Available online at www.sciencedirect.com
ScienceDirect
International Journal of Forecasting 26 (2010) 448–459
international journal of forecasting
www.elsevier.com/locate/ijforecast

Prediction accuracy of different market structures — bookmakers versus a betting exchange

Egon Franck, Erwin Verbeek*, Stephan Nüesch

Institute of Strategy and Business Economics, University of Zurich, Plattenstrasse 14, 8032 Zürich, Switzerland

Abstract

There is a well-established body of literature on separately testing the prediction power of different betting market settings. This paper provides an inter-market comparison of the forecasting accuracy of bookmakers and a major betting exchange. Employing a dataset covering all football matches played in the major leagues of the "Big Five" (England, France, Germany, Italy, Spain) during three seasons (5478 games in total), we find evidence that the betting exchange provides more accurate predictions of a given event than bookmakers. A simple betting strategy of selecting bets for which bookmakers offer lower probabilities (higher odds) than the betting exchange generates above average, and in some cases even positive returns.

Keywords: Prediction accuracy; Betting; Bookmaker; Bet exchange; Probit regression

1. Introduction

Similarly to financial securities, betting markets trade contracts on future events. The price of a contract reflects the owner's claim, which is tied to the event's outcome. Therefore, the market price can be interpreted as a prediction of the future event. According to Vaughan Williams (1999), betting markets are particularly well suited to the investigation of forecasting accuracy because – in contrast to most financial markets – the contracts have a definite value that becomes observable after a clear termination point.

The traditional form of gambling on sports events is bookmaker betting. In this market setting, the bookmaker acts as a dealer announcing the odds against which the bettor can place his bets. However, in recent years a different market structure has evolved: betting exchanges. Whereas the bookmaker defines the odds ex ante, the prices in the bet exchange are determined by a multitude of individuals trading the bets among themselves. This form of person-to-person betting has lately experienced rapid growth.

Empirical research on the prediction accuracy of bookmaker odds is well established in the literature. While some papers document a good forecasting performance of bookmaker odds (e.g., Boulier & Stekler, 2003; Forrest, Goddard, & Simmons, 2005), other research provides evidence of biases in bookmaker predictions. However, these biases turn out to be rather small, and thus hardly provide opportunities to sys-

* Corresponding author. Tel.: +41 44 634 29 61.
E-mail address: erwin.verbeek@isu.uzh.ch (E. Verbeek).

0169-2070/$ - see front matter
doi:10.1016/j.ijforecast.2010.01.004

tematically beat the odds (e.g., Cain, Law, & Peel, 2000; Dixon & Pope, 2004; Goddard & Asimakopoulos, 2004).

Furthermore, there is a growing body of literature concerned with the predictive power of bet exchange markets. It is found that these markets exhibit high predictive accuracy, as they regularly outperform non-market forecasting methods (e.g., Berg, Nelson, & Rietz, 2008; Forsythe, Nelson, Neumann, & Wright, 1992; Snowberg, Wolfers, & Zitzewitz, 2008; Spann & Skiera, 2003; Wolfers & Leigh, 2002.

The coexistence of different betting markets offering quotes on the very same event enables us to compare their predictive power. Surprisingly, examples of this kind of research are rare.[1] To the best of our knowledge, this paper is the first to contrast the forecast accuracy of the bookmaker market with that of a major betting exchange. Using a dataset covering all football matches played in the major leagues of the "Big Five" (England, France, Germany, Italy, Spain) during three seasons (5478 matches in total), we compare the prediction accuracy of eight different bookmakers' odds with the forecasting power of the corresponding odds traded at *Betfair*, a common bet exchange platform. Our results indicate that the prices of the bet exchange market exhibit higher power than the bookmaker odds. Furthermore, we develop a simple betting strategy in order to test the economic relevance of our findings. We show that a strategy of selecting bets for which the bookmaker announced lower probabilities (and thus, offered higher odds) than the person-to-person market, is capable of yielding above average, and in some cases even positive returns. This betting strategy is not restrictive in terms of betting opportunities.

Our findings contribute to the ongoing discussion about the predictive properties of different market structures by providing empirical evidence of the superiority of exchange betting in delivering more accurate forecasts of the outcomes of sporting events.

2. Different betting market structures

In this section, we present some preliminary background information on how to interpret betting odds as outcome probabilities. We then outline the structures of the bookmaker market and the bet exchange and summarize the literature on their relative forecasting effectiveness.

2.1. Betting odds and outcome probabilities

In football matches, there are three different outcomes $e \in \{h, d, a\}$ – home win, draw and away win – on which a bet can be placed. The market prices of these outcomes are typically presented as 'decimal odds' o_e, which stand for the payout ratio of a winning bet. The inverse of the decimal odds $\frac{1}{o_e}$ can be interpreted as the probability of occurrence of the underlying event, which is offered to the betting audience. These market probabilities on all possible outcomes of an event usually sum to greater than one because of the transaction costs, the so-called 'overround'. Thus, $\sum_e \frac{1}{o_e} \geq 1$ holds. In order to obtain the market's prediction of the outcome, we assume that the overround is equally distributed over the outcome probabilities.[2] Therefore, we obtain the market's 'implicit probabilities' by a linear transformation,

$$Prob_e = \frac{1}{o_e} \frac{1}{\sum_e \frac{1}{o_e}}.$$

In what follows, we refer to this expression as the market's prediction of a future event.

2.2. The bookmaker market

Bookmaker betting is among the most popular forms of sports gambling. In this setting, the bookmaker acts as a market maker. He determines the odds on a given event and takes the opposite side of every transaction.[3] The bettor is left with a take-it-or-leave-it decision: he can either hit the market quotes

[1] Comparing bookmaker odds and bet exchange odds in UK horse races, Smith, Paton, and Vaugham Williams (2006) discover that person-to-person betting is more efficient, as it lowers transaction costs for consumers. Spann and Skiera (2008) compare the predictions of a bookmaker (*Oddset*) with the prices of a virtual football stock exchange market (www.bundesligaboerse.de), and find that they perform equally well.

[2] This assumption is in line with the literature. See, for example, Forrest et al. (2005).

[3] The bookmakers have the right to change the odds after the market has opened, but they rarely make adjustments (Forrest et al., 2005). The bettor's claim is tied to the initially taken odds, and does not depend on subsequent price changes. We therefore speak of 'fixed-odds betting'.

or refrain from participating. This is why bookmaker markets are sometimes called quote-driven markets, by analogy to the same setting in financial markets.

The prediction accuracy is determined by the price-setting behavior of the bookmaking firm. If the odds are fixed such that they reflect true outcome probabilities, the bookmaker will, on average, earn a profit margin equal to the commission charged to the bettors. Alternatively, the bookmaker can 'balance his book' by setting the odds to attract equal relative betting volumes on each side. In this case, he is able to pay out the winners with the stakes of the losers and earn the overround independently of the outcome of the event. Levitt (2004) has pointed out that bookmakers might use a combination of the two extreme cases in order to increase their profits. Forrest and Simmons (2008) and Franck, Verbeek, and Nüesch (2010) demonstrate, for example, that bookmakers actively shade prices to attract betting volume evoked by sentiment in Spanish and English football, respectively. Here, bookmakers offer more (less) favorable terms for bets on teams with a comparatively large (small) fan base in order to attract a disproportionately large betting volume. Thus, the bookmaker odds are likely to be influenced by both the true outcome probabilities and the bettors' demand. The latter can lead to deviations from the true outcome probability; nevertheless, such deviations are clearly limited. In practice, it might be a difficult task to balance the book by shading the odds, and therefore, the bookmaker is exposed to substantial risks if his prices deviate from the true outcome probabilities.

The empirical literature on the prediction accuracy of bookmaker odds is mixed. Forrest et al. (2005) compare the prediction accuracy of published bookmaker odds for English football games with the forecasts from a benchmark statistical model that incorporates a large number of quantifiable variables which are relevant to match outcomes. They find evidence that bookmaker odds are more effective in predicting game outcomes than the statistical model. A longstanding empirical regularity that challenges the suitability of bookmaker odds as predictors is the 'longshot bias'. This refers to the observation that odds often underestimate high-probability outcomes (favorites to win the game) and overestimate low-probability outcomes (underdogs to win the game). As a result, it has frequently been found that bets on low-probability outcomes ('longshots') yield lower average returns than bets on high-probability outcomes (e.g., Cain et al., 2000). Dixon and Pope (2004), as well as Goddard and Asimakopoulos (2004), find that bookmakers' odds are weak-form inefficient, as they do not incorporate all information that has proven to be significantly related to the game's outcome according to a statistical forecasting model.

2.3. The bet exchange market

In recent years, person-to-person exchange betting has evolved as a different betting market structure. Here, individuals contract their opposing opinions with each other. On an online platform, they can post the prices at which they are willing to place a bet either on or against a given event. The latent demand for wagers is collected and presented in the order book, which displays the most attractive odds, with the corresponding available volume, in a canonical manner. Such a market design is often referred to as an order-driven market. The bettor has the choice to either submit a limit order and wait for another participant to match his bet or submit a market order and directly match an already offered bet. As a result, there is a continuous double auction process taking place at the online platform. If two bettors with opposing opinions agree on a price, their demands are automatically translated into a transaction. After the bets have been matched, both of the individuals hold a contract on a future cash flow. The size of the cash flow is determined by the price of the contract, while the direction of the cash flow is tied to the outcome of the underlying event. The provider of the platform charges a commission fee, which is typically lower than the bookmaker's overround, on the bettors' net profits.

Online betting exchanges have experienced a fast boom. The odds analyzed in this paper are from *Betfair,* which is one of the most prominent bet exchange platforms. With a weekly turnover of more than \$50m and over two million registered users, *Betfair* accounts for 90% of all exchange-based betting activity worldwide (Croxson & Reade, 2008; www.betfaircorporate.co.uk). It has been online since 2000, and claims to process five million trades a day.

From a theoretical perspective, bet exchanges should yield accurate forecasts. First, the betting exchange provides incentives to gather and process information. Traders who have superior knowledge are able to generate higher average returns than naïve bettors. Second, the betting exchange provides incentives for the truthful revelation of information. Based on their knowledge, traders put money at stake, and in doing so, they reveal their expectations of the outcome's probability. Third, through the price mechanism, the betting exchange provides an efficient algorithm for collecting and aggregating diverse information in a dynamic way (Berg et al., 2008; Snowberg et al., 2008; Wolfers & Zitzewitz, 2004). As a matter of fact, empirical studies have shown that bet exchanges provide highly accurate predictions. They routinely produce better predictions of the outcomes of political elections than opinion polls (Berg et al., 2008; Forsythe et al., 1992; Wolfers & Leigh, 2002), and outperform expert opinions in forecasting future business outcomes (Pennock, Lawrence, Nielsen, & Giles, 2001; Spann & Skiera, 2003). In addition to the specific prediction literature, there are a few papers which examine the efficiency of *Betfair* prices in particular. Smith et al. (2006) used matched data on UK horse races from both *Betfair* and traditional bookmakers to test the well-documented longshot bias. They find that the bet exchange is significantly more efficient than the bookmaker market, as the tendency to overvalue underdogs is less pronounced in person-to-person betting. Croxson and Reade (2008) employ high-frequency *Betfair* data to test for efficiency in relation to the arrival of goals. They conclude that prices incorporate the relevant news swiftly and fully, indicating a high level of efficiency of *Betfair* odds.

3. Prediction accuracy of the different markets

3.1. The data

Our data cover all football games of the English *Premier League*, the Spanish *Primera Division*, the Italian *Serie A*, the German *Bundesliga* and the French *Ligue 1* over three seasons (2004/05–2006/07), with 5478 games in total. We analyze the odds of eight different bookmakers,[4] taken from www.football-data.co.uk, where they are recorded on Friday afternoons for weekend games and on Tuesday afternoons for midweek games. In addition, we matched the bookmaker data with corresponding betting exchange prices from www.betfair.com, which were collected at the same time.[5] The decimal odds from both *Betfair* and the bookmakers are converted into implicit probabilities according the procedure described in Section 2.1.

The correlations between the implicit probabilities from *Betfair* and a random bookmaker are 0.917 for draw bets, 0.978 for away win bets and 0.981 for home win bets. Thus, the odds traded on the betting exchange are very similar to the bookmaker odds. Fig. 1 graphically relates the *Betfair* probabilities to the (random) bookmaker probabilities for all three possible match outcomes separately; the black line indicates the cases for which the probabilities of the two markets are equal. It can be seen that the probabilities of the two markets are closely aligned. At first glance, the differences are somewhat unsystematically distributed, and a closer look shows that the bookmaker probabilities appear to be higher (lower) than the *Betfair* probabilities in the area of low (high) probability outcomes for home and away win bets.

In Table 1 we present some summary statistics in order to provide a first impression of the effectiveness of the two markets in forecasting the outcomes. The first column outlines the observed overall proportions of the three possible outcomes of a game, while the second and third columns contain the predicted probabilities implied by the odds of the betting exchange and the bookmaker market,[6] respectively.

Table 1 suggests that the average probabilities of *Betfair* are closer to the overall proportions of home wins, draws and away wins than those of the bookmaker. However, both *Betfair* and the bookmaker underestimate the occurrence of home wins relative to away wins. These numbers provide only a rough picture of the markets' prediction accuracy. In what follows, we will test how well the markets' implicit probabilities correspond to the actual outcome of each game.

[4] The bookmakers are *B365*, *Bet&Win*, *Gamebookers*, *Interwetten*, *Ladbrokes*, *William Hill*, *Stan James* and *VC Bet*.

[5] We used the *Betfair* odds on which bets were actually matched.

[6] For the sake of clarity, we report the probabilities of only one bookmaker, who is picked randomly for each match from our set of eight bookmakers.

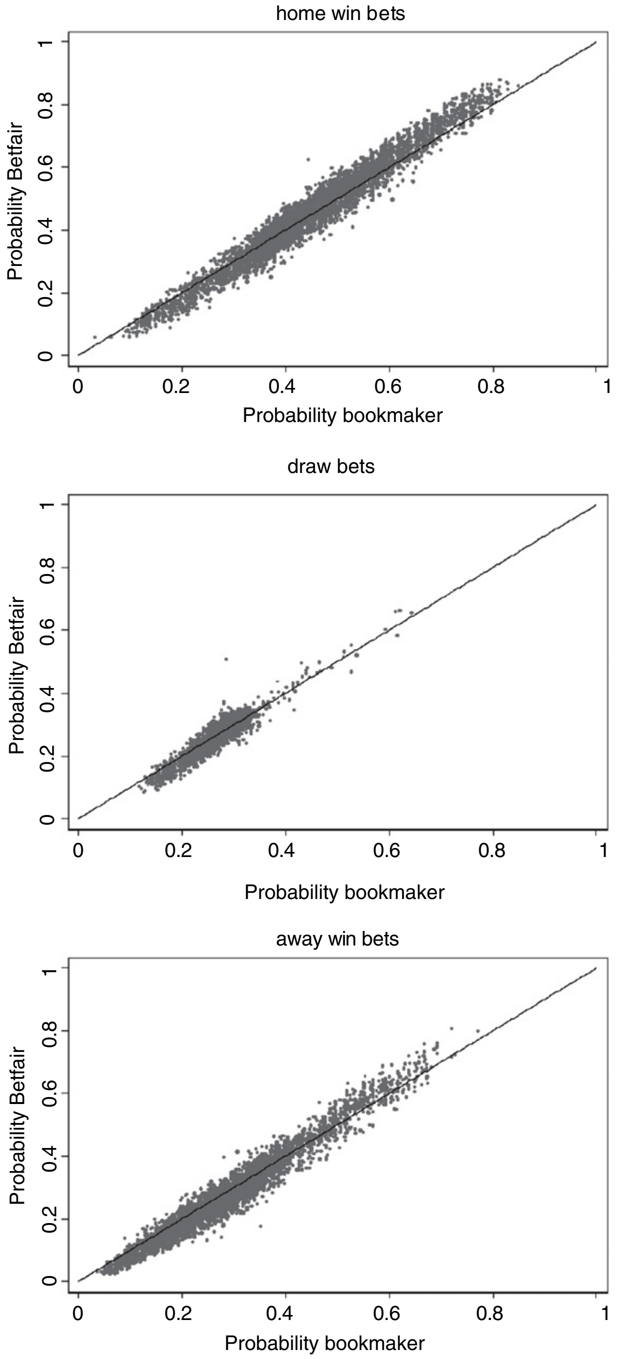

Fig. 1. The implicit probabilities of *Betfair* plotted against those of a random bookmaker. The black line indicates the cases for which the probabilities of the two markets are equal.

3.2. Goodness-of-fit of discrete response models

We estimate the following model to explain the actual outcome (win or loss) of a certain bet $Y_{ei} \in \{0, 1\}$ for a given match i using the implicit probabilities of the different markets $Prob_{eij}$:

Table 1
Summary statistics of outcome probabilities and forecasts.

	True probabilities	Betfair	Bookmaker
Home win	0.462 (0.498)	0.456 (0.158)	0.448 (0.139)
Draw	0.281 (0.449)	0.280 (0.048)	0.278 (0.038)
Away win	0.256 (0.436)	0.263 (0.135)	0.273 (0.122)
Observations	5478	5478	5478

Notes: The table presents the outcome probabilities and the forecasts of the exchange market and a randomly picked bookmaker. The mean and standard deviation are given. In terms of these summaries, the exchange market's probabilities are closer to the true outcome probabilities.

$$Y_{ei} = G(\alpha_{ej} + \beta_{ej} Prob_{eij} + \varepsilon_{eij}).$$

For each event e (home wins, draws and away wins) and every market j (eight bookmakers and *Betfair*), the coefficients $\widehat{\beta}_{ej}$ are estimated using a probit model. The probit model relates the probability of occurrence of discrete events to some set of explanatory variables, where $G(\cdot) = \phi(\cdot)$ is the standard normal cumulative distribution.[7]

The prediction accuracy is examined using various goodness-of-fit measures. While the first three are common goodness-of-fit measures proposed for discrete choice models, the fourth indicator, the *Brier Score*, is a descriptive measure which is often used in the literature on prediction accuracy (e.g. Boulier & Stekler, 2003; Forrest et al., 2005).

In a linear model, the percentage of the variance of the dependent variable explained by the model, R^2, would be the obvious measure. In non-linear discrete response models, however, the R^2 measure is not directly applicable, as a proper variance decomposition is not possible. A number of so-called *pseudo*-R^2 measures have been suggested for discrete response models.[8] The most common was proposed by

[7] Alternatives to the probit model are the logit model and the linear probability model (LPM). The logit model assumes a logistic distribution, and is therefore, like the probit model, a non-linear model, whereas the LPM is based on ordinary least squares and assumes constant marginal effects. In order to test the robustness of our results, we also ran logit and LPM estimations. However, the results, are not sensitive to alternative estimation procedures.

[8] Winkelmann and Boes (2005) and Wooldridge (2002) provide excellent reviews of goodness-of-fit measures in non-linear discrete response models.

McFadden (1974), and is defined as follows:

$$R^2_{McFadden,ej} = 1 - \frac{\log L_{ur,ej}}{\log L_{0,ej}},$$

where $\log L_{ur,ej}$ is the value of the (maximized) log-likelihood function for the estimated model for a given event and market, and $\log L_{0,ej}$ is the value of the (maximized) log-likelihood function in the model with only an intercept for a given event and market. As the value of the log-likelihood function is always negative, $\frac{\log L_{ur}}{\log L_0} = |\log[(L_{ur})]|/|\log[(L_0)]|$ holds. Further, $|\log[(L_{ur})]| \leq |\log[(L_0)]|$, which implies that the *pseudo*-R^2 is always between 0 and 1. The *pseudo*-R^2 of McFadden is 1 if the model is a perfect predictor and zero if the model has no explanatory power.

Another *pseudo*-R^2 measure was proposed by McKelvey and Zavoina (1975). Unlike McFadden's R^2, it is based on a linear model $Y_{ei} = \beta_{ej} Prob_{eij} + \varepsilon_{eij}$. Thus, the goodness-of-fit is defined as:

$$R^2_{McKelvy\&Zavoina,ej} = \frac{\sum_{i=1}^{I} (\widehat{y}_{eij} - \bar{Y}_{ej})^2}{I + \sum_{i=1}^{I} (\widehat{y}_{eij} - \bar{Y}_{ej})^2},$$

where $\sum_{i=1}^{I} (\widehat{y}_{eij} - \bar{Y}_{ej})^2$ in the numerator denotes the explained sum of squares and $I + \sum_{i=1}^{I} (\widehat{y}_{eij} - \bar{Y}_{ej})^2$ in the denominator is the model's total sum of squares. I is the number of observations that are used for estimating the model, which corresponds to the number of games in our context.

A common alternative measure of prediction accuracy is the *percentage of correct predictions* (e.g. Berg et al., 2008; Spann & Skiera, 2008). Therefore, if $\widehat{\beta}_{ej} Prob_{eij} > t$, $\widehat{y}_{ei}$ is predicted to be unity, and if $\widehat{\beta}_{ej} Prob_{eij} \leq t$, $\widehat{y}_{ei}$ is predicted to be zero. Usually, the cut-off value t equals 0.5. If the distribution of the dependent variable is skewed, however, the percentage correctly predicted can be misleading as a measure of prediction accuracy (Wooldridge, 2002). In such cases other cut-off values have to be chosen in order to minimize the forecasting errors. All combinations of a given sample and possible cut-off values can be summarized in the so-called *Receiver Operating Characteristic (ROC)* curve. The area under the *ROC* curve indicates the goodness-of-fit of a certain discrete response model. The *ROC* area varies between 0.5, indicating no prediction power at all, and 1, which means perfect prediction.

As a fourth measure of prediction accuracy, we use the *Brier Score* (Brier, 1950), which is defined as the mean squared difference between the actual outcome and the predicted outcome:

$$Brier\ Score_{ej} = \frac{\sum_{i=1}^{I} (Y_{ei} - Prob_{eij})^2}{I}.$$

Unlike the other goodness-of-fit measures, a small *Brier Score* indicates not low but high forecasting accuracy. If the predictions are perfectly accurate, the *Brier Score* is 0, and vice versa for a *Brier Score* of 1.

In the following, we illustrate the prediction accuracy of *Betfair* and various bookmakers for home win bets, draw bets and away win bets separately. Table 2 suggests that the implied probabilities of *Betfair* explain the actual outcomes better than the bookmakers' probabilities do. The model with the implicit probabilities of *Betfair* (first column) as the explanatory variable has better goodness-of-fit scores than either the regressions using the average of bookmaker probabilities (second column) or the probability of each individual bookmaker (third to tenth columns). With the exception of *VC Bet* for home and draw bets and *Stan James* for draw bets, the two R^2 measures and the *ROC area* are always higher and the *Brier Score* is always lower for the bet exchange probabilities.

There are some additional patterns that are worth mentioning. First, the prediction accuracy of draws is considerably worse than that for home and away wins. The goodness-of-fit measures in the middle row are considerably lower (and higher in the case of the *Brier score*). This observation is in line with Dobson and Goddard's (2001) conclusion that, in football matches, draws appear to be almost random events. Second, the marginal effects of the implied probability are substantially above unity for all bookmakers and events. Thus, the actual winning probability increases disproportionately with the implied bookmaker probabilities. This indicates the presence of a longshot bias. Hence, the odds underestimate high-probability outcomes (e.g., favorites to win the game) and overestimate low-probability outcomes (e.g., underdogs to win the game). This effect is strongest for draw bets and weakest for away win bets. Most importantly, the

Table 2
The prediction accuracy of the bet exchange versus the bookmaker markets.

	Betfair	Average	B365	B&W	GB	IW	LB	WH	SJ	VC
Home win bets										
$Prob_i$	1.124	1.264	1.225	1.194	1.231	1.318	1.275	1.275	1.214	1.256
	(0.047)	(0.054)	(0.052)	(0.051)	(0.052)	(0.057)	(0.054)	(0.054)	(0.063)	(0.065)
Observations	5478	5478	5457	5475	5474	5442	5413	5438	3637	3602
McFadden's R^2	0.082	0.079	0.078	0.077	0.079	0.077	0.079	0.079	0.080	0.082
McKelvey & Zavoina's R^2	0.167	0.164	0.162	0.159	0.163	0.159	0.163	0.163	0.165	0.170
ROC area	0.6842	0.6800	0.6795	0.6777	0.6794	0.6772	0.6796	0.6790	0.6790	0.6824
Brier score	0.2221	0.2235	0.2236	0.2239	0.2236	0.2248	0.2238	0.2239	0.2227	0.2223
Draw bets										
$Prob_i$	1.298	1.621	1.451	1.414	1.521	1.491	1.627	1.505	1.461	1.520
	(0.135)	(0.173)	(0.169)	(0.155)	(0.167)	(0.180)	(0.199)	(0.183)	(0.201)	(0.222)
Observations	5478	5478	5457	5475	5474	5442	5413	5438	3637	3602
McFadden's R^2	0.015	0.014	0.012	0.013	0.013	0.011	0.011	0.011	0.013	0.012
McKelvey & Zavoina's R^2	0.033	0.032	0.027	0.030	0.030	0.024	0.025	0.025	0.023	0.027
ROC area	0.5688	0.5679	0.5612	0.5657	0.5669	0.5631	0.5635	0.5612	0.5727	0.5631
Brier score	0.1989	0.1993	0.1994	0.1993	0.1995	0.1993	0.1993	0.1993	0.1975	0.1972
Away win bets										
$Prob_i$	0.998	1.084	1.055	1.017	1.062	1.171	1.072	1.102	1.057	1.073
	(0.044)	(0.049)	(0.047)	(0.047)	(0.048)	(0.053)	(0.049)	(0.049)	(0.058)	(0.059)
Observations	5478	5478	5457	5475	5474	5442	5413	5438	3637	3602
McFadden's R^2	0.088	0.083	0.082	0.070	0.083	0.082	0.082	0.084	0.083	0.084
McKelvey & Zavoina's R^2	0.159	0.153	0.152	0.145	0.152	0.152	0.152	0.155	0.153	0.156
ROC area	0.6975	0.6900	0.6897	0.6866	0.6895	0.6887	0.6880	0.6915	0.6891	0.6901
Brier score	0.1714	0.1730	0.1732	0.1735	0.1728	0.1739	0.1736	0.1731	0.1761	0.1760

Notes: The table presents the prediction power for home win (upper block), draw (middle block) and away win (lower block) bets of the bet exchange versus different bookmakers. The explaining variable is the probability implied by the odds of the different markets ($Prob_i$). The marginal effects of a probit regression (with standard errors in parantheses) and a variety of goodness-of-fit measures are reported. It can be seen that the bet exchange (first column) outperforms every single bookmaker, as well as the average bookmakers' prediction (second column), in terms of forecasting accuracy.

marginal effects of the *Betfair* probabilities are closer to unity than those of the probabilities of any other bookmaker. Therefore, at least part of the better prediction accuracy of the bet exchange is a consequence of the weaker longshot bias in person-to-person betting compared to the bookmaker market, which confirms the findings of Smith et al. (2006).

3.3. Direct comparison of prediction accuracy

The differences in the goodness-of-fit measures between the two markets in Table 2 are rather small. In the following, we include the predictions of the two betting markets in the same model. In so doing, we are able to test whether the probabilities of the bet exchange contribute additional explanatory power beyond the bookmaker's forecasts.

We rerun the regressions described in the previous section, but we include the ratio of the bet exchange probability to the bookmaker probability $R_{eij} = \frac{Prob_{ei,BF}}{Prob_{eij}}$ as a variable capturing the difference between the two markets' predictions.[9] Thus, we estimate the following probit model for each individual

[9] Another possibility would be to include both the bookmaker's probability and the probability of the bet exchange in the same model directly. A potential problem with this procedure is the high multicollinearity between the two variables. Nevertheless, this

Table 3
The additional explanatory power of the bet exchange forecast.

	Average	B365	B&W	GB	IW	LB	WH	SJ	VC
Home win bets									
$Prob_i$	1.139***	1.107***	1.064***	1.110***	1.180***	1.147***	1.150***	1.084***	1.133***
	(0.062)	(0.061)	(0.059)	(0.061)	(0.065)	(0.063)	(0.063)	(0.072)	(0.074)
R_i	0.409***	0.390***	0.449***	0.399***	0.431***	0.420***	0.405***	0.479***	0.447***
	(0.104)	(0.105)	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.131)	(0.131)
Observations	5478	5457	5475	5474	5442	5413	5438	3637	3602
McFadden's R^2	0.081	0.080	0.079	0.080	0.079	0.080	0.080	0.082	0.084
Draw bets									
$Prob_i$	1.423***	1.223***	1.221***	1.318***	1.222***	1.338***	1.245***	1.225***	1.265***
	(0.194)	(0.193)	(0.174)	(0.189)	(0.209)	(0.224)	(0.207)	(0.229)	(0.255)
R_i	0.228*	0.254*	0.250*	0.235*	0.266*	0.294**	0.278**	0.274*	0.258*
	(0.102)	(0.104)	(0.102)	(0.103)	(0.106)	(0.103)	(0.103)	(0.126)	(0.127)
Observations	5478	5457	5475	5474	5442	5413	5438	3637	3602
McFadden's R^2	0.015	0.012	0.014	0.014	0.012	0.012	0.012	0.014	0.012
Away win bets									
$Prob_i$	0.869***	0.841***	0.801***	0.851***	0.926***	0.844***	0.884***	0.854***	0.873***
	(0.057)	(0.056)	(0.054)	(0.056)	(0.062)	(0.057)	(0.058)	(0.067)	(0.068)
R_i	0.441***	0.444***	0.467***	0.438***	0.462***	0.474***	0.442***	0.456***	0.445***
	(0.064)	(0.064)	(0.063)	(0.064)	(0.064)	(0.064)	(0.064)	(0.079)	(0.079)
Observations	5478	5457	5475	5474	5442	5413	5438	3637	3602
McFadden's R^2	0.090	0.090	0.088	0.090	0.090	0.090	0.091	0.090	0.091

Notes: The table shows the additional prediction power which is provided by the bet exchange for home win bets (upper block), draw bets (middle block) and away win bets (lower block). The explanatory variables are the probabilities implied by the odds of the different bookmakers ($Prob_i$) and the ratio between the bet exchange probability and the bookmaker probability (R_i). The marginal effects of a probit regression (with standard errors in parantheses) are given. It can be seen that the bet exchange probabilities contain relevant information which is not fully reflected in the bookmakers' odds.

* Denotes significance at the 5% level.

** Denotes significance at the 1% level.

*** Denotes significance at the 0.1% level.

bookmaker j and all three events e:

$$Y_{ei} = G(\alpha_{ej} + \beta_{1,ej} Prob_{eij} + \beta_{2,ej} R_{eij} + \varepsilon_{eij}).$$

If $\widehat{\beta}_{2,ej} \neq 0$, the prediction of the bet exchange provides some relevant information that is not fully captured by the odds of the bookmaker.

Table 3 shows that the coefficient $\widehat{\beta}_{2,ej}$ is significantly positive in each case. Thus, the inclusion of the exchange market's predictions improves the forecasting accuracy of the bookmaker odds. This demonstrates that the odds offered by the bookmakers fail to incorporate some relevant information which is delivered by the odds traded at *Betfair*.[10]

4. A simple betting strategy

Our results suggest that the betting exchange market predicts future outcomes more accurately than the bookmakers do. Next, we set out to test the economic relevance of this observation. We look at the return on a bet as a combination of its price and its winning probability. If the exchange market provides

method produces results that could be interpreted in the same way as the results of the method reported in the paper: the coefficients of each individual bookmaker probability lose their significance against the *Betfair* probability in the home win and away win regressions. In the regressions for draws, both coefficients lose their statistical significance.

10 Furthermore, comparing Tables 2 and 3, one can see that the *pseudo*-R^2 values increase with the inclusion of R_{eij} in all cases (except for draw bets with *VC Bet*, for which the *pseudo*-R^2 remains the same).

Table 4
The mean returns of a simple betting strategy compared to average returns.

Bookmaker	All events		Home win bets		Draw bets		Away win bets	
	All	$R_i^* > 1$	All	$R_i^* > 1$	All	$R_i^* > 1$	All	$R_i^* > 1$
Random	−0.124 (16 434)	−0.028 (8234)	−0.084 (5478)	−0.027 (3219)	−0.096 (5478)	−0.053 (3339)	−0.192 (5478)	0.019 (1676)
Highest odd	−0.072 (16 434)	0.014 (8234)	−0.037 (5478)	0.012 (3219)	−0.055 (5478)	−0.016 (3339)	−0.124 (5478)	0.082 (1676)
B365	−0.109 (16 371)	−0.019 (8203)	−0.069 (5457)	−0.019 (3205)	−0.083 (5457)	−0.043 (3329)	−0.177 (5457)	0.027 (1669)
B&W	−0.111 (16 425)	−0.020 (8229)	−0.074 (5475)	−0.021 (3217)	−0.085 (5475)	−0.045 (3338)	−0.174 (5475)	0.030 (1674)
GB	−0.109 (16 422)	−0.017 (8228)	−0.067 (5474)	−0.015 (3217)	−0.086 (5474)	−0.045 (3337)	−0.175 (5474)	0.032 (1674)
IW	−0.141 (16 326)	−0.039 (8177)	−0.084 (5442)	−0.022 (3203)	−0.121 (5442)	−0.081 (3313)	−0.218 (5442)	0.009 (1661)
LB	−0.134 (16 239)	−0.034 (8135)	−0.096 (5413)	−0.039 (3185)	−0.102 (5413)	−0.051 (3292)	−0.204 (5413)	0.009 (1658)
WH	−0.137 (16 314)	−0.042 (8169)	−0.089 (5438)	−0.033 (3196)	−0.115 (5438)	−0.071 (3311)	−0.208 (5438)	−0.002 (1662)
SJ	−0.111 (10 911)	−0.030 (5524)	−0.88 (3637)	−0.045 (2083)	−0.103 (3637)	−0.063 (2301)	−0.141 (3637)	0.062 (1140)
VC	−0.125 (10 806)	−0.039 (5471)	−0.090 (3602)	−0.046 (2068)	−0.108 (3602)	−0.068 (2280)	−0.176 (3602)	0.032 (1123)

Notes: The table compares the mean returns for a simple betting strategy (right hand side of each column) with normal returns (left hand side of each column). The number of bets is displayed in parentheses. The trading rule is to place a bet at a given bookmaker whenever the probability of *Betfair* is higher than the average probability of the bookmakers. The results are broken down by the events on which to place a bet (columns) and the bookmakers (rows). The first row presents the results for a randomly chosen bookmaker and the second row for the bookmaker offering the most favorable odds. It can be seen that the rule enables above-average returns in all cases, and, in some cases, even positive returns.

better forecasts of this probability than the bookmaker does, a betting rule exploiting forecasting differences between the two markets should yield above average returns.

In a first step, we compare the mean return of a simple betting strategy with normal returns. The trading rule is to place a bet against a given bookmaker in all cases in which the implicit probability of *Betfair* exceeds the average implicit probability of the bookmakers. Thus, we use the prices of the exchange market as a source of information in order to detect favorable bookmaker odds. We place a bet at the bookmaker market whenever the (average) odds offered by the bookmakers are higher than the odds traded at *Betfair*. Table 4 presents the mean returns when following this betting strategy; the number of available bets is given in parentheses.

The results in Table 4 are broken down by the events on which a bet is placed (columns) and the bookmakers (rows). The first row presents the results for a randomly chosen bookmaker, and the second row the results for the bookmaker offering the most favorable odds. It can be seen that the strategy enables above-average returns in all cases, as the mean returns following the trading rule (right hand side of each column) are less negative than the average return of all bets on a given event (left hand side of each column), and are even positive in some cases. The markup is strongest for away win bets, where the trading rule is capable of generating positive returns, except for *William Hill* bets.

As a second step, we compute the observed average returns for different levels of disagreement between the two markets. In doing so, we get a better picture of the findings documented in Table 4. If the implied probabilities of *Betfair* are closer to the true outcome probabilities, the expected return on a bet against a given bookmaker increases with the difference between the two markets' probabilities. Thus, in line with our previous findings, we expect a positive relationship between the observed returns and the ratio of bet exchange to (average) bookmaker probability.

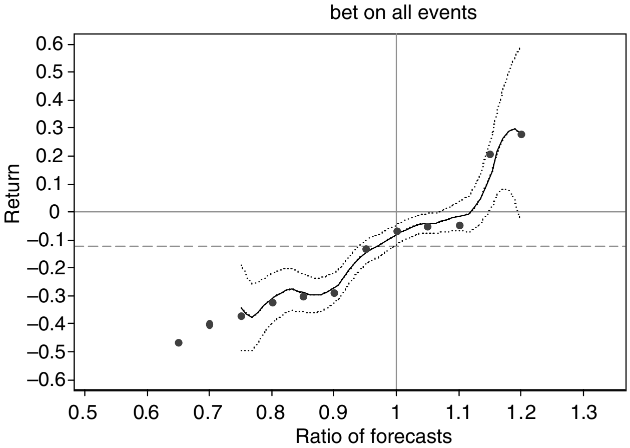

Fig. 2. Observed mean returns of bets placed at a random bookmaker, plotted against the ratio of the different markets' implicit probabilities for all events (R_i^*). The horizontal lines are for a zero return (solid line) and the expected return under random betting (broken line). The graph shows the mean returns for the different categories of the ratio (dots) and the local polynomial smoothing (solid line) with 95% confidence intervals (dotted lines).

To investigate this relationship by means of our data, we rank all bets according to their ratio of *Betfair* to average bookmaker probability, defined as

$$R_{ei}^* = \frac{Prob_{ei,BF}}{\frac{1}{J_i}\sum_j Prob_{eij}},$$

where J_i is the number of participating bookmakers in match i.[11] We then plot the observed mean returns of the bets against different categories of R_{ei}^*. The categories are specified by a bandwidth of 0.05 for R_{ei}^*, and at least 50 observations are required for each group. Furthermore, we run a locally weighted polynomial regression (Fan, 1992; Fan & Gijbels, 1996). In doing so, we do not have to make any assumptions about the functional form of the relationship between the returns and R_{ei}^*.[12] Fig. 2 graphs the results of this procedure for bets against a random bookmaker on all events, while Fig. 3 presents the results for home win, draw and away win bets separately.

It can be seen that for $R_{ei}^* = 1$, the observed mean returns are roughly at the level of normal returns (the dashed horizontal line), and, more importantly, that they increase with R_{ei}^*. Both the mean returns for the different categories of R_{ei}^* (dots) and the local poly-

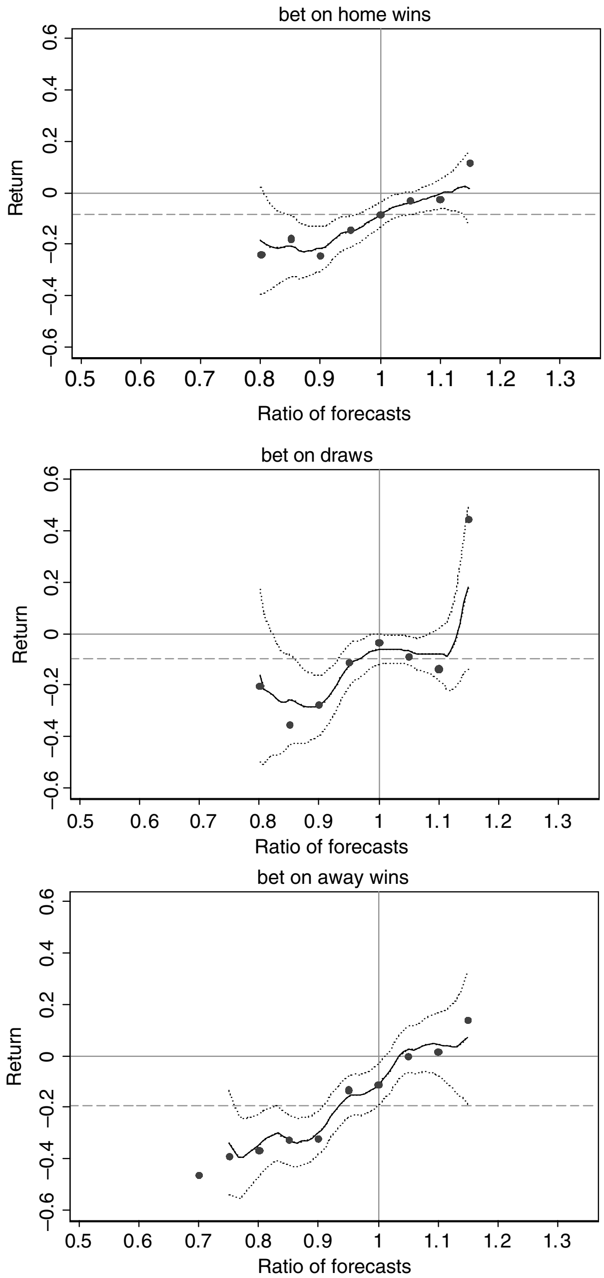

Fig. 3. Observed mean returns of bets placed at a random bookmaker, plotted against the ratio of the different markets' implicit probabilities for home win, draw and away win bets separately (R_i^*). The horizontal lines are for a zero return (solid line) and the expected return under random betting (broken line). The graph shows the mean returns for the different categories of the ratio (dots) and the local polynomial smoothing (solid line) with 95% confidence intervals (dotted lines).

[11] In contrast to R_{eij} in the previous section, R_{ei}^* only varies across matches and events, and is constant across bookmakers.

[12] Local polynomial regression involves fitting the response (the observed returns) to a polynomial form of the regressor (R_{ei}^*) via locally weighted least squares. We estimate a local cubic polynomial weighted by the Epanechnikov kernel function. The amount of smoothing is controlled by a bandwidth, chosen here to be 0.2.

nomial smoother (solid line) increase with R^*_{ei} in the case of home and away win bets (Fig. 3), and also in the case of all events taken together (Fig. 2). The relationship is steeper for away win bets than for home win bets. Moreover, the figures demonstrate that the betting strategy enables positive returns for some levels of R^*_{ei}. For example, betting against the random bookmaker on all events in the top 5%-quantile of R^*_{ei} (821 bets in total) yields an average return of +10%; betting on all home wins in the top 10%-quantile (547 bets in total) yields +3%; and away win bets in the top 10%-quantile (547 bets in total) yield an average return of +7%.

This demonstrates that the odds traded at *Betfair* provide information on the outcome probabilities of the matches that is useful in selecting under-priced bets in the bookmaker market. Taken together, these findings further confirm the superiority of the betting exchange in terms of prediction accuracy.

5. Summary and conclusions

A considerable amount of research has been conducted on separately testing the prediction accuracy of different betting market settings. This paper exploits the coexistence of different market structures offering odds on the same event in order to provide an inter-market comparison of the predictive power of bookmakers and a major betting exchange. We analyze a dataset covering 5478 matches of the major European football leagues and containing the odds of eight bookmakers, together with corresponding prices of the leading person-to-person betting platform *Betfair*. Our results reveal a clear superiority of the betting exchange over the bookmaker market. First, we estimate a univariate probit regression to explain the actual outcome of a certain bet with the implicit probabilities of the different markets. The goodness-of-fit measures indicate that the bet exchange prices predict the actual match results better. Second, we rerun this regression for all of the bookmakers and include a variable capturing the difference between the two different markets' implicit probabilities. The estimated coefficient of this variable suggests that the bet exchange has additional explanatory power beyond the bookmakers' odds. Finally, we assess the economic relevance of the previous results. A simple betting rule of selecting bookmaker bets for which the average bookmaker offers lower probabilities (higher odds) than the bet exchange is capable of generating abnormal, and in some cases even positive, returns.

However, we are reluctant to interpret these findings as a failure of the bookmakers to process relevant information. The underlying reasons for the higher prediction accuracy of the bet exchange market are not clear a priori. Bettors with more accurate information and beliefs may self-select into the exchange market while less skilled bettors may place their bets in the bookmaker setting. Alternatively, our findings could be due to the different market structures dealing with similar but potentially biased demand. Bookmaker odds may reflect not only the dealer's true prediction of the outcome but also his (profit-maximizing) response to the expected (biased) demand. As Levitt (2004), Forrest and Simmons (2008) and Franck et al. (2010) suggest, bookmakers actively shade prices in the presence of a partly irrational betting audience in order to increase their profits. With regard to our findings, the price impact of a biased demand may be less pronounced in the person-to-person situation than in the bookmaker market setting. Nevertheless, a proper examination of these suggestions lies beyond the scope of this paper, and needs further research.

Acknowledgements

We thank Leighton Vaughan Williams and an anonymous referee for their helpful comments. Isabelle Linder and Angelo Candreia provided excellent research assistance. The usual disclaimer applies.

References

Berg, J., Nelson, F., & Rietz, T. (2008). Prediction market accuracy in the long run. *International Journal of Forecasting*, *24*, 285–300.

Boulier, B., & Stekler, H. (2003). Predicting the outcomes of National football league games. *International Journal of Forecasting*, *19*, 257–270.

Brier, G. (1950). Verification of weather forecasts expressed in terms of probability. *Monthly Weather Review*, *78*, 1–3.

Cain, M., Law, D., & Peel, D. (2000). The favourite-longshot bias and market efficiency in UK football betting. *Scottish Journal of Political Economy*, *47*, 25–36.

Croxson, K., & Reade, J. (2008). *Information and efficiency: Goal arrival in soccer betting*. Working Paper, Oxford University.

Dixon, M., & Pope, P. (2004). The value of statistical forecasts in the UK association football betting market. *International Journal of Forecasting*, *20*, 697–711.

Dobson, S., & Goddard, J. (2001). *The economics of football*. Cambridge: Cambridge University Press.

Fan, J. (1992). Design-adaptive nonparametric regression. *Journal of the American Statistical Association*, *87*, 998–1004.

Fan, J., & Gijbels, I. (1996). *Local polynomial modelling and its applications*. London: Chapman & Hall.

Forrest, D., Goddard, J., & Simmons, R. (2005). Odds-setters as forecasters: The case of English football. *International Journal of Forecasting*, *21*, 551–564.

Forrest, D., & Simmons, R. (2008). Sentiment in the betting market on Spanish football. *Applied Economics*, *40*, 119–126.

Forsythe, R., Nelson, F., Neumann, G. R., & Wright, J. (1992). Anatomy of an experimental stock market. *American Economic Review*, *82*, 1142–1161.

Franck, E., Verbeek, E., & Nüesch, S. (2010). *Sentimental preferences and the organizational regime of betting markets*. Working Paper, University of Zurich.

Goddard, J., & Asimakopoulos, I. (2004). Forecasting football results and the efficiency of fixed-odds betting. *Journal of Forecasting*, *23*, 51–66.

Levitt, S. (2004). Why are gambling markets organized so differently from financial markets? *Economic Journal*, *114*, 223–246.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). New York: Academic Press.

McKelvey, R., & Zavoina, W. (1975). A statistical model for the analysis of ordinal level dependent variables. *Journal of Mathematical Sociology*, *4*, 103–120.

Pennock, D., Lawrence, S., Nielsen, F., & Giles, D. (2001). Extracting collective probabilistic forecasts from web games. In *Proceedings of the 7th ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 174–183).

Smith, M., Paton, D., & Vaugham Williams, L. (2006). Market efficiency in person-to-person betting. *Economica*, *73*, 673–689.

Snowberg, E., Wolfers, J., & Zitzewitz, E. (2008). Information (in)efficiency in prediction markets. In L. Vaughan Williams (Ed.), *Information efficiency in financial and betting markets* (pp. 366–386). Cambridge: Cambridge University Press.

Spann, M., & Skiera, B. (2003). Internet-based virtual stock markets for business forecasting. *Management Science*, *49*, 1310–1326.

Spann, M., & Skiera, B. (2008). Sports forecasting: A comparison of the forecast accuracy of prediction markets, betting odds and tipsters. *Journal of Forecasting*, *28*, 55–72.

Vaughan Williams, L. (1999). Information efficiency in betting markets: A survey. *Bulletin of Economic Research*, *51*, 1–39.

Winkelmann, R., & Boes, S. (2005). *Analysis of microdata*. Heidelberg: Springer.

Wolfers, J., & Leigh, A. (2002). Three tools for forecasting federal elections: Lessons from 2001. *Australian Journal of Political Science*, *37*, 223–240.

Wolfers, J., & Zitzewitz, E. (2004). Prediction markets. *The Journal of Economic Perspectives*, *18*, 107–126.

Wooldridge, J. (2002). *Econometric analysis of cross section and panel data*. Cambridge: The MIT Press.