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Issues in sports forecasting

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Abstract

A large amount of effort is spent on forecasting the outcomes of sporting events, but few papers have focused exclusively on the characteristics of sports forecasts. Instead, many papers have been written about the efficiency of sports betting markets. As it turns out, it is possible to derive a considerable amount of information about the forecasts and the forecasting process from studies that have tested the markets for economic efficiency. Moreover, the huge number of observations provided by betting markets makes it possible to obtain robust tests of various forecasting hypotheses. This paper is concerned with a number of forecasting topics in horse racing and several team sports. The first topic involves the type of forecast that is made: picking a winner or predicting whether a particular team will beat the point spread. Different evaluation procedures will be examined and alternative forecasting methods (models, experts, and the market) compared. The paper also examines the evidence with regard to the existence of biases in the forecasts, and concludes by discussing the applicability of these results to forecasting in general.

Keywords: Sports forecasting; Betting markets; Efficiency; Bias; Sports models

1. Introduction

A large amount of effort is spent on forecasting the outcome of sporting events. Moreover, there are large quantities of data regarding the outcomes of sporting events and the factors which are assumed to contribute to those outcomes. However, despite the 40,000 entries in JSTOR and 3700 entries in Econ Lit that refer to sports, few papers have focused exclusively on the characteristics of sports forecasts. Instead, many papers have been written about the efficiency of sports betting markets[1] (see Sauer, 1998, 2005; and Vaughan Williams, 1999, 2005, for surveys of the efficient-market literature).

Since most previous betting-markets studies have been concerned with economic efficiency, they have not evaluated the actual (or implied) forecasts

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[1] Sports data have also been used to investigate topics such as: the strategies (minmax, risk taking) which 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 racehorses.

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associated with those markets; i.e., the studies' emphases have been on profitability rather than predictability. As it turns out, it is possible to derive a considerable amount of information about the forecasts and the forecasting process from studies that have tested the markets for economic efficiency. Moreover, the huge numbers of observations provided by betting markets make it possible to obtain robust tests of various forecasting hypotheses. It is not necessary to base findings on laboratory experiments with a small number of observations that may not replicate real-world conditions. For example, one study (Song, Boulier, & Stekler, 2007) which compared the predictive accuracies of judgmental forecasters and statistical systems was based on 31,000 observations of real-time predictions of the outcomes of American professional football games.[2] Although we make extensive use of data from these betting markets, we do not examine the markets' economic efficiency.

This paper is concerned with a number of forecasting topics in horse racing and several team sports. 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, while in other betting markets, individuals predict the number of points by which the winning team will win (called the point spread). It should be noted that the information (summary forecasts) that is obtained from these markets is related to the underlying characteristics and scoring systems of each sport. In sports where there is no binary outcome (horse racing, soccer, etc.), the market provides odds (probabilities) about the likelihood of each outcome. Even when there is a binary outcome, such as in baseball, the market sometimes quotes odds against each of the outcomes. However, in other binary outcome sports, such as basketball and American football, odds (probabilities) are not quoted; rather, the summary statistic is the point spread. This number is the median value of the probability distribution for the difference in scores,[3] and thus the statistic provides information that distinguishes between pairs of teams which are closely matched and those where there is a clear favorite.

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 each sport, forecasts have been made by both models (systems) and experts, and in some sports it is also possible to analyze a forecast that is made by the market. The final topic is on determining whether or not the forecasts are biased, and if they are, what the sources of the biases are.

These topics will not be discussed on a sport-by-sport basis. Rather, we integrate the results across sports, and in the process provide extensive citations referring to each sport. We then determine whether the results for individual team sports and horse racing yield valid generalizations about sports forecasting. Finally, we compare the findings from sports forecasts with the profession's generally accepted beliefs about forecasting knowledge and see whether they are consistent.

2. Types of forecasts

The forecasts that we examine come from three sources. First, there is the betting market forecast itself. Second, forecasts can be derived from statistical models that are based on either the fundamentals of the sports or variables that are proxies for these characteristics. Finally, experts, be they bookmakers, handicappers or sports commentators, also issue forecasts about the likely outcomes of sporting events.

2.1. Betting market forecasts

Given that these forecasts are generally associated with and obtained from the gambling market, it is first necessary to discuss the way in which the markets are structured and the type of forecast that can be analyzed. Gambling markets are constituted differently from sport to sport. In horse racing, baseball and soccer, the bet (forecast) involves picking a winner, and the market quotes odds that a particular horse or team will win.[4] For example, if there were only two teams and there were no commissions, the

[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 as to the future, as is necessary in other asset markets.

[3] We wish to thank a referee for pointing this out.

[4] The betting markets in golf and tennis, two markets that are not analyzed here, function similarly.

odds on Team A might be 2 to 1, in which case the odds on Team B would be 1 to 2. This forecast implies that Team B will beat Team A 2/3 of the time. This type of forecast can be evaluated in two ways: (1) was the market correct and did Team B win more frequently? or (2) in repeated trials, did teams that were favored 2–1 win 2/3 of the time? (i.e., were the probability forecasts calibrated?)

In markets where odds are quoted and there are either more than two competitors (horse racing) or more than two outcomes (soccer: win, draw or lose), it is not possible to determine whether the market forecasts predicted the winners correctly. Rather, the forecast evaluation must be based on a comparison of the market odds (ex ante probabilities) and the ex post relative frequencies of the actual outcomes. The betting odds must therefore be converted into probabilities by the formula $p = 1/(1 + \text{odds})$.[5] For each ex ante probability p_i, the ex post proportion of winning horses that went off at those odds, f_i, should be equal to p_i. Using statistical terminology, the ex ante probabilities and the ex post winning percentage should be calibrated, and thus horses whose ex ante probability of winning was 0.30 should win 30% of the time.[6]

The betting market that involves baseball has a unique way of presenting the odds. While bets in this market are made on the outcome of a game, the odds are not quoted directly. The bookmaker quotes a line, for example +140, −150. This 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 \$100. The difference is the commission. From these odds it is possible to calculate the betting market's forecast that the underdog will win. The probability is calculated at the midpoint of the line, i.e. $1/(1.45 + 1) = 0.41$. This probability can then be compared with the percentage of times that the underdog won when those odds were quoted, to determine whether the ex ante probabilities are calibrated with the observed relative frequencies.

The forecasts and evaluation procedures are different in the markets where bets are placed on the margin of victory. In American football and basketball, bets are not made on which team will win, nor are odds quoted in the market; rather, there is a bet on whether the favored team will win by more or less than the specified margin (point spread) that is set in the market.[7] While this type of 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 forecasts from this type of 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?

It is also possible to determine whether the market forecasts are more accurate than those of other forecasting methods, such as models and the opinions of experts.

2.2. Models

Many different types of models have been constructed in order to predict the outcomes of sporting events, but unfortunately, many of these models have never been used in forecasting beyond the period of fit. Only the major characteristics of these models are explained here. Some models are disaggregated, while others are based on production functions or power scores. There are even models that use payrolls as predictors of success within a sport (see Smyth & Smyth, 1994, for baseball; and Szymanski, 2003, p. 1154, and Forrest, Goddard, & Simmons, 2005, for soccer). The form of each of the models and the variables that are included in the equations are presented on a sport-by-sport basis in the Appendix.

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, Harold, & Palacios, 1997,[8] and Sauer, 2005; for

[5] The sum of the betting odds exceeds one because of the bookmakers' commissions or the parimutuel take; they must therefore be adjusted so that they sum to one.

[6] The quadratic probability score (QPS), also known as the Brier Score, can be used to evaluate probability forecasts when the relative frequencies of the outcomes are known.

[7] 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 of money on both sides of the bet, the deviation from the even-money bet represents the bookmakers' commissions.

[8] Bukiet et al. (1997) modeled each at-bat as a 25× 25 transition probability 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.

soccer see Carmichael, Thomas, & Ward, 2000). At a more aggregated level, production functions are used. These functions focus on the fundamental factors that determine the outcome of a game. For offense, the *factors* determine the number of points, runs, or goals scored; for defense, the *factors* determine the number of points, runs, or goals allowed. The model which is used to forecast the outcome of a game is then based on the differences between the fundamental characteristics of the two teams.

An alternative statistical procedure is to construct a power score or index that is a *proxy* for these fundamental characteristics, or the latent skills and strengths of the teams. Such a model uses the difference in runs (points, goals) scored as a predictor. Then there are models which use power scores based on relative performances 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 National Football League (NFL) team which summarized each team's relative performance in previous games. It was based on the winning percentage of each team, its margin of victory, and a quality measure for each of its opponents. Similar measures which include the strength of schedule have been constructed for other sports. These power scores can be further transformed into ordinal rankings (Boulier & Stekler, 2003).

Statistical scoring systems are variants of power scores. As an example, Sagarin has developed a system that can be used to predict the expected game scores of any two teams. This system is based on the number of victories of each team, the strengths of the teams that were defeated, the margin of victory (adjusted for blowouts), and an adjustment for the home court advantage.[9]

2.3. 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, while others are tipsters. The odds makers in the betting markets and the race-track handicappers should also be considered experts.

3. Results: Betting market

In presenting our results it should be remembered that 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.

3.1. Horse racing

The evidence shows that the betting market yields accurate forecasts. The horse racing results indicate that the market can distinguish between horses of different qualities. With one particular exception, the probabilities obtained from the odds ranks of the horses are well calibrated with the observed frequency of wins (Sauer, 1998, pp. 2035, 2044). The exception to the aforementioned calibration occurs at the extremes of the odds distributions. This result, which has been found in most studies of horse racing in the US, yields what has been called "the favorite-longshot bias". This means that an insufficient amount is bet upon the horses that are favored to win and an excessive amount is bet on the long shots, thus distorting the odds at the extremes.[10]

3.2. Baseball

In the baseball market, Woodland and Woodland (1994, p. 275), Woodland and Woodland (1999, p. 339) and Gandar, Zuber, Johnson, and Dare (2002, p. 1313) all indicate that the odds are related to the observed outcomes, but that the relationship is not strictly monotonic.[11] Woodland and Woodland (1994) argued that betting in baseball yielded a reverse favorite-underdog bias, with underdogs being underbet. Gandar et al. (2002) made a minor correction to the Woodland-Woodland methodology, and found that if there was any bias, it was very slight.

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

10 This bias does not exist in race-horse betting in Hong Kong or Japan, for example. It also does not exist in most other sports.

11 The QPS statistic, also known as the Brier score, was not calculated and decomposed to determine the degree of calibration.

3.3. American football

When the forecasting performance of the American football betting market is evaluated, we must distinguish between picking winners and betting against the spread. Boulier and Stekler (2003) and Song et al. (2007) showed that the football betting market correctly predicted the winner of NFL games at least 63% of the time in every year from 1994 to 2001. 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. Moreover, there was a positive relationship between the point spread and the ex post winning percentage of the home team, though the increase was not monotonic.

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 of determining whether a forecast is unbiased is to run the regression:

$$A = a + bF + e, \tag{1}$$

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:

$$DP = a + bPS + e, \tag{2}$$

where DP is the difference in the game score (actual points) and PS is the betting-market point spread.[12] 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 a considerable amount of unexplained variation.[13]

3.4. Basketball

The studies that have examined the basketball betting market have not found any *significant* biases. There is a slight but insignificant underestimation of the home-court advantage (Brown & Sauer, 1993a), and large favorites may be overbet (Paul & Weinbach, 2005a,b). Gandar, Dare, Brown, and Zuber (1998) and Gandar, Zuber, and Dare (2000) examine the differences between the opening and closing point lines for NBA games,[14] and show that there are frequently large changes between the opening and closing quotations. Since they show that the opening line is not as accurate as the closing line in forecasting the margin of victory, they conclude that informed bettors have eliminated some of the bias in the opening line.

3.5. Soccer

Gambling in soccer is based on odds, but this betting market is different from those which have been analyzed above. The bookmakers set the odds at the beginning of a week and do not change them during the betting period. In one of the few studies that have searched for biases, Cain, Law, and Peel (2000) showed that there was a favorite-longshot bias in the soccer betting market similar to that found in horse racing. Many studies have found that models contain information that is not embodied in the odds (Dixon & Pope, 2004; Goddard & Asimakopoulos, 2004; Kuypers, 2000; Pope & Peel, 1989). These findings suggest that the forecasts embedded in the bookmakers' odds were inefficient.

3.6. Summary and discussion of biases

There are mixed results regarding the existence of biases in market forecasts.[15] Biases in horse racing

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

13 Gray and Gray (1997) use a different method to test the hypothesis that the forecasts are efficient. They estimate a probit model where the dependent variable is whether the team beat the spread or not. They find that two variables, whether a team plays at home or not 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.

14 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 on which the game is played, while the closing line is established just before the game begins. It is unlikely that much *new* information about the teams will have become available over the course of the day.

15 Biases were also found in the betting markets for two sports that are not considered in this paper, namely golf (Shmanske, 2005) and tennis (Forrest & McHale, 2007).

occur at the two extremes: favorites are underbet and longshots are overbet; however, these results do not hold in all countries. Similarly, Cain et al. (2000) and Deschamps and Gergaud (2007) found biases in soccer. On the other hand, in markets where odds are quoted, the ex ante betting probabilities and the ex post relative frequencies are calibrated. The betting spread is an unbiased predictor of winning margins in American football and basketball. Moreover, the betting market predicted the winner of NFL games correctly about 2/3 of the time.

However, the presence of a forecast bias in this type of financial market, such as the horse race and sports event betting markets, is an anomaly, and explanations have been based on forecasting characteristics or bettor preferences (see Forrest & McHale, 2007; Sauer, 1998; Vaughan Williams, 1999, 2005; Vergin, 2001). There are several explanations for this bias. One concerns bettors' preferences, while another involves issues in forecasting, namely the role of information and individuals' abilities to interpret the information. We are only concerned with the forecasting issues.

When the odds are wide and less information is available, a longshot bias is more likely (Forrest & McHale, 2007; Vaughan Williams & Paton, 1998). When more information is available publicly and the bettors are better informed, it is more likely that the consensus forecast (represented by the market odds) will converge to the true odds. The empirical evidence involving horse racing is consistent with this view. The bias is diminished if either the betting pool or the number of horses in a race is increased (Busche & Hall, 1988; Gramm & Owens, 2005).

On the other hand, it is possible that new information, especially if it is positive, might introduce a bias. Vergin (2001) argued that bettors (forecasters) in the NFL market were subject to an overreaction bias. 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).[16] Vergin found that in most cases, over 15 seasons, bettors displayed a bias in interpreting recent positive data. Gray and Gray (1997) also found that the market overreacted to the most recent information.[17]

The non-sports forecasting literature has also analyzed the way in which individuals interpret information. Kahnemann and Tversky (1982) argued that individuals place too much emphasis on new information, but some experimental data have suggested the opposite: people anchor on past observations and place too little emphasis on new information. The data from the football betting market seem to favor the former view of the role that new information plays in generating a forecast.

The manner in which information is interpreted has also been discussed in the context of the "hot hand" belief in the basketball betting market. This is a belief that a team which wins one 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) conclude that the hot hand belief is embodied in the point spread, and is therefore an important effect.[18] However, they were unable to determine whether this was a real phenomenon or whether bettors misperceived the real process and thus displayed a cognitive bias.

An alternative, and perhaps supplementary, explanation involves the forecasting abilities of the individuals who place bets. Golec and Tamarkin (1991) argued that bettors were overconfident in their abilities to predict. 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.[19]

We conclude that, on average, the betting markets in all sports generate unbiased forecasts. A continuing debate on the existence of a longshot bias should

16 Vergin and Scriabin (1978) were also concerned with this issue.

17 In addition, Gray and Gray observed that the market had a slight degree of overconfidence in the favorite's ability to cover the spread. In the 1976–94 seasons, that team tended to win by slightly less than the market had expected.

18 Also see Paul and Weinbach (2005b).

19 In fact, Vaughan Williams (1999, p. 8) cites one study which finds that bettors are overconfident.

provide a greater understanding of the roles of information and individuals' forecasting abilities.

4. Results: Models

Again, we must note that many of these models have not been used to make ex ante forecasts. Consequently, we have only a limited amount of information about the forecasting records of these models.

4.1. Horse racing

A multinomial logit model of horse racing which incorporated characteristics of both the horse and the jockey had an adjusted R^2 of 0.09 (Bolton & Chapman, 1986). The equation explains only 9% more than the null that each horse has an equal chance of winning. Expanded versions of this model improved the explanatory power of the equation somewhat, yielding an 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. This finding is consistent with results obtained from the non-sports forecasting literature, indicating that combining forecasts usually improves the accuracy.

4.2. Baseball

There is so much information about baseball that it is surprising how few forecasts are available for analysis. The Bukiet et al. (1997) model, based on modeling the effects of every play, was used to predict the actual number of games that each team in the National League would win in 1989. The results were mixed: the model failed to predict one of the two divisional winners and the number of runs scored was underestimated. Nevertheless, the Spearman Rank Correlation between the predicted and actual number of games that each team won was 0.77 (authors' calculations).

Two other models have been used to predict divisional winners. Barry and Hartigan (1993) used a binary-choice model to calculate the probability that a National League team would win its division in 1991, and, using simulations, the model successfully showed that Atlanta's probability of winning its division increased 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.[20]

4.3. Football

Models forecasting the outcomes of football games are frequently evaluated based on their ability to predict the margin of victory rather than the outright winner. The models of Zuber, Gandar, and Bowers (1985) and Sauer, Brajer, Ferris, and Marr (1988), which were based on the fundamental characteristics of the teams, 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.[21] The Dana and Knetter (1994) model, using proxy variables, was accurate less than 50% of the time. On the other hand, the predictions of the Glickman and Stern (1998) model for the last eight weeks of the 1993 season were comparable to the betting line, and would have been profitable.

Variants of power scores have been used for 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.[22] Boulier and Stekler (2003) used the power scores published in the *New York Times* and analyzed the forecast: the team with the higher power score would win. These forecasts had an accuracy ratio of 61%, less than that of the betting market, which had an accuracy ratio of approximately 65%, and only comparable to a naïve forecast that the home team will win.

[20] 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 team's payroll. Forrest, Simmons, and Buraimo (2005) use payrolls as a measure of team quality.

[21] The papers did not indicate the number of times when 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.

[22] These success rates are higher than the accuracy that has been observed in more recent seasons. One possible explanation for this is that more ties occurred in the earlier seasons and Harville counted a tie as 1/2 of a successful forecast. Harville did not report the methods' records in betting against the spread.

An intensive evaluation of the forecasting record of statistical systems indicated that they had a 62% average accuracy 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.[23] In forecasting against the betting spread, however, most systems were not even as accurate as the naïve forecast of flipping a coin.

4.4. Basketball

Zak, Huang, and Siegfried (1979) developed a production function that represented the defensive and offensive elements of a basketball game, yielding a team's productive efficiency. The rankings of the teams in terms of their productive efficiencies were identical to the rankings based on winning percentages in the 1976 NBA season. Berri (1999) used a similar model which was designed to measure the contributions of individual players to a team's wins. The ranking obtained by summing each player's contributions to team victories was remarkably close to the ranking based on the teams' actual win–lose records in the 1997–1998 season. The Spearman Rank Correlation was 0.986 (authors' calculations).

Alternatively, in a tournament, the seedings of the teams, which are obtained from a statistical scoring system, can be used as a predictor. Since 1985, the NCAA has selected 64 college basketball teams to participate in a tournament in order to select a field to compete for the men's national championship. The 64 teams are divided into four regional tournaments of 16 teams that are ranked from 1 to 16.[24] Boulier and Stekler (1999), Caudill (2003), Caudill and Godwin (2002), Harville (2003), and Kaplan and Garstka (2001) all found that the difference in ranks predicted the winner around 70% of the time.[25]

The accuracy of forecasts based on ranks has also been compared with that of other methods. Kaplan and Garstka (2001) found that forecasts based on picking the higher seeds were 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 forecast accuracy of his statistical method with that of (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 experts or statistical systems.[26]

4.5. Soccer

The Poisson distribution is a model used to predict 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. Dixon and Pope (2004) then showed that the probabilities obtained from the Dixon and Coles (1997) model are similar to those of the bookmakers (as derived from the odds).[27] The model of Cain et al. (2000) used the win–lose odds prices quoted by the bookmakers, rather than attack–defense proxies, as independent variables for predicting the total number of goals each team scored. The model generated probability forecasts that approximated the observed distribution of particular scores. Goddard (2005) showed that models based on numbers of goals and those derived from scores gave similar results.

Since the abilities and performances of teams can change over time, some models have become dynamic

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

[24] The seeds are determined from a statistical scoring system, the RPI, called the ratings percentage index. It gives weights of 0.25, 0.50, and 0.25 to the team's winning percentage, the winning percentage of its opponents, and the winning percentage of the opponents' opponents, respectively.

[25] Caudill (2003) pointed out that probit models do not maximize the number of correct predictions. Instead, he uses a maximum score estimator and achieves a slight increase in predictive accuracy.

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

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

in order to capture these effects. Dixon and Coles were among the first to incorporate dynamic factors into a model. Crowder, Dixon, Ledford, and Robinson (2002) derived an approximation to the Dixon-Coles model, and showed that the two models yield similar results. However, the success ratio, associated with the prediction that the home team will win, is only around 50%. The Bayesian dynamic model of Rue and Salvesen (2000) yielded model likelihood measures that were very similar to the bookmakers' odds. Moreover, they used 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 1997–98 season was not perfect. The model gave Manchester United a 43% chance of being the highest-ranked team; in actual fact, it finished second to an Arsenal team that had been given a 25% chance of being the highest-ranked team. Nevertheless, the model did correctly select 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) and Goddard and Asimakopoulos (2004) both indicated that there was little difference between their models' probabilities and the bookmakers'.

4.6. Summary

Models that explain the outcomes of games or matches have been estimated for many 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. The forecasts of many models were not available. Betting systems, however, predicted the winners of NFL games correctly more than 60% of the time, which was comparable to the accuracy of experts but less than that of the market. The soccer models were comparable in accuracy to bookmaker odds.

5. Results: Experts

5.1. Horse racing

Figlewski (1979) examined the forecasting records of a number of horse-racing handicappers. While the handicappers were successful in selecting the winning horse 28.7% of the time, 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 the forecasting accuracy.[28] In Britain, the odds in the handicapper's morning line were also less accurate at predicting the probability of winning than were the final market odds (Crafts, 1985).

The experts also displayed a favorite-longshot bias. Snyder (1978) found that the favorite-longshot 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 the handicappers' morning-line odds was even larger than that of the final odds of the betting market.

5.2. Baseball

Despite all of the predictions that are made every year by experts about the relative expected performances of the Major League teams, we found only one study that examined the quality of those forecasts. Smyth and Smyth (1994) found that the experts' forecasts were better than random guesses. The predictions of those experts, however, were not significantly different from those based on the rankings of teams' payrolls.

5.3. Football

We found information about two types of experts: bookmakers and sports commentators (analysts).[29] In both NFL and college football games, the bookmakers set an opening line that is biased. In both cases, the opening line contains the sentimental beliefs of some bettors. The final line is more accurate, indicating that some of the inefficiencies are eliminated (Avery & Chevalier, 1999; Dare, Gandar, Zuber, & Pavlik, 2005).

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

29 For information about the process of setting the opening line (spread) for football games, see Schoenfeld (2003).

Song et al. (2007) undertook a comprehensive analysis of the other group of experts, the sports commentators, and examined their ability to predict either the outcome of NFL football games or the margin by which a given team was expected to win. Song et al.'s study was based on 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. Based on this sample of nearly 18,000 forecasts for the 2000 and 2001 seasons, Song et al. (2007) concluded that experts predicted the game winner correctly 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 experts and systems in forecasting against the betting line were 50%. On average, the experts did worse than if they had used the naïve model of flipping a coin. Avery and Chevalier (1999) reported a similar result.

Less comprehensive studies yielded similar findings. Boulier and Stekler (2003) report that the sports-editor of the New York Times selected the winner of the games played during the 1994–2000 seasons correctly 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%.

5.4. Basketball

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 (Gandar et al., 1998).[30] This indicates that experts are not as accurate as the market in forecasting winning margins. This result, however, 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, the point of no change (Gandar et al., 1998, Table IV, p. 395).

[30] While the results are significantly different, the differences are too small to be economically meaningful.

5.5. Soccer

We have data that evaluates the forecasts of two types of experts. The first is the group of tipsters who write for newspapers,[31] while the second consists of the bookmakers who provide the fixed odds. The evidence suggests that the tipsters' forecasts have little value and that they do not process public information properly (Forrest & Simmons, 2000; Pope & Peel, 1989).

In contrast, Forrest et al. (2005) demonstrate that there is virtually no difference between the accuracies of the forecasts of the odds makers and that of the forecasts obtained from a complex statistical model. This result is consistent with previous results, because Kuypers (2000, Table 2, p. 1359) showed that bookmakers' odds, when converted into probabilities, are closely related to the relative frequencies of the outcomes of the events (also see Goddard & Asimakopoulos, 2004).

5.6. Summary

There are many types of experts, and the extent of their knowledge differs among the various groups. Experts who have a financial stake in the forecast are likely to be more knowledgeable. There is no evidence that experts consistently outperform the betting market, and in football their accuracy is about the same as that of statistical systems. It should, however, be noted that models which tried to explain the behavior of bookmakers, who can be considered to be experts, showed that these individuals had not omitted important information in setting odds (see Graham & Stott, 2008).

6. Applicability of these results to forecasting in general

The results relating to the various sports are so similar that the conclusions must be considered robust.

[31] Andersson, Edman, and Ekman (2005) evaluated the predictions of the outcomes of the 2002 World Cup matches made by individuals who had some familiarity with soccer. The participants were called experts, but they were not actually "real" experts. In any event, their predictions were no better than those that could have occurred by chance.

Some of these results are in accord with the generally accepted views of the forecasting profession, while others are in conflict with those beliefs or require further research.

6.1. Findings that agree with our a priori views

1. Forecasters used information correctly 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); and in basketball and NFL games the closing spread was closer to the margin of victory than was the opening quote.
2. Forecasters are overconfident of 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.

6.2. Findings that conflict with our generally accepted views

1. 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 31,000 NFL forecasts by Song et al. (2007) showed that the accuracies of the two methods of forecasting were virtually identical. However, the accuracy of the statistical methods was less variable.
2. Similarly, in soccer, there was no difference between the accuracies of the models' and bookmakers' forecasts.

6.3. Further research required

One 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 depends on events that have previously occurred, even though it is actually independent of previous events. This fallacy has been observed in horse-racing studies and in the hot hand belief in basketball. 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 anchoring on the old forecast and adjusting it in the face of the new data. Sauer (1998, p. 2059), however, reports on situations where recent information is given too little weight relative to what is optimal.

6.4. Most important result

There is no evidence that either statistical systems or experts *consistently* outperform the market. Kaplan and Garstka and Harville have been the only authors who have found that forecasts obtained from the market (basketball in this case) were not more accurate than those obtained from either experts or statistical systems. This finding agrees not only with the theory about economic efficiency, but also with the evidence that the market price is the best predictor of the event, because the market aggregates all of the information that is relevant to the event (Wolfers & Zitzewitz, 2004).

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Appendix. Characteristics of the models

A.1. Horse racing

Bolton and Chapman (1986) construct a multinomial logit model of horse racing that includes characteristics of both the horse and the jockey.[32] While the final equation includes many variables that are not statistically significant, the characteristic that contributes the most to explaining the variance of the horse races is the speed of the horse. Expanded versions of this multinomial logit model improve the explanatory power of the equations (Bentner, 1994; Chapman, 1994).

[32] 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.

A.2. Baseball

Many of the basic models of baseball games 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 team's slugging average and its strike-out-to-walk pitching ratio.[33] Other models provide more detail about baseball's offense and pitching; for example, Bennett and Flueck (1983) examined various characteristics of offense, to determine the number of runs that would be scored, but did not make explicit predictions using their model.[34]

Rosner, Mosteller, and Youtz (1996) estimated relationships that measured pitcher performance, and determined the number of runs that would be scored in each innings. 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 fitted 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: the negative binomial distribution and a conditional distribution of the number of runs scored, given that the pitcher has faced a specific number of batters (Rosner et al., 1996, p. 352). Other studies include those of 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.

Barry and Hartigan (1993) used a binary-choice model to calculate the probability that a given National League team would win its division in 1991. The model was based on the strengths of the teams as the season progressed, with greater weight being placed on the most recent sequence of games, as well as the teams' home-field advantage.

[33] This model was not used to make predictions, but rather was employed to measure the relative performances 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 Horowitz (1997) and Ruggiero, Hadley, Ruggiero, and Knowles (1997) for a further discussion of this subject. Hadley, Poitras, Ruggiero, and Knowles (2000) used a similar approach to evaluate football coaches.

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

A.3. Football

The many statistical systems that are designed to predict the margin of victory of NFL or college football games are estimated in various different ways. Sauer et al. (1988) and Zuber et al. (1985) derived models using the fundamental characteristics of a team's offense and defense to explain the margin of victory. Dana and Knetter (1994) developed a dynamic model using point score indices as a measure of the abilities of the teams, while Glickman and Stern (1998) developed a state space model based on Bayesian techniques for predicting NFL scores.

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; for example, see Boulier and Stekler (2003) and Harville (1980).

A.4. Basketball

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 contributions of each of those elements to the winning margin, and each team's productive efficiency was then calculated. Berri (1999) used a similar model that was designed to measure the contributions of individual players to a team's wins. Rather than predicting a team's wins directly, each player's contribution towards his team's wins was summed.

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 as a measure of the comparative strengths of the two (Brown & Sauer, 1993a; Harville, 2003; Harville & Smith, 1994; Kaplan & Garstka, 2001; Oorlog, 1995). A variant of this approach is a statistical scoring system. For example, Sagarin's system 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.

Alternatively, in a tournament, the seedings of the teams, which are obtained from a statistical scoring system, can be used as a predictor. Since 1985, the NCAA has selected 64 college basketball teams to participate in a tournament to select a field to compete for the men's national championship. The 64 teams are divided into four regional tournaments of 16 teams that are ranked from 1 through 16.[35] Boulier and Stekler (1999), Caudill (2003), Caudill and Godwin (2002), Harville (2003), and Kaplan and Garstka (2001) all base their analyses on the differences in the ranks of the teams, but their statistical models differ.

Boulier and Stekler (1999) used a probit model 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 which placed a limit on the margin of victory. He then compared the forecasts of the model solely with the difference in ranks (see also Carlin, 1996; Schwertman, McCready, & Howard, 1991; Schwertman, Schenk, & Holbrook, 1996).

A.5. Soccer

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. (2000) estimated the effects of specific types of plays on the difference in the number of goals scored by the two teams. 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 also add attack and defense parameters to the basic model of Maher (1982). Moreover, they permit the parameters to vary in order to reflect changes in team strength that may have occurred over time. The model of Cain et al. (2000) differs from that of Dixon and Coles in two ways: it used the negative binomial distribution 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.[36]

Since the abilities and performances 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 a model. Crowder et al. (2002) derived an approximation to the Dixon-Coles model and showed that the two models yield similar results. The Bayesian dynamic model of Rue and Salvesen (2000) yielded likelihood measures.

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).

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[35] The seeds are determined from a statistical scoring system, the RPI, called the ratings percentage index. It gives weights of 0.25, 0.50, and 0.25 to the team's winning percentage, the winning percentage of its opponents, and the winning percentage of the opponents' opponents, respectively.

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

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