Forecasting football match results: Are the many smarter than the few?

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FORECASTING FOOTBALL MATCH RESULTS: ARE THE MANY SMARTER THAN THE FEW?

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Abstract: An empirical analysis of Spanish football betting odds is carried out here to test whether football matches final result estimates by experts (bookmakers) differ (better/worse) from those by the 'crowd' (football pools bettors). Examination of implied probabilities for each of the possible outcomes evidences the existence of favourite long-shot bias in the betting market for Spanish football. A further study of the accuracy of probability forecasts concludes that experts seem to be better in forecasting football results than the 'crowd'.

Keywords: betting odds, forecasting, wisdom-of-crowds hypothesis, favourite long-shot bias

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Introduction

Forrest and Simmons (2000) reported empirical evidence consistent with the general opinion in the forecasting literature that predictions from statistical models are better than predictions by experts when forecasting football match results using data from English football. In a more recent paper Forrest et al (2005), using also data from the English football, conclude that “a much more detailed benchmark statistical model proves to be far from dominant over the views of a group of experts”. They also concluded that “the performance of these experts has improved in a number of dimensions through a period when an intensification of competitive pressure in bookmaking has made the consequences of poor forecasting performance increasingly costly”. In particular in both papers the authors where looking at the odds from several bookmakers (experts). In this paper we complement the analysis of experts’ performance by paying attention to bettors’ behaviour. In this case, the focus is on bettors’ choices and impressions before the games, employing data from Spanish football pools (*La Quiniela*); a long-odds high-prize pari-mutuel betting medium based on correctly forecasting the outcome in a number of football games.

The main target is to test whether forecasting by experts (bookmakers) differs (better/worse) from that by the ‘crowd’ (football pools bettors)[1]. According to the wisdom-of-crowds hypothesis (Surowiecki, 2004), *La Quiniela* bettors, who are likely to be football fans, should collectively forecast optimally. So, one could expect that the many (*La Quiniela* bettors) may make better predictions than the few (bookmakers).

The sample database includes decimal odds on full time result (home win, draw, away win) set by nine bookmakers - *Bet365* (B365), *Bet & Win* (BW), *Gamebookers* (GB),

[1] On average, more than 1.6 million of *La Quiniela* tickets/coupons were sold each fixture during 2005-2011 period. This leads to close to 20 million bets placed on each *La Quiniela* fixture.

Interwetten (IW), *Ladbrokes* (LB), *Sportingbet* (SB), *Stan James* (SJ), *VC Bet* (VC) and *William Hill* (WH) – for 2,280 Spanish First Division matches (top professional football division in Spain) from seasons 2005/06 – 2010/11. Betting odds for the same matches are estimated from information on the number of tickets containing a particular given final result from *La Quiniela*.

First, a descriptive comparison of the odds offered by the bookmakers is carried out in order to test whether their distributions are similar. An additional analysis of the coefficients of correlation between the odds of a particular outcome for pairs of bookmakers (including *La Quiniela*) is performed next.

Since the main characteristics of a bet differ due to take-out and overround[2], alongside the previously mentioned study, an inquiry into the total take-out rate the bookmakers return offers the possibility of evaluate the presence of the favourite long-shot bias (on average, bettors tend to undervalue high-probability events and overvalue low-probability ones) in the betting market for Spanish football. Evidence of higher take-out rates for low-probability events may corroborate the existence of this statistical bias.

A further test of the accuracy of probability forecasts is finally developed by using a modified version of the "Brier scores" (Forrest *et al.* 2005) and a set of ordered logit regressions by bookmaker (including *La Quiniela*) where the dependent variable is the final result of any match. The empirical findings should bring evidence whether experts (bookmakers) are better in forecasting football results than 'crowd' (football pools bettors).

The paper is organised as follows. The next section describes the football betting market in Spain focusing on the main features of *La Quiniela* game. Later, a descriptive analysis of the odds offered by the bookmakers and those estimated in the case of *La*

[2] The pari-mutuel betting system puts a type of implicit tax on wagering called the take-out. The take-out rate is then the percentage of each betting pool that is withheld by the operator (bookmaker). In fixed odds betting markets a similar term is overround that represents bookmakers' expected profit as shown by Cortis (2015). It is equivalent to a commission and can be calculated as the amount by which the sum of the percentages (relative probabilities) derived from the odds exceeds 100%. Even though these two different terms are not exactly the same, in this paper we opt to use take-out rate as general term.

Quiniela is developed. The take-out rates and the favourite long-shot bias are then discussed. The analysis of the forecasting performance is considered in the following section. Finally, a summary of the more relevant conclusions is presented.

The football betting market in Spain

Legal sports betting in Spain was largely limited to people gambling on the outcome of professional football matches through football pools. Since the introduction of *La Quiniela* in the season 1946-47 the pools have long occupied a predominant place in the Spanish gambling market. For many years La Quiniela was the only football betting game available in Spain, but recently the pools' industry has experienced several changes and even the introduction of a new product in 2005: *El Quinigol*[3].

In 2008 several bookmakers were awarded the first licences to operate sports betting in some Spanish regions opening up a completely new football betting market. However, it should be noted that online gambling in Spain was not regulated till 2011, so Spaniards could bet on football in the Internet since some years before and so most bookmakers used to accept bets on Spanish football matches.

The Spanish football pools: La Quiniela

As explained in Forrest and Pérez (2013) the term 'football pools' could be applied to a pari-mutuel wagering concerning the outcomes of football matches. More specifically it refers to a long-odds high-prize betting product where players have to correctly guess the results of a long list of football results to win a share of the jackpot.

In particular, *La Quiniela* (commercial name for Spanish football pools) consists of a ticket or coupon (betting slip) that includes a list of 15 football matches (mainly from

[3] This game's name is derived from the fact that bettors are required to predict the number of goals that will be scored by the teams involved in a particular football match.

the Spanish First Division[4]). Players must forecast the result of each match, home win, draw or away win. Those who correctly guess the 15 results win a share of the jackpot pool. If there is no winner of the jackpot, the amount devoted to this first prize category rolls over into the next fixture. There are also minor prizes for those who correctly guess a lower number of results.

The entry fee is €0.50 from season 2003/04 and the take-out rate is 45%. *La Quiniela* is operated by *Sociedad Estatal Loterías y Apuestas del Estado* (SELAE) the same state-owned entity that runs national lottery games in Spain.

The main aggregate figures of the game (over the sample period) are shown in Table 1. Some empirical evidence about the determinants of the demand for *La Quiniela* can be found in García and Rodríguez (2007) and García et al (2008).

Table 1: *La Quiniela* aggregate figures (2005-2011)

(in millions)	Mean	Max.	Min.	S.D.
… per season				
Tickets or coupons sold	83.31	69.04	90.90	7.22
Bets placed	994.49	1114.78	762.59	118.99
Bets placed/coupon ratio	11.91	12.66	11.05	0.58
Fixtures	51.29	62	41	7.99
… per fixture				
Tickets or coupons sold	1.66	2.04	1.26	0.29
Bets placed	19.83	24.08	13.87	3.98

Odds descriptive analysis

The odd $Q_{i,j}^{k}$ is the amount of money a particular bookmaker i will return for a bet of one unit for the event k in game j. In the case of football matches the events are: (H)

[4] It should be noted that that not all the coupons include Spanish First Division games; occasionally the coupon list of games is composed of Second Division and Second Division B games, national teams or even teams from other European leagues such as the *English Premier League*. In addition, some specific fixtures in the pools referring to European Champions League or other international competitions have also been introduced.

home win, (D) draw and (A) away win[5]. In this paper we use a panel data set composed of the odds corresponding to the matches of the Spanish First Division offered by nine bookmakers for the seasons 2005/06 until 2010/11. The bookmakers are: *Bet365* (B365), *Bet & Win* (BW), *Gamebookers* (GB), *Interwetten* (IW), *Ladbrokes* (LB), *Sportingbet* (SB), *Stan James* (SJ), *VC Bet* (VC) and *William Hill* (WH). In Table 2 we provide some basic statistics (mean and standard deviation) of the odds of the three events corresponding to the six seasons we consider aggregated across bookmakers.

Table 2: Odds descriptive statistics by season (excluding *La Quiniela*)

	Home win		**Draw**		**Away win**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
2005/06	2.225	0.972	3.368	0.509	4.010	2.202
2006/07	2.319	1.123	3.415	0.575	4.074	2.415
2007/08	2.290	0.982	3.423	0.577	4.105	2.543
2008/09	2.314	1.076	3.510	0.635	4.154	2.622
2009/10	2.550	1.800	3.840	1.174	4.635	3.937
2010/11	2.643	2.204	3.942	1.327	4.752	4.054
Total	2.391	1.450	3.584	0.893	4.290	3.071

We can distinguish two different periods in terms of values of the average odds and its variability. In the first four seasons the odds look very similar (around 2.3 for the home win, 3.4 for the draw and 4.1 for the away win) and, if any, there is an almost negligible positive trend. In contrast, in the last two seasons the average odds significantly increase for the three events and also its variability. These particular increases in both statistics are associated to the substantial increase in the odds of those games where either *FC Barcelona* or *Real Madrid CF* are involved, which correspond to situations where the odds are very high depending on whether these teams are the home team or the visitor. The maximum odds for a home win move from 9 in the first four seasons to 19 in the last two when they are the away teams, for an away win from 22 to 43 when they are the home teams, and for a draw from 8 to 14. This is a consequence of the dominating role of these two clubs in the Spanish League during this period. In

[5] This is at contrast with what happens in the English football betting market where the odds are quoted as a to b for each particular event. This means that a bet of b in a particular event gets a return of a if the event occurs.

fact, if we look at the evolution of the competitive balance in the Spanish League, the coefficient of variation of the number of points in the final standings changes from 0.27, in the first four seasons of the period we consider, to 0.34 in the last two, mainly as a consequence of the performance of both clubs. That means that bookmakers took into account when posting the odds the abovementioned dominance of these two clubs[6].

As it was commented in the previous section, information from traditional football pools in Spain (*La Quiniela*), provided by SELAE, is used to approximate the implicit odds of the previously mentioned three events (football match results) by using a corollary of the constant expected return model establishing that the relative bet on one event should be equal to the probability of that event and the odds should be the inverse of that probability[7]. In the case of *La Quiniela* we use the number of tickets containing a particular event for a given match (T_j^k) to calculate the associated odds ($Q_{LQ,j}^k$)[8]:

$$Q_{LQ,j}^k = \frac{1}{\frac{T_j^k}{\sum_{l=H,D,A} T_j^l}} \qquad k = H, D, A$$

In Table 3 we report the some basic statistics (mean and standard deviation) for the estimated odds for *La Quiniela*. The first thing we should mention is that we observe the same pattern across seasons as we did when discussing the odds for the bookmakers. The last two seasons in our sample show odds which are substantially higher than those in the previous seasons. On the other hand, if we compare these figures with those in Table 2 we can observe that the odds are higher in the case of *La Quiniela* than for the considered bookmakers, being this difference more relevant for the draw and the away win events than for the home win. This a consequence of the

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6 See the presentations in the *1ª Conferència Acadèmica Ernest Lluch d'Economia i Futbol* (Fundació Ernest Lluch and FC Barcelona, 2013) for the most recent discussion about the competitive balance in the Spanish Football League.

7 See Sauer (1998) for a complete review of the economics of wagering markets.

8 Notice that in this particular case we are calculating a kind of odds which do not include the take-out rate by the bookmaker, as included in the odds offered by the bookmakers (our original data). Consequently, they are higher than those including the take–out rate.

fact mentioned in footnote 9 that the odds are not including the take-out rate in the case of *La Quiniela*. If we recalculate the odds for the nine bookmakers not considering the rake out rates, still the odds of *La Quiniela* are significantly higher in the case of the draw and away win events. This could be explained by the fact that the information available for *La Quiniela* corresponds to tickets including a particular result for a match instead of bets, given that each ticket can have a different number of bets with a particular result[9].

Table 3: Odds descriptive statistics of *La Quiniela* by season

	Home win		Draw		Away win	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
2005/06	2.615	1.511	4.256	1.854	5.865	4.214
2006/07	2.560	1.322	4.130	1.397	5.365	3.274
2007/08	2.558	1.346	4.292	1.584	5.431	3.457
2008/09	2.547	1.384	4.366	1.555	5.385	3.432
2009/10	2.794	2.017	4.872	2.481	6.172	4.717
2010/11	2.864	2.332	5.025	2.735	6.322	5.115
Total	2.657	1.703	4.495	2.027	5.755	4.108

In Table 4 we present the basic statistics of the odds for each of the bookmakers, the second dimension of our panel data set[10]. The differences among bookmakers both in terms of the average values and the standard deviations do not seem to be very important; although the degree of similarity is greater for the home win odds than for the draw and the away win odds. It is also worth to mention that the variability of the odds is substantially higher in the case of the away win odds as a consequence of the odds for those games in which the home team is clearly the favourite, as in the case of *FC Barcelona* and *Real Madrid CF*. Also the standard deviations are more dissimilar in the case of the visitor's odds, ranging from 2.6 (IW) to 3.7 (SJ). In addition, we can identify the bookmaker B365 as the one with the highest odds for the three events,

[9] In fact, in *La Quiniela*, as mentioned in the previous section, bets correspond to a set of 15 games, not individual games, and the take-out rate by the public company in charge of *La Quiniela* is larger than the ones we will observe for bookmakers.

[10] The estimated odds for *La Quiniela* are not included in Table 4 given that, as mentioned above, they cannot be properly compared to those of the bookmakers.

whereas IW and LB are at the opposite side in this classification with the corresponding implications in terms of the take-out rates as it will become evident in the next section.

Table 4: Odds descriptive statistics by bookmaker

	Home win		Draw		Away win	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
B365	2.454	1.551	3.690	0.946	4.508	3.440
BW	2.397	1.427	3.623	0.955	4.229	2.791
GB	2.422	1.443	3.600	0.864	4.332	3.012
IW	2.336	1.254	3.463	0.702	4.117	2.624
LB	2.334	1.379	3.512	0.810	4.122	2.722
SB	2.376	1.385	3.574	0.829	4.189	2.830
SJ	2.423	1.560	3.648	0.994	4.583	3.660
VC	2.412	1.593	3.627	1.002	4.364	3.403
WH	2.363	1.420	3.520	0.869	4.158	2.947

Table 5: Number of odds paired t-tests for which H_0 is rejected (5%)

Bookmaker	Home win	Draw	Away win	Total
B365	0	2	3	5
BW	0	3	2	5
GB	0	3	2	5
IW	1	5	3	9
LB	0	4	3	7
SB	0	3	2	5
SJ	0	5	4	9
VC	1	5	5	11
WH	0	2	0	2
Total	1	16	12	29

We have proceeded to make a formal comparison of the average odds for the different bookmakers and different events by testing whether the average odds are statistically the same by using t-tests to compare averages for pairs of bookmakers[11]. In Table 5 we report for each bookmaker the number of tests for which the null hypothesis of

[11] The tests are performed based on the assumption that the distributions of the odds are homoscedastic.

equality of the means is rejected[12]. In that sense, and corroborating the previous comments about the different patterns of the odds means depending on the event we consider, the number of rejections is higher in the case of a draw (16 pairs out of 36) and is also relevant for the away win (12 out of 36). In total we reject the null hypothesis in 29 out of the 108 pair comparisons (27%). When looking at the detail by bookmakers, we can identify three cases (IW, SJ and VC) for which the number of rejections is above one third of the pair comparisons. These are cases associated either to high odds (SJ and VC) or low odds with the smallest variability (IW)[13].

One way of analyzing whether the differences between odds averages respond more to differences in level (intercept different from zero) than to differences in the pattern (slope coefficient different from 1) is by looking at the coefficients of correlation between the odds of a particular event for pairs of bookmakers.

Table 6a: Odds correlation matrix (Home win)

	B365	BW	GB	IW	LB	SB	SJ	VC	WH	L-Q
B365	1.0000									
BW	0.9885	1.0000								
GB	0.9932	0.9912	1.0000							
IW	0.9817	0.9844	0.9848	1.0000						
LB	0.9807	0.9794	0.9824	0.9752	1.0000					
SB	0.9907	0.9892	0.9929	0.9841	0.9829	1.0000				
SJ	0.9888	0.9844	0.9876	0.9812	0.9864	0.9858	1.0000			
VC	0.9900	0.9852	0.9900	0.9841	0.9815	0.9866	0.9884	1.0000		
WH	0.9898	0.9788	0.9840	0.9763	0.9770	0.9818	0.9896	0.9859	1.0000	
L-Q	0.9185	0.9323	0.9212	0.9287	0.9183	0.9231	0.9170	0.9168	0.9075	1.0000

[12] Notice that the figures in the row "Total" are just half of the total number of rejections in each column. This is because each rejection of odds equality within each pair affects two bookmakers.

[13] Rossi (2011) also performs an alternative approach based on running the regression of the odds of one event for a particular bookmaker on the odds associated to another bookmaker. The null hypotheses to be tested are: the slope coefficient is equal to one and, the second one, the intercept equal to zero. In our case that would imply to run 36 regressions. All the rejections are associated to the null hypothesis corresponding to the intercept, which gives us evidence of very high linear correlation between the odds of different bookmakers but with different levels (intercept different from zero).

Table 6b: Odds correlation matrix (Draw)

	B365	BW	GB	IW	LB	SB	SJ	VC	WH	L-Q
B365	1.0000									
BW	0.9727	1.0000								
GB	0.9822	0.9802	1.0000							
IW	0.9610	0.9618	0.9658	1.0000						
LB	0.9364	0.9383	0.9536	0.9242	1.0000					
SB	0.9732	0.9739	0.9799	0.9634	0.9375	1.0000				
SJ	0.9557	0.9583	0.9641	0.9432	0.9482	0.9513	1.0000			
VC	0.9681	0.9635	0.9708	0.9546	0.9379	0.9567	0.9542	1.0000		
WH	0.9608	0.9573	0.9686	0.9413	0.9579	0.9476	0.9610	0.9555	1.0000	
L-Q	0.8720	0.8692	0.8810	0.8865	0.8341	0.8824	0.8381	0.8532	0.8492	1.0000

Table 6c: Odds correlation matrix (Away win)

	B365	BW	GB	IW	LB	SB	SJ	VC	WH	L-Q
B365	1.0000									
BW	0.9712	1.0000								
GB	0.9832	0.9744	1.0000							
IW	0.9688	0.9723	0.9706	1.0000						
LB	0.9659	0.9715	0.9701	0.9651	1.0000					
SB	0.9809	0.9816	0.9841	0.9755	0.9749	1.0000				
SJ	0.9682	0.9738	0.9720	0.9622	0.9706	0.9743	1.0000			
VC	0.9797	0.9622	0.9786	0.9611	0.9580	0.9698	0.9660	1.0000		
WH	0.9696	0.9587	0.9637	0.9447	0.9593	0.9622	0.9657	0.9620	1.0000	
L-Q	0.8695	0.8979	0.8769	0.8891	0.8935	0.8941	0.8756	0.8572	0.8539	1.0000

The correlation matrices for the three events are reported in Table 6a to Table 6c[14]. In this case we included *La Quiniela* (L-Q) in this analysis because, although the level of its odds cannot be compared to those of the other bookmakers, the coefficient of correlation is capturing patterns no matter the level of the odds.

According to figures in the above tables there is a strong evidence of similar patterns for the odds of the nine bookmakers in our data set. All the coefficients of correlations for the three events are higher than 0.95 with the exception of the coefficients associated to bookmaker LB in the case of draw, but even in this case the coefficients are higher than 0.90, still a very high degree of positive correlation. On the other hand,

[14] Notice that the correlation matrices are symmetric. This is why we only report in Table 6a to Table 6c the coefficients of correlation for half of the matrix.

the coefficients of correlation in which *La Quiniela* is involved are smaller than the previous ones but still quite high and above 0.85 with just two exceptions in the case of a draw. As mentioned above, that could be a consequence of having information on the number of tickets for each particular event but not the exact number of bets.

Take-out rates (overround) and the favourite long-shot bias

We can calculate the implied probabilities ($P_{i,j}^{k}$) for each of the three events from the corresponding odds ($Q_{i,j}^{k}$) according to the following expression:

$$P_{i,j}^{k} = \frac{1}{Q_{i,j}^{k}} \quad k = H, D, A \quad i = B365, BW, GB, IW, LB, SB, SJ, VC, WH$$

where, in general,

$$\sum_{l=H,D,A} P_{i,j}^{l} > 1$$

and the total take-out rate (r_i), the bookmakers return, is:

$$r_i = \left[\frac{1}{N}\sum_{j}\sum_{l=H,D,A} P_{i,j}^{l}\right] - 1$$

where N is the number of games, and r_i decomposed into the contributions of each event:

$$r_i = r_i^H + r_i^D + r_i^A$$

In Table 7 we report the aggregate take-out rates for all the seasons included in the panel data set and the contribution of each event to the total. We can identify a clear pattern: the overall take-out rate is decreasing with time. In the period we consider this rate moves from 10.7% in season 2005/06 to 7.4% in season 2010/11., with an overall 9.5% for the whole period. As mentioned above, we can decompose this take-out rate into the three components: 1.7 percentage points correspond to the home win bets, 4.9 points to the draw event and 2.8 points to the away win. That means that odds are not approximating equally well the three events. The difference between the observed frequencies and those implied by the odds are more important for the draw and the visitor's win results. On the other hand, this pattern for the decomposition of the overall rate is not uniform through seasons. The part of the take-out rate associated to the home win is decreasing through season. It accounted for almost 75% of the total figure in season 2005/06 and it is even negative for the last two seasons. This is compensated by an increase in the participation of the other two events in the overall figure and the draw seems to have, in general, the largest contribution.

Table 7: Average take-out rates by season

Season	Home win	Draw	Away win	Total
2005/06	0.075	0.025	0.006	0.107
2006/07	0.042	0.041	0.023	0.106
2007/08	0.014	0.070	0.017	0.101
2008/09	0.009	0.073	0.011	0.094
2009/10	-0.014	0.024	0.077	0.087
2010/11	-0.023	0.063	0.034	0.074
Total	0.017	0.049	0.028	0.095

Table 8: Average take-out rates by bookmaker

Bookmaker	Home win	Draw	Away win	Total
B365	0.010	0.042	0.020	0.072
BW	0.018	0.047	0.030	0.095
GB	0.011	0.047	0.023	0.081
IW	0.019	0.057	0.030	0.106
LB	0.026	0.053	0.035	0.114
SB	0.018	0.049	0.032	0.100
SJ	0.016	0.046	0.019	0.081
VC	0.019	0.047	0.029	0.095
WH	0.019	0.054	0.035	0.109
Total	0.017	0.049	0.028	0.095

When looking at the take-out rates by bookmakers in Table 8 we observe that in all cases the aggregate pattern of the draw having the largest contribution and the home win the smallest one is repeated. At the same time the aggregate rates show a substantial heterogeneity, moving from 7.2% for B365 to 11.4% for LB. In general, this difference in terms of the aggregate figures is uniformly distributed among the different types of events. B365 show the smallest contributions for all the three results and LB has the largest ones with exception of the draw event.

The evidence of the take-outs rates for the nine bookmakers and six seasons we are considering in this work allows us to analyse to what extent the favourite long-shot bias is present in the betting market for Spanish football. This bias is characterized by a systematic pattern in which bettors tend to undervalue events that are characterized by a high probability and overvalue those with a low probability[15]. As mentioned by Rossi (2011) there are several potential explanations behind the favourite long-shot bias: the concavity of the bettors' utility function, bettors' loss aversion, bettors' different weighting of gains and losses, biases in bettors' subjective probabilities, a supply side explanation of asymmetric information among traders or more casual evidence as the example of match rigging in the Italian football discussed by Rossi (2011). The existence of this type of bias has been tested for several sports, in particular horseracing, with different conclusions, although its existence seems to be quite common[16].

To provide evidence of the existence of this type of bias in the betting market of the Spanish football, we follow the approach by Rossi (2011) and we define three sets of games for each type of event (home win, draw and away win) according to the values of the implied probabilities ($P_{i,j}^{k}$) coming from the observed odds (low, medium and high implied probabilities). For each bookmaker in each season we have 380 observations (odds) for each event. We include the 30 observations with the smallest probabilities in the "low" group, the 30 with the highest probabilities in the "high" group and the remaining in the "medium" group[17]. We perform the analysis in two

[15] See Shin (1991, 1992) for how insider trading affects optimal odds by bookmakers.

[16] See Thaler and Ziemba (1988), Vaughan Williams and Patton (1997), Cain *et al*. (2000), Schnytzer and Weinberg (2008) and Woodland and Woodland (2011), among others, as examples of evidence about testing the presence of the favourite long-shot bias in different sports.

[17] We use the proportions 30/380 for the size of the extreme groups instead of 1/6 (more or less defined by one standard deviation) used by Rossi because in our case the distributions of the odds by

different ways: aggregating the odds (and implied probabilities) by season and aggregating by bookmakers[18]. If there is evidence of the favourite long-shot bias we should be finding that the take-out rates are higher for the subsets with low probabilities than for the one associated to the highest probabilities.

In Tables 9a to 9c we report the take-out rates by season for the three events and the three sets according to the values of the implied probabilities. The evidence is mainly in favour of the existence of this type of favourite long-shot bias. The take-out rate is higher in the "low" group than in the "high" group for the home win (Table 9a) and the draw (Table 9b) events but not in the case of the away win event (Table 9c). In fact, the take out rates for the "high" group in Table 9a are even negative for the last seasons and the pattern has been reversed compared to what we had in the first two seasons in our data set. Of course, the pattern is not completely uniform and there are some seasons with some peculiar evidence, as it is the case of season 2008/09 for the draw event, in which the take-out rates are very high for all three groups and smaller in "low" group compared to that of the "high" group against the evidence for the whole period. Finally, the evidence for the away win event should be qualified because the aggregated pattern is mainly due to two seasons (2007/08 and 2010/11), whereas in two other seasons (2008/09 and 2009/10) the pattern of the take-out rates is according to what we expect in the presence of favourite long-shot bias.

Table 9a: Take-out rates for subgroups by season (home win)

Season	Low	Medium	High
2005/06	0.028	0.082	0.046
2006/07	-0.002	0.043	0.063
2007/08	-0.051	0.032	-0.105
2008/09	0.063	0.007	-0.024
2009/10	0.098	-0.020	-0.077
2010/11	0.050	-0.030	-0.006
Total	0.031	0.019	-0.018

bookmaker and season were not symmetric generating some distortion in the analysis. Some further research should be devoted to this asymmetric distribution issue.

[18] In the analysis of the favourite long-shot bias we have not included the bookmaker WH since we miss almost 25% of the observations for the season 2007/08.

Table 9b: Take-out rates for subgroups by season (draw)

Season	Low	Medium	High
2005/06	0.064	0.018	0.051
2006/07	0.058	0.040	0.020
2007/08	0.142	0.064	0.044
2008/09	0.077	0.067	0.129
2009/10	0.104	0.013	0.056
2010/11	0.063	0.063	0.052
Total	0.085	0.044	0.059

Table 9c: Take-out rates for subgroups by season (away win)

Season	Low	Medium	High
2005/06	0.005	0.003	0.036
2006/07	-0.019	0.021	0.076
2007/08	0.054	-0.004	0.196
2008/09	0.030	0.020	-0.116
2009/10	0.069	0.085	-0.013
2010/11	-0.036	0.037	0.077
Total	0.017	0.027	0.043

In Tables 10a to 10c we report the take-out rates by bookmaker for the three events and the three sets according to the values of the implied probabilities. The evidence is clearer than that from the previous analysis by season, but goes in the same direction. For the home win and draw events the implications of the favourite long-shot bias are satisfied (higher take-out rates for the "low" group than for the "high" group) for all bookmakers and even for the home win event the take-out rates of the "high" group are all of them negative. On the other hand, for the away win event the take-out rates are higher in the "high" group, with the exception of the bookmaker IW, which has the largest rate in the "low" group and higher than that of the "high" group. Consequently, we can conclude that there is substantial evidence of the existence of favourite long-shot bias in the betting market of the Spanish football, but more research should be devoted to take into account the specific characteristics of the odds distributions.

Table 10a: Take-out rates for subgroups by bookmaker (home win)

Bookmaker	Low	Medium	High
B365	0.027	0.010	-0.008
BW	0.026	0.020	-0.010
GB	0.027	0.012	-0.021
IW	0.055	0.021	-0.043
LB	0.037	0.028	-0.012
SB	0.026	0.020	-0.010
SJ	0.021	0.018	-0.013
VC	0.028	0.022	-0.022
Total	0.031	0.019	-0.018

Table 10b: Take-out rates for subgroups by bookmaker (draw)

Bookmaker	Low	Medium	High
B365	0.070	0.038	0.050
BW	0.090	0.041	0.067
GB	0.100	0.040	0.073
IW	0.085	0.052	0.081
LB	0.092	0.048	0.071
SB	0.083	0.044	0.066
SJ	0.090	0.042	0.036
VC	0.066	0.047	0.027
Total	0.085	0.044	0.059

Table 10c: Take-out rates for groups by bookmaker (away win)

Bookmaker	Low	Medium	High
B365	0.012	0.019	0.042
BW	0.024	0.028	0.056
GB	-0.002	0.025	0.033
IW	0.028	0.032	0.012
LB	0.016	0.035	0.059
SB	0.023	0.031	0.058
SJ	0.016	0.018	0.041
VC	0.020	0.029	0.039
Total	0.017	0.027	0.043

Analysis of the forecasting performance

There have been several papers in the literature trying to analyse whether the forecasts of the results of professional sports games by experts are better than those based on statistical models, i.e. whether experts process the information included in the models in a similar way adding some specific information not captured by the observed variables[19]. Forrest *et al.* (2005) perform a similar exercise but using published odds on football games as proxies for the experts' views. The evidence from these studies is mixed in the sense that it is not clear that forecasts by experts are worse than those obtained from a statistical model.

In this section following an approach similar to that used by Forrest *et al.* (2005) we try to bring evidence about to what extent forecasts based on football fans bets on *La Quiniela* are better than those based on the odds from different bookmakers. We use two approaches to measure the forecasting performance of bookmakers (through odds) and bettors of *La Quiniela*: one based on the use of a modified version of the Brier scores and the second one based on a probabilistic model where implied frequencies (from the bookmakers' odds) and observed frequencies (*La Quiniela*) are used as explanatory factors of the result of a football match.

The Brier score (BS), introduced by Brier (1950) when verifying weather forecasts, is basically the mean square error associated to the forecast of whether a particular result k happens in match j (R_j^k), where k is either home win, draw or away win, by using a specific predictor. In our case we use the implied probabilities from the odds of the different bookmakers ($P_{i,j}^k$) except for *La Quiniela* where we use the observed frequencies associated to each particular result. The three Brier scores we can define for each predictor (bookmaker) and each season have the following definition:

$$BS_i^k = \frac{\sum_{j=1}^{N}\left(R_j^k - P_{i,j}^k\right)^2}{N}$$

$$k = H, D, A \quad i = B365, BW, GB, IW, LB, SB, SJ, VC, WH, LQ$$

[19] See Forrest and Simmons (2000) and Boulier and Stekler (2003), among others.

where R_j^k is a 0-1 variable associated to a particular result k in match j and N the number of matches. By definition the original Brier scores take values between 0 (perfect forecast) and 1 (worst forecast).

We propose a modified version of the Brier scores which takes into account the fact that the variance of the errors is not constant but it depends on $P_{i,j}^k$. We weight each error by the inverse of its standard deviation, to allow for the possibility of giving more weight to those errors associated to forecasts ($P_{i,j}^k$) close to either 1 or 0, i.e. without too much uncertainty. The modified version of the Brier score (MBS) is the following:

$$MBS_i^k = \frac{\sum_{j=1}^{N} \frac{\left(R_j^k - P_{i,j}^k\right)^2}{P_{i,j}^k\left(1 - P_{i,j}^k\right)}}{N}$$

In Tables 11a to 11c we report the values of the modified Brier scores for the three events by season and bookmaker, including *La Quiniela*. The forecasts by experts seem to improve through seasons, in particular for the home win event, although the evidence is a bit more erratic in the case of the draw. There is also a strange result, which applies to all, in the season 2009/10 with very low values of the modified Brier score. On the other hand, forecasts from bookmakers seem to work better than those from the observed frequencies in *La Quiniela*, in particular, for the away win event[20].

Table 11a: Modified Brier scores for forecasting performance (home win)

Bookmaker	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11
B365	0.968	1.018	0.991	0.959	0.937	0.951
BW	0.961	1.031	1.005	0.973	0.941	0.946
GB	0.962	1.019	0.991	0.959	0.936	0.947
IW	0.955	1.017	0.986	0.949	0.935	0.953
LB	0.964	1.013	0.996	0.965	0.940	0.951
SB	0.968	1.019	0.995	0.962	0.937	0.951
SJ	0.969	1.022	0.996	0.954	0.936	0.952
VC	0.958	1.008	0.993	0.962	0.934	0.953
WH	0.960	1.012	1.024	0.959	0.933	0.948
LQ	1.102	1.132	1.074	1.034	1.043	1.048

[20] As mentioned, information from *La Quiniela* corresponds to tickets, not to bets, and this could be worsening the forecasting power.

Table 11b: Modified Brier scores for forecasting performance (draw)

Bookmaker	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11
B365	1.008	0.966	0.887	0.873	0.979	0.876
BW	1.007	0.975	0.874	0.875	0.985	0.870
GB	0.998	0.963	0.876	0.866	0.968	0.867
IW	0.994	0.947	0.873	0.856	0.974	0.865
LB	1.009	0.964	0.885	0.876	0.972	0.868
SB	1.002	0.971	0.884	0.868	0.980	0.876
SJ	1.000	0.971	0.874	0.866	0.977	0.876
VC	1.015	0.970	0.882	0.874	0.968	0.878
WH	0.993	0.958	0.866	0.873	0.973	0.858
LQ	1.122	1.016	0.948	0.896	1.086	0.949

Table 11c: Modified Brier scores for forecasting performance (away win)

Bookmaker	2005/06	2006/07	2007/08	2008/09	2009/10	2010/11
B365	1.061	1.034	1.098	1.006	0.762	1.033
BW	1.060	1.047	1.087	1.005	0.764	0.982
GB	1.068	1.022	1.078	0.995	0.764	0.985
IW	1.026	1.035	1.069	1.002	0.761	0.976
LB	1.063	1.025	1.089	0.991	0.764	0.979
SB	1.054	1.018	1.079	0.984	0.759	0.973
SJ	1.068	1.042	1.106	1.036	0.778	1.013
VC	1.048	1.007	1.086	0.984	0.766	1.048
WH	1.040	1.011	1.083	0.990	0.764	0.984
LQ	1.328	1.264	1.276	1.169	0.904	1.249

To corroborate the evidence from the modified Brier scores we estimate a model for each bookmaker where the dependent variable is the result of a football game and the explanatory variables are the implied probabilities or the observed frequencies of the results. Given that each football match has three possible results[21], we define as our dependent variable (Y_j) a qualitative variable with three possible values (3 = home win;

[21] This approach is similar to that used by Forrest and Simmons (2008), but they use only home and away win bets and, consequently, they estimate a binary Probit model.

2 = draw; 1 = away win) which are subject to a specific "order". This is why for each bookmaker we use an ordered Logit model which has the following definition[22]:

$$L_j^* = X_j'\beta + \varepsilon_j$$

$$Y_j = 1 \quad if \;\; L_j^* < \mu_1$$

$$Y_j = 2 \quad if \;\; \mu_1 \leq L_j^* < \mu_2$$

$$Y_j = 3 \quad if \; \mu_2 \leq L_j^*$$

where X_j' is the vector of explanatory variables, which in our case includes the odds associated to the home win and the draw, but not the away win odds to avoid multicollinearity problems; β, μ_1 and μ_2 are parameters to be estimated and ε_j is the error term capturing unobserved factors affecting the result of a match and it is assumed to have a logistic distribution[23].

In Table 12 we report some statistics of the goodness of fit of the ordered models estimated for the different bookmakers. The base model includes the odds associated to the home win and the draw, and we also estimate a model including season dummies. We use the same sample for all the bookmakers and since the dependent variable is the same for all the models we can compare the non-nested specifications by means of comparing the values of the log likelihood function which is equivalent to using the Akaike Information Criterion given that the number of parameters to be estimated is the same for all the models (bookmakers).

We can point out the following pieces of evidence from the statistics in Table 12. First, corroborating what we obtained when using the modified Brier scores, the fit of the model using frequencies from *La Quiniela* (log L = -2104.7) is worse than that of the other models using odds by bookmakers (log L higher than -2087.07 in all the cases).

[22] See, for instance, Cameron and Trivedi (2005). As it is well known there are no substantial differences from the fact of using a Probit or a Logit version of the ordered model. In our case there are no substantial differences depending on the distributional assumptions of the error term, i.e. whether we use a Logit or a Probit ordered mode.

[23] Rossi (2011) uses a similar approach but he estimated a multinomial Logit model. We also estimated this alternative model and the results do not change but from the goodness of fit perspective and also the "ordered" nature of the attributes of the dependent variable, the ordered version is preferred.

This finding is also verified if we look at the values of the pseudo-R^2. As usual with microdata, these values are small but we can appreciate a difference between bookmakers' models and the model using information from *La Quiniela*[24]. Second, the basic results are qualitatively the same if we include a set of season dummies to control the time effect. The null hypothesis of the coefficients of these dummies being equal to zero is rejected in all cases at a 10% significance level, and at a 5% for some, but not all, the cases. The predictive power of the different bookmakers looks very much similar, although VC and B365 seem to perform better than the other.

Table 12: Explanatory power of the ordered Logit models by bookmaker

	Base model		Base model + season dummies	
Bookmaker	Log L	Pseudo-R^2	Log L	Pseudo-R^2
B365	-2077.54	0.070	-2071.99	0.073
BW	-2083.90	0.068	-2078.11	0.070
GB	-2080.05	0.069	-2074.09	0.072
IW	-2081.01	0.069	-2076.05	0.071
LB	-2087.07	0.066	-2081.36	0.069
SB	-2080.29	0.068	-2077.37	0.070
SJ	-2081.70	0.069	-2076.51	0.071
VC	-2076.85	0.071	-2071.79	0.073
WH	-2080.47	0.069	-2075.75	0.071
L-Q	-2104.66	0.058	-2098.82	0.061

We also estimated ordered Logit models for the different seasons in our data set aggregating the information from the different bookmakers. The results are reported in Table 13 and they allow us to identify a clear trend in terms of the predictive performance of the estimated models. A substantial increase in the value of the pseudo-R^2 can be identified for the last two seasons in the sample (10.5% on average) compared with the performance in the previous four (around 5% on average)[25].

[24] Rossi (2011) reports and emphasizes the high values (above 80%) of the pseudo-R^2 in the multinomial models he estimated. This is very surprising, and doubtful given the usual experience, although this does not invalidate the basic results he reports.

[25] In Table 13 we do not report the value of the log likelihood given that the sample size is different in each season.

Bookmakers seem to learn about the determinants of the result of a match and this information is incorporated in the odds proposed.

Table 13: Explanatory power of the ordered Logit models by season

Season	Pseudo-R^2
2005/06	0.046
2006/07	0.041
2007/08	0.035
2008/09	0.076
2009/10	0.109
2010/11	0.100

Concluding remarks

Overall, the empirical analysis of information and forecasting performance on Spanish football betting odds suggests that experts (bookmakers) seem to be better in estimating football results than the 'crowd' (football pools bettors).

By comparing the odds offered by the nine bookmakers in our data set, their distributions seem quite similar in their first two moments. However, an additional examination of the coefficients of correlation between the odds of a particular outcome for pairs of bookmakers (including *La Quiniela*) hints at *La Quiniela* to be a "different thing". A further study of the probabilities derived from the odds suggests that they are not properly approximating the three possible examined results (home win, draw and away win) in the same way. Even though the predictive power of the different bookmakers looks very much similar, the analysis of the forecasting performance through both the calculated values of the modified Brier scores and the goodness of fit of the estimated ordered models shows that forecasts from bookmakers seem to work better than those from *La Quiniela* bettors. However, the fact that the data correspond to the number of tickets but not exactly the number of bets could have an influence in the reported evidence.

Notwithstanding, global explanatory power improves as time goes by maybe as a consequence of the existence of a learning process.

Substantial evidence of the existence of favourite long-shot bias in the betting market for Spanish football is also found.

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