Bookmakers' Efficiency in English Football Leagues

Patrice Marek
University of West Bohemia

Bookmakers’ Efficiency in English Football Leagues

Patrice Marek[1]

Abstract. In 2015, the online gambling market had a volume of almost 38 billion U.S. dollars, and the largest portion – 48 percent – was held by sports betting. It is expected that online gambling market will be worth of 60 billion U.S. dollars by the year 2020.
Large number of sports bets are placed on football, especially English football leagues. The high competition in this area forces bookmakers to lower their margins, and this leads to a requirement of better – more precise – models of probabilities of possible match results. This paper analyses margins of selected bookmakers over the last years and compare efficiency of their models based on implied probabilities. Results and odds of five top level English leagues since 2005/2006 season are chosen for the analysis and demonstration of basic characteristics development.

Keywords: Fixed odds betting, football, bookmaker, efficiency, margin, analysis, England.

JEL classification: C58, Z29
AMS classification: 94A17, 62P05

1 Introduction

Gambling market is a largely expanding area, especially in its online form. According to Statista [10], the online gambling market had a volume of 20.51 billion U.S. dollars in 2009, and the volume was almost doubled in 2015 to 37.91 billion U.S. dollars. The largest portion – 48 percent – of the volume in 2015 was held by sports betting. The expected volume of the online gambling market by the year 2020 is 59.79 billion U.S. dollars. The gambling market is, therefore, interesting for bookmakers, and the competition is increasing.

This paper studies fixed odds betting, where bookmakers offer odds on possible match results – home team win, draw, and away team win. Bookmakers has their own models to estimate probabilities of match results. These probabilities and chosen value of margin are used to construct odds that are sub-fair, i.e. if a bettor places stakes exactly according to the estimated probabilities on every possible outcome, he will always lose an amount that is equal to the margin of a bookmaker. This can be illustrated on coin flipping. The probabilities for a fair coin are known, and we do not need to estimate them (0.5 for tail and 0.5 for head). The fair odds with no margin would be 2.0 for each outcome (meaning that if we place 1 unit on head, and this will be the result of the coin flipping, we will win 2 units, i.e. net profit of 1 unit). Nevertheless, in the real world, bookmakers offer sub-fair odds; therefore, a bookmaker who calculates with 10% margin would use odds of 1.8 for each outcome. Now, if a bettor places 0.5 unit on tail and 0.5 on head (exactly according to the real probabilities), then the bookmaker accepts 1 unit, and for each possible outcome the bookmaker will pay only 0.9 unit ($0.5 \cdot 1.8$). This secures him 0.1 unit of profit, i.e. 10% margin, or 11.1% markup.

One important effect of increasing competition is decreasing margin of bookmakers. Nevertheless, to reduce margin in fixed-odds betting can be dangerous as bookmakers do not know the real probabilities and use only estimates. This indicates necessity of good models for modelling probabilities of possible match results; threfore, interest of research in this area is increasing. Models used for estimation of outcomes can be tracked back into 1980s. Maher [7] showed that it is possible to use the bivariate Poisson distribution to estimate football match results. His models were improved in many following papers, e.g. Dixon and Coles [3] introduced model that allowed negative dependencies and possibility to discount information from older matches. Both these papers were concerned by football. Karlis and Ntzoufras [5] studied not only football but also water polo, ice hockey was studied in Marek, Šedivá, & Ťoupal [9], Buttrey [1], and Šedivá [11], and tennis was studied by Kovalchik [6]. As can be seen, theory in this area is developing, and it is – with the increasing computing power – possible to obtain more precise estimates of probabilities and to reduce margin to attract new customers.

Che, Feddersen, & Humphreys [2] studied over-round (or, in accounting terms, markup) of two bookmakers, William Hill and Ladbrokes – both are later used in this paper –, from the 2004/05 season to the 2011/12 season in the English Premier League. These two bookmakers operated both betting shops and online bookmaking operation. They found out that, in a response to increased competition, the over-round – and thus also the margin – substantially dropped for the 2008/09 season. The over-round of William Hill and Ladbrokes are also compared

[1]University of West Bohemia, European Centre of Excellence NTIS – New Technologies for Information Society, Faculty of Applied Sciences, Univerzitní 8, Plzeň, Czech Republic, patrke@kma.zcu.cz

with four pure online bookmakers: Bet365, Bwin, Interwetter, and Sportingbet (first three bookmakers are also used in this paper). They found that over-round of these online bookmakers (mixed together as one) declined more slowly but from lower values. Malarić [8] used results of 10 European leagues during seasons 1999/2000, 2000/01, and 2001/02 and obtained average margin of 13% for average odds computed from 15 bookmakers. He showed that the fixed odds market at that time was inefficient.

The main goal of this paper is to demonstrate changes in margins of studied bookmakers and to – indirectly with usage of implied probabilities based on odds – evaluate their models.

2 Data

Results and odds of five top level English football leagues are used for the analysis, i.e. Premier League (level 1, EN_1), English Football League Championship (level 2, EN_2), English Football League One (level 3, EN_3), English Football League Two (level 4, EN_4), and National League (level 5, EN_5). Data obtained from Football-Data [4] comprise results and odds between the 2005/06 season and 2017/18 season. The 2017/18 season in not finished yet, and only results up to March 27, 2018 are used. However, more than 3/4 of the season are played; therefore, even these data are used so that the paper comprises the most actual results. Totally, 17 229 matches are used for the analysis.

Odds of six bookmakers are analysed – Bet365 ($B365$), Bwin (BW), Interwetten (IW), Ladbrokes (LB), BetVictor (VC), and William Hill (WH). Moreover, two fictitious bookmakers are created from odds of these six companies – MAX that uses maximal odds that are found for each outcome, and AVG that uses average odds of listed bookmakers. Odds are available for the most of the matches; however, for some of them, the database Football-Data [4] does not contain odds. Usually, this is for several matches in higher level leagues and for small percent of matches in lower level leagues. The only exception is the 2007/08 season where the database does not contain odds of WH for 1/3 of matches (other bookmakers are not affected and usually all matches are listed with odds). Results in the following part are standardized for one match; therefore, several missing matches will not significantly affect the final results. The only exception is the 2007/08 season for WH, as mentioned before.

3 Methods and Results

First, we need to compute margin and probabilities that are used by a bookmaker for every single match. To do this, we need to specify model that is used by the bookmaker to compute odds. The simple and common model use assumption that the same margin (ζ) is used for each possible outcome of a match (see Malarić et al. [8]), i.e. that the bookmaker computes odds of the home team win (o_H), draw (o_D), and away team win (o_A) according to

$$o_r = \frac{1-\zeta}{p_r}, r = H, D, A, \tag{1}$$

where $p_r, r = H, D, A$ are probabilities estimated by the bookmaker (see Štrumbelj [12] for more models how to calculate probabilities from odds). Equation (1) can be used to compute margin used for a match according to

$$\zeta = 1 - \frac{1}{\sum_r o_r^{-1}}, r = H, D, A. \tag{2}$$

Equations (1) and (2) can be easily used to compute so-called implied probabilities that were used by the bookmaker in each match, i.e. for each match with odds in used database this offers information about margin and probabilities used by the bookmaker.

3.1 Average Margins

Average margins of each bookmaker in each season and league were computed, and results are presented in Figure 1. We can see that the average margin decreased in time, e.g., average margins used by bookmakers in the Premier League 2005/06 season were between 7.33% ($B365$) and 11.10% (WH), and margins in the current Premier League season are between 2.71% (VC) and 5.79% (LB). Margins are usually higher in the lower level leagues, and the highest margins in the 2017/18 season are in the National League (between 5.64% (VC) and 11.54% (IW)). High margins in lower level leagues indicates possible uncertainty of bookmakers' models. Qualities of their models are investigated in the following parts where three measures – inspired by Kovalchik [6] – are used. Results of MAX, a fictitious bookmaker with the highest odds, show that his average margin in the current season is 1.05%; there is also around 20% of matches with negative margin (62 out of 304 played matches; the lowest margin recorded was -4.12%). Two bookmakers, $B365$ and VC, use margin that is usually lower than the average margin (represented by AVG).

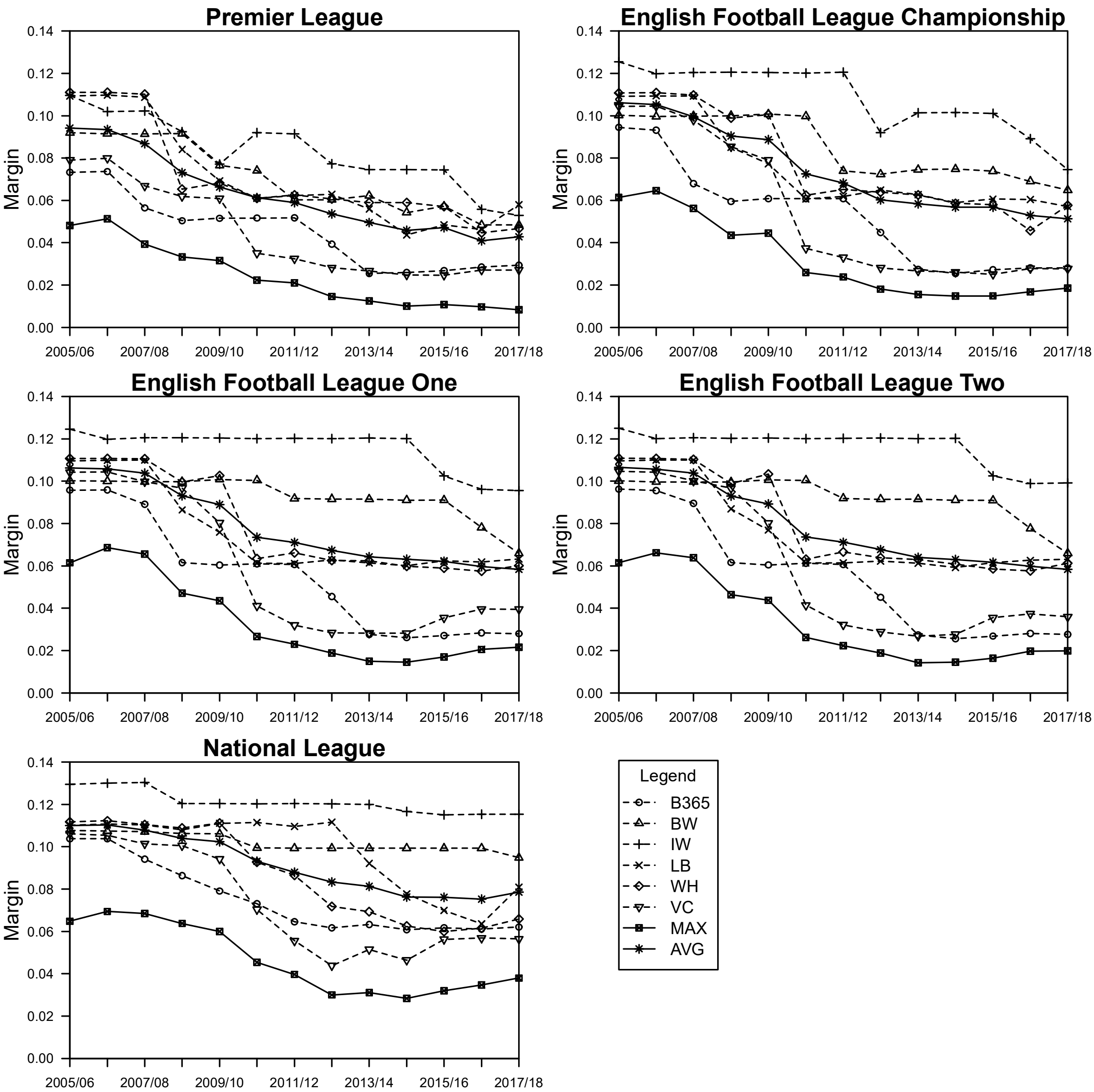

Figure 1 Margins of bookmakers

3.2 Calibration

The calibration is a measure of the model's accuracy which focuses on the number of expected wins. The model is well calibrated when for all matches with the predicted probability p for given outcome the observed proportion is close to p. To decide whether the model is well calibrated or not, the calibration ratio (C) can be used.

$$C = \frac{\sum_{m=1}^{M} \max(p_m^H, p_m^D, p_m^A)}{\sum_{m=1}^{M} \delta_m}, \tag{3}$$

where M is total number of matches, $p_m^r, r = H, D, A$ are probabilities used by the bookmaker (obtained from his odds by Equations (1) and (2)), and $\delta_m = 1$ in the mth match if this match ends with the result that has the highest probability according to the bookmaker, and $\delta_m = 0$ otherwise. In some cases – usually in less than 15 matches of a season –, the number of possible outcomes of a match has to be changed. The first case is when two outcomes have the same probability, and this probability is also equal to the maximum of all probabilities. In this case, these two outcomes are combined together as one with summed probability. The second and very rare case is when all three probabilities in a match are equal, then all three are combined together as one outcome that will happen with probability 1. The most matches in a season with some correction were recorded for WH in EN_4 in the 2014/15 season – 57 out of 552 matches. In the Premier League, the most matches with some correction were recorded in the 2005/06 season for IW – 15 out of 380 matches.

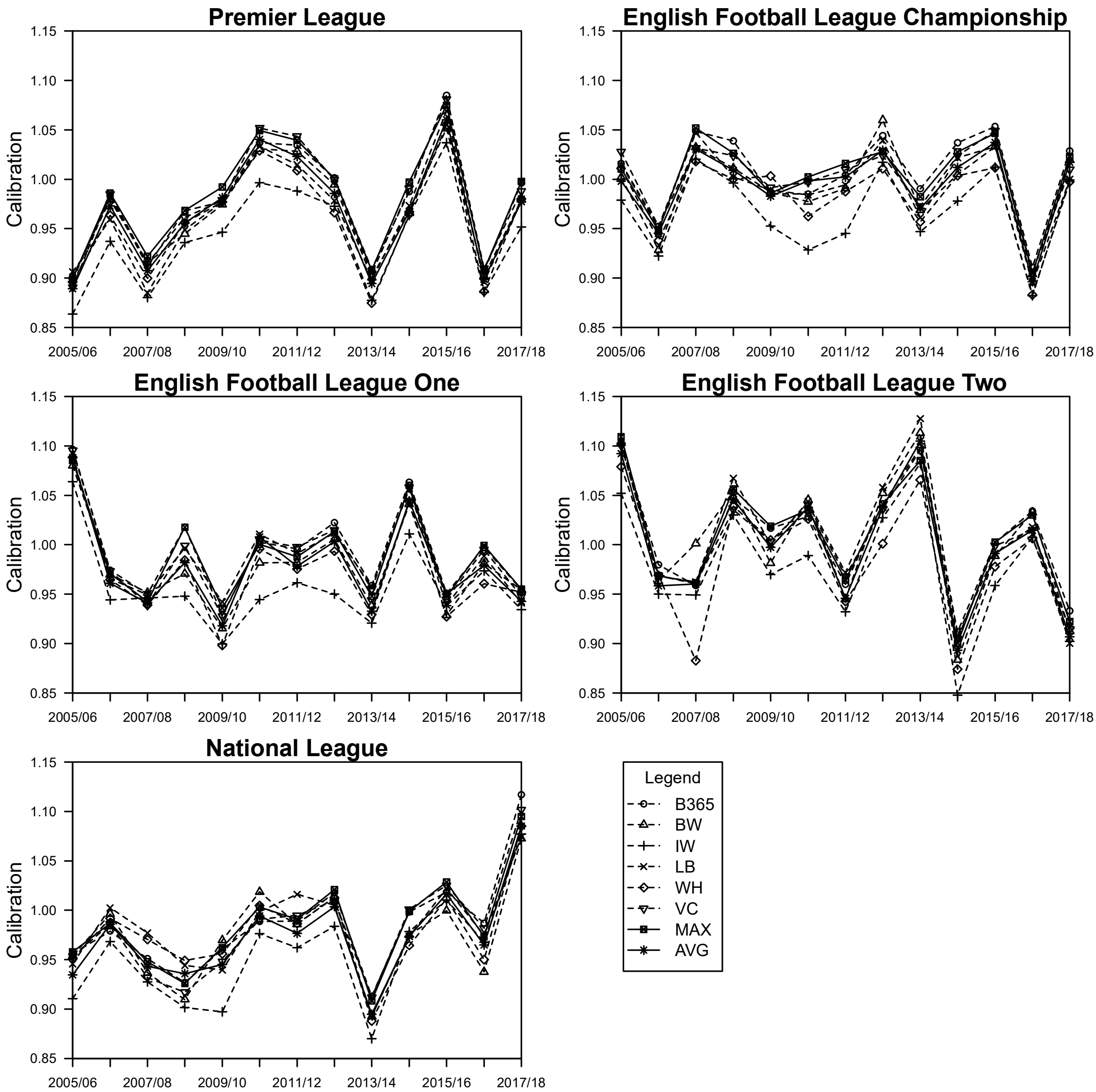

Figure 2 Calibration of bookmakers

Results of calibration are presented in Figure 2. The usual situation is that calibration is around 1 with some exceptions. A situation where the calibration is less than one indicates that probabilities of the most probable outcome are underestimated and vice versa. Figure 2 also indicates that bookmakers use similar models – or at least similar odds – as differences among bookmakers are usually not as high as differences between two seasons. Some minor differences can be identified for IW that has usually the lowest value of calibration, i.e. in the comparison with other bookmaker IW calculates with lower probabilities for the most probable outcome. Next, it is not possible to identify improvements in models as values are still in the same intervals.

3.3 LogLoss Function

The next measure, usually suitable for betting, is $LogLoss$ function. The function for sports with three possible outcomes of a match is defined as

$$LogLoss = -\frac{1}{M} \sum_{m=1}^{M} (\kappa_m^H \ln p_m^H + \kappa_m^D \ln p_m^D + \kappa_m^A \ln p_m^A), \tag{4}$$

where M is total number of matches, $p_m^r, r = H, D, A$ are probabilities used by the bookmaker, and κ_m is an indicator function, e.g., $\kappa_m^H = 1$ if match m ends with a home win, and $\kappa_m^H = 0$ otherwise. This function gives high penalty to situations where outcomes with small predicted probability occur; the lower value of $LogLoss$

function, the better model. $LogLoss$ function is expressed for one match; therefore, leagues with different number of matches in a season can be directly compared.

The highest recorded difference is in the 2007/08 season between WH (1.042) and LB (1.061) in EN_4. Nevertheless, as mentioned before, database contained only 2/3 of odds for WH for this season. If we exclude results of WH in the 2007/08 season, then the highest difference was recorded in the 2008/09 season between IW (1.019) and LB (1.030) in EN_3. These differences are low in the comparison to differences between two consecutive seasons (in some cases, the difference is more than 0.1). Therefore, Figure 3 presents results only of $B365$ (chosen because it is one of the biggest bookmakers, and it offers low margins) in each season and league. It is clear that the best values of $LogLoss$ function are obtained for the Premier League with very different results from other leagues. Quite surprisingly, the second best results are obtained for the National League (EN_5). The second surprise is that there is no clear trend in time, and it does not seem that models of bookmakers are improved in the view of $LogLoss$ function. The lowest values of $LogLoss$ were usually recorded by $B365, VC$, and WH.

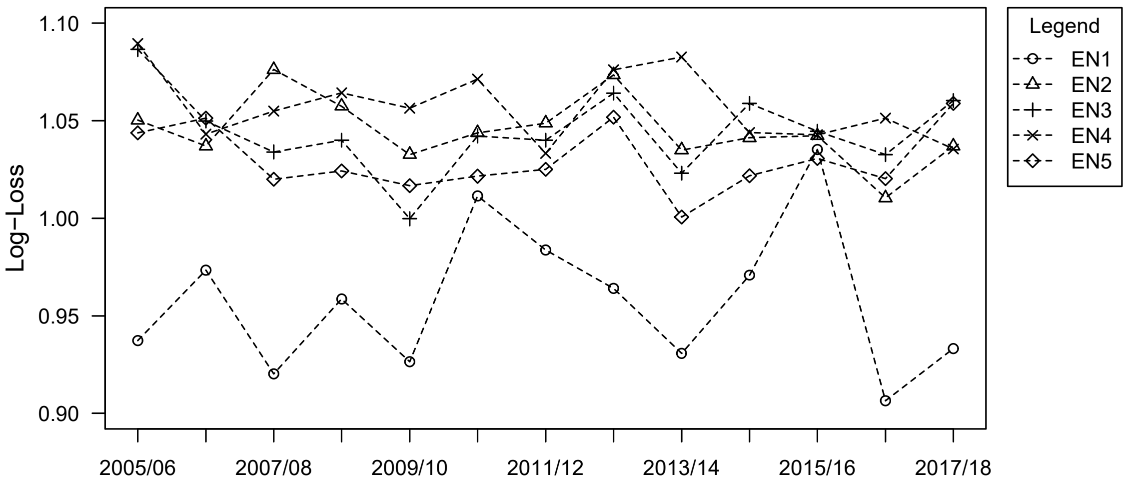

Figure 3 $LogLoss$ function of $B365$

3.4 Prediction Accuracy

The prediction accuracy is the percentage of matches that ended with the result that was the most probable according to the bookmaker. As in the case of calibration, we have to resolve small number of cases, where two or even all three outcomes have the same probability. In this case, both outcomes (or in rare situation all three outcomes) are counted as a correct prediction. This means, that the baseline for prediction accuracy is little higher than 1/3, i.e. random prediction with three possible outcomes and in small number of cases with two or even one possible outcome (e.g., for a situation where 10 matches out of 380 have only two possible outcomes, the baseline is 0.338).

Differences between bookmakers are again relatively small when compared to differences between consecutive seasons. If we exclude results of WH in the 2007/08 season (because of 1/3 of missing odds in this season), then the highest difference was recorded in the 2014/15 season between $B365$ (0.493) and WH (0.533) in EN_4. As stated before, higher differences of accuracy are common between seasons; therefore, Figure 4 presents results only of $B365$ in each season and league. It is clear that the best results are obtained for the Premier League and usually with very different results from other leagues. The second best results are again obtained for the National League (EN_5). As in the previous part, there is no clear trend in time. Results of the prediction accuracy are consistent with the results of the $LogLoss$ function. The comparison of bookmakers is not as clear as in the $LogLoss$ function. However, if we restrict ourselves only on the Premier League, then the best results (almost in each season) are recorded by IW and poor results are recorded by $B365, BW$, and VC. We remind that the lowest values of $LogLoss$ were usually recorded by $B365, VC$, and WH.

4 Conclusion

This paper investigated margins of six well known bookmakers and qualities of their models in five top level English leagues between the 2005/06 season and 2017/18 season. It is clear that margins were lowered in recent years, mainly in the Premier League. Bookmakers' models were compared using three measures – calibration, $LogLoss$ function, and prediction accuracy. These measures were also used to evaluate changes of models in time. Calibration showed that differences among bookmakers are usually lower than differences between two

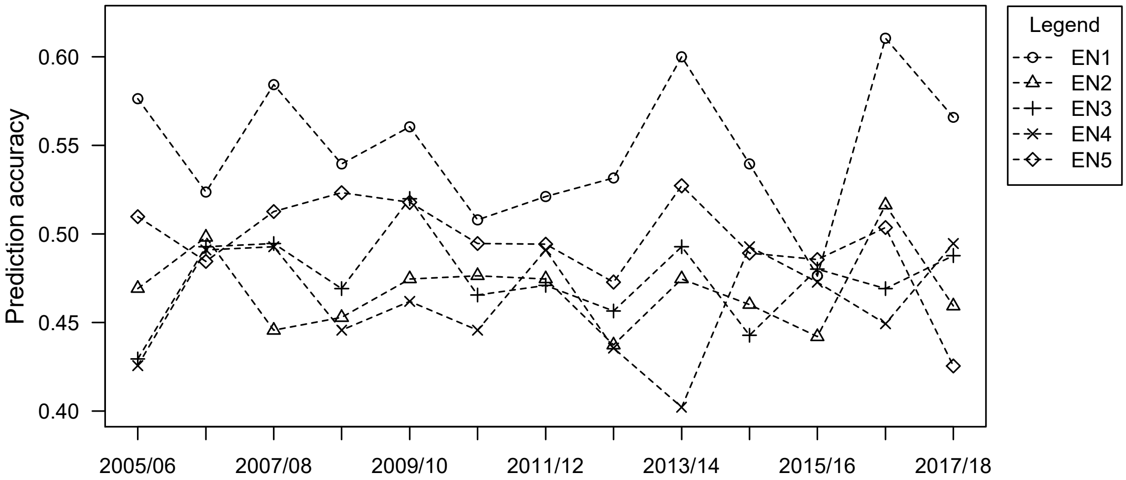

Figure 4 Prediction accuracy of $B365$

consecutive seasons. One possible explanation is that bookmakers use very similar models. This was confirmed by two following measures. Calibration also showed that models can be considered as good; however, no clear improvement in time was seen. From the view of $LogLoss$ function the best results of bookmakers' models were recorded in the Premier League, with other leagues substantially behind. This result was also confirmed by the prediction accuracy of models. There is no clear winner among bookmakers, and their models can be considered as similar. Finally, no significant improvement of models was recorded in the selected seasons.

Acknowledgements

This publication was supported by the project LO1506 of the Czech Ministry of Education, Youth and Sports.

References

[1] Buttrey, S. E. (2016). Beating the market betting on NHL hockey games. *Journal of Quantitative Analysis in Sports*, 12(2), 87–98.

[2] Che, X., Feddersen, A. & Humphreys, B. R. (2017).Price setting and competition in fixed odds betting markets. In P. Rodríguez, B. R. Humphreys & R. Simmons (Ed.). *The Economics of Sports Betting* (pp. 38–51). Cheltenham: Edward Elgar Publishing Limited.

[3] Dixon, M. J. & Coles, S. G. (1997). Modelling Association Football Scores and Inefficiencies in the Football Betting Market. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 46, 265–280.

[4] Football-Data.co.uk (2018). *Football Results, Statistics & Soccer Betting Odds Data*. (Retrieved March 28, 2018, from http://www.football-data.co.uk/data.php)

[5] Karlis, D. & Ntzoufras, I. (2003). Analysis of Sports Data by using Bivariate Poisson Models. *The Statistician*, 52, 381–393.

[6] Kovalchik S. A. (2016). Searching for the GOAT of tennis win prediction. *Journal of Quantitative Analysis in Sports*, 12(3), 127–138.

[7] Maher, M. J. (1982). Modelling Association Football Scores. *Statistica Neerlandica*, 36, 109–118.

[8] Malarić, R., Katić, T. & Sabolić, D. (2008). The market efficiency of the soccer fixed odds internet betting market. *Applied Economics Letters*, 15(3), 171–174.

[9] Marek, P., Šedivá, B. & Ťoupal, T. (2014). Modeling and prediction of ice hockey match results. *Journal of Quantitative Analysis in Sports*, 10(3), 357–365.

[10] Statista.com (2018). *Market value of online gambling worldwide 2009–2020*. (Retrieved April 10, 2018, from https://www.statista.com/statistics/270728/market-volume-of-online-gaming-worldwide/)

[11] Šedivá, B. (2015). Dynamic Forecasting Model Based on Ranking System for Hockey Match. In *Mathsport International 2015 Conference Proceedings.*, Loughborough: Loughborough University, 177–182.

[12] Štrumbelj, E. (2014). On determining probability forecasts from betting odds. *International Journal of Forecasting*, 30, 934–943.