, and winning percentage of the opponents' opponents, respectively.

[30] Harville also found that there was no significant difference between the market and statistical systems in the football bowl games played after the 2001 regular season.

E. Soccer

Gambling in soccer is based on odds, but this betting market is different from those that have been analyzed above. The bookmakers set the odds at the beginning of a week and do not change them during the betting period. While some studies have tested for bias and inefficiencies, the focus of the literature relating to this sport has been on statistical procedures and the performance of these models relative to the bookmakers' odds.

1. Betting Market and Bookmakers

In one of the few studies that searched for biases, Cain et al. (2000) showed that there was a favorite- longshot bias, similar to that found in horse racing, in the soccer betting market. Many studies have found that models contained information that was not embodied in the odds. (Pope and Peel, 1989; Kuypers, 2000; Goddard and Asimakopoulos, 2004; Dixon and Pope (2004) These findings suggests that the bookmakers' odds were inefficient.

2. Models

The modeling has been done at three levels. In the production function approach variables that are associated with attack and defense are embodied in the model. A second approach is to model each team's goal scoring abilities and then predict which team will win based on the difference in the predicted number of goals. Finally, discrete choice models based on past performance are used to directly predict the probabilities of the home team winning, drawing or losing.

In the production function approach, Carmichael et al. (2004) estimated the effects of specific types of plays on the difference in the number of goals scored by the two teams. Their

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[31] While the results are significantly different, the differences are too small to be

equation was able to capture the relative performance of teams in the English Premier league, but they did not make any forecasts beyond the period of fit.

The Poisson distribution is an alternative model for predicting the number of goals that teams will score. Dixon and Coles (1997) show that this distribution provides a good fit to the score data for the 1992-95 seasons, but they add attack and defense parameters to the basic model of Maher (1982).. Moreover, they permit the parameters to vary to reflect changes in team strength that may have occurred over time. The probabilities obtained from the Dixon-Coles model are similar to those of the bookmakers (as derived from the odds).[32] (Dixon and Pope, 2004). The model of Cain et al. differed from that of Dixon-Coles for two reasons. It used the negative binomial distribution[33] to model the number of goals scored, and the independent variables were the win-lose odds prices quoted by the bookmakers rather than proxy attack-defense variables. The Cain et al. model predicted the total number of goals each team scored and yielded probability forecasts that approximated the observed distribution of particular scores.

Since the abilities and performance of teams can change over time, some models have become dynamic to capture these effects. Dixon and Coles were among the first to incorporate dynamic factors into their model. Crowder et al. (2002) derive an approximation to the Dixon-Coles model, show that the two models yield similar results, but the success ratio associated with the prediction, home team will win, is only around 50%.

The Bayesian dynamic model of Rue and Salveson (2000) yielded model likelihood

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economically meaningful.

[32]Dixon and Coles do not provide a detailed evaluation Nor do they compare their predictions with a naive forecast that the home team wins 46%, draws 27%, and loses 27% of the time.

[33]The Poisson distribution is a limiting case of the negative binomial.

measures that were very similar to the bookmakers' odds. Moreover, they used a Markov chain Monte Carlo retrospective analysis to predict the posterior final rankings of the teams in the English Premier League. The relationship between the actual and predicted rankings in the 1997-1998 season was not perfect. The model forecast that Manchester United had a 43% chance of being the highest ranked team; it finished second to Arsenal that had been given a 25% chance. Nevertheless, the model correctly selected the top four teams in the League.

The discrete choice models were based on ordered probits that included a variety of explanatory variables. Kuypers (2000) included the bookmakers' odds as well as some performance variables in his model.   The win ratios of the two teams playing the match were included as independent variables in the model of Goddard and Asimakopoulos (2004). Neither study compared the models' predicted probabilities with the outcomes, but both indicated that there was little difference between the models' and bookmakers' probabilities.

3. Experts

We have data that evaluates the forecasts of two types of experts. The first is the group of tipsters who write for newspapers;[34] the second consists of the bookmakers who provide the fixed odds. The evidence is that the tipsters' forecasts have little value and that they do not process public information properly. (Pope and Peel, 1989; Forest and Simmons, 2000).

On the other hand, Forrest et al. (2005) demonstrate that there is virtually no difference between the accuracy of the forecasts of the odds-makers and those obtained from a complex statistical model. This result is consistent with previous results because Kuypers (2000, Table 2,

[34]Andersson et al. (2005) evaluated the predictions of the outcome of the 2002 World Cup matches made by individuals who had familiarity with soccer. The participants were called

p.1359) had shown that the bookmakers' odds, when converted into probabilities are closely related to the objective ratios of the outcome of the events. (Also see Goddard and Asimakopoulos, 2004).

4. Summary

a. There is no serious bias in the fixed-odds soccer betting market, but there are some inefficiencies.

b. Many types of models involving soccer have been estimated and have generated predictions that are comparable to those of the bookmakers.

c. The tipster forecasters were not very valuable, but there was no difference between the forecasts of bookmakers and those of a sophisticated statistical model.

IV. Results

A. Cross-Sport results

So far we have considered the forecasting procedures and results only on a sport by sport basis. The results relating to the various sports are so similar that the conclusions have to be considered robust.

1. In every sport, except for horse racing, the market forecast is unbiased. The bias in horse racing occurs at the two extremes: favorites are underbet and long-shots are overbet, but these results do not hold in all countries.

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experts but in reality they were not "real" experts. In any event, their predictions were no better than those that could have occurred by chance.

2. In markets where odds are quoted, the ex ante betting probabilities and the ex post outcome ratios are calibrated.

3.The betting spread is an unbiased predictor of the winning margins in American football and basketball. Moreover, the betting market correctly predicted the winner of NFL games about 2/3 of the time.

4. Models that explain the outcomes of games or matches have been estimated for all sports. Sometimes the models were derived from the fundamental characteristics of the sport. In other instances, variables that were proxies for these fundamental characteristics were used as explanatory variables or discrete choice models were used.

5. The forecasts of many models were not available. However, systems correctly predicted the winners of NFL games more than 60% of the time. This was comparable to the accuracy of experts but less than that of the market. The soccer models were comparable in accuracy to bookmaker odds.

6. In analyzing the forecasts of experts, it is important to realize that there are many types of experts and that the extent of knowledge differs among the various groups. Experts who have a financial stake in the forecast are likely to be more knowledgeable.

7. There is no evidence that either statistical systems or experts consistently outperform the betting market.

B. APPLICABILITY OF THESE RESULTS TO FORECASTING IN GENERAL

The analysis of the sports forecasts also provided insights about the forecasting process. Some of these results are in accord with the generally accepted views of the forecasting profession; others are in conflict with those beliefs or require further research. The findings that agree with our a priori views:

1. Forecasters correctly used information to reduce the biases that they observed. In horse racing, more information reduced the favorite- longshot bias; the final odds in horse racing were less biased than those of the racetrack's handicapper; in basketball the closing spread was closer to the margin of victory than was the opening quote. AVERY AND CHEVALIER

2. Forecasters are overconfident in their ability to predict.

3. Many forecasters have a misunderstanding of random processes as evidenced by their belief in the hot hand.

4. Combining forecasts does improve accuracy.

C. CONFLICTING RESULTS

However, our analysis of these sports forecasts seriously conflicts with the widely held belief that the predictions derived from statistical methods are more accurate than those of experts. The analysis of 31000 NFL forecasts by Song et al. showed that the accuracy of the two methods of forecasting was virtually identical. The accuracy of the statistical methods was, however, less variable. Similarly in soccer, there was no difference between the accuracy of the models' and bookmakers' forecasts.

An area that requires further research concerns the relative weight that forecasters place on new and old information. There is a gambler's fallacy that the next outcome, even though it is independent of previous events, depends on events that have previously occurred. This fallacy has been observed in horse racing studies. This is akin to placing too much weight on new information. (Vaughan Williams, 1999, pp. 15-16). The majority of the evidence indicates that forecasters overreact to new information rather than anchor on the old forecast and adjust it in the face of the new data. On the other hand, Sauer (1998, p. 2059) reports on situations where recent information is given too little weight relative to what is optimal.

D. MOST IMPORTANT RESULT

There is no evidence that either statistical systems or experts consistently outperform the market. This not only agrees with the findings about economic efficiency but also with the evidence that prediction models, in general, are the most accurate predictors in other fields. The market price is the best predictor of the event because the market aggregates all the information that is relevant to the event. (Wolfers and Zitzewitz, 2004).

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