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Sentimental Preferences and the Organizational Regime of Betting Markets
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Abstract

We analyze the price impact of sentimental bettor preferences within a bookmaker betting market. Our model demonstrates that, under reasonable assumptions about the nature of demand in a market with strong competition, the bookmaker will offer lower prices for bets with comparatively stronger demand. Using a sample of more than 16,000 English soccer matches we find evidence that more favorable odds are extended to bets on more popular clubs and that this effect is amplified on weekends when sentimental bettors face lower opportunity costs to wager. Our findings help to explain why the market for sports gambling operates as a hybrid structure with bookmakers able to attract a considerable share of the betting volume although identical contracts are traded on exchange markets at lower costs; the organizational design of a quote-driven market enables the dealer to take advantage of sentimental bettor preferences.
Introduction

There are a variety of different institutional regimes in which options contingent on the outcome of future events can be traded. At the beginning of 1990's, markets for financial products relied mainly on a quote-driven mechanism. Here, the so-called specialist acts as a dealer and intermediates between buyers and sellers by unilaterally determining the prices on a given contract. NASDAQ and the London Stock Exchange were, at that time, two leading examples of such a trading structure. Since then, order-driven systems have become more prevalent. Essentially, this organizational setting involves a platform on which a double auction process between individual traders is enabled. An investor has the choice to submit a limit order and wait for another participant to hit his quote, or alternatively, he can submit a market order matching an already offered quote. Most financial markets have now adopted either a pure limit order book or a mixed structure in which both market mechanisms coexist. On the NASDAQ or the New York Stock Exchange (NYSE), for example, orders from the public compete with dealer quotes (e.g., Schwartz and Weber, 1997; Madhavan, 2000; Marshall and Young, 2003).

Similar to financial markets, also the sports betting industry involves different organizational systems. Gambling has traditionally been designed as a pari-mutual or totalisator system. Here, the payout ratio of a winning bet is calculated by sharing the pool among all winning bets reduced by the totalisator's commission. An apparent drawback of this procedure is that the payout ratio is not determined ex ante because it depends on the final betting volume placed at a given outcome relative to the overall pool. Consequently, the pari-mutual system has partly been replaced by fixed-odds mechanisms in which the bettor's claim is tied to the initially taken odd and does not depend on subsequent price changes. Bookmaker markets have become the dominant form of gambling on team sports in the US, in the UK and in many other Commonwealth countries in general (Forrest and Simmons, 2001). Similarly to the specialist in a quote-driven market setting, the bookmaker acts as a dealer announcing the odds against which the bettors can place their bets. In
recent years, person-to-person exchange betting has evolved as a third market mechanism. Here, as in the order-driven setting of financial markets, it is not the dealer but another individual trader taking the opposite side of a contract.

In the gambling industry, the different organizational structures coexist and compete with each other to attract order flow. In team sports betting, for example, traditional bookmakers (like Ladbrokes, William Hill, Interwetten among others) and emerging bet exchanges (like Betfair or World Bet Exchange among others) provide the opportunity to place bets on the very same events. The obvious appeal of the order-driven mechanism is that the market operator’s revenues are independent of the specific game outcome. Bet exchanges simply provide an electronic trading platform and claim their commission fee on every transaction being processed between two bettors. Meanwhile, traditional bookmakers are exposed to substantial risk as they take the contrary position of every bet. Therefore, bookmakers need to calculate their postings by using costly forecasting models, which have to be continuously updated for new information reaching the market as well as the incoming order flow from the bettor’s side. Thus, not surprisingly, bet exchanges offer more favorable odds than bookmakers on average (e.g., Franck, Verbeek, and Nuesch, forthcoming; Koning and van Velzen, 2009). It is, therefore, puzzling that the market for sports gambling operates as a hybrid structure with bookmakers able to attract a considerable share of the betting volume although identical contracts are traded elsewhere at lower costs. How have bookmakers remained competitive against rival order-driven market forms? More specifically: what is the benefit of actively managing quotes compared to passively matching supply and demand?

The survey article of Madhavan (2000) names some reasons for the coexistence of an order-driven and quote-driven market offering the same fundamentals. He argues that dealers may be valuable to the market as they help to discover and stabilize prices and provide liquidity. A further explanation for the coexistence of bookmakers and order-driven systems in betting markets, explicit in Levitt (2004) and implicit elsewhere (e.g., Bruce and Johnson, 2005; Kuypers, 2000), is that the organizational design of a dealer market facilitates exploitation of sentimental bettor preferences. These studies argue
that bookmakers are more skilled at predicting the outcome of the underlying events than the bettors, and are, therefore, able to take advantage of sentimental bettor perceptions by posting odds which deviate from efficient prices. Betting volume is expected to spread equally across all possible outcomes of a certain event if prices represent the implicit true probabilities. If, however, bettors prefer options with a particular characteristic and stronger demand goes to one of the outcomes, then, bettors’ perceptions are seen to be sentiment-driven. Under the modeling of Kuypers (2000) and Levitt (2004) the bookmakers can earn higher profits by increasing the price (deteriorating the odds) on more heavily demanded bets.

Although intuitive, we demonstrate that this result relies on rather strong assumptions about the nature of the demand an individual bookmaker is facing. The shape of an individual bookmaker’s demand function, in turn, reflects the market’s competitive situation; the stronger the competition, the more sensitively demand will react to the bookmaker’s pricing decision. In the modeling of Kuypers (2000) and Levitt (2004), the overall betting volume on a given match is exogenously given and only the fraction of the overall volume placed on an outcome is influenced by the preferences of the bettors and the bookmaker’s price setting. This corresponds to a situation where bettors, at first, decide whether at all to bet on a given match with a given bookmaker and, thereafter, they choose on which outcome to place their bets. This simplification may be consistent with the market environment in the U.S., where regulative interventions have created a monopoly for sports betting.1 These assumptions, however, do not meet the apparent conditions of European sports betting, where the market is highly competitive. Several bookmakers post their odds on the very same event, thus offering a quasi perfect substitute to the betting audience. Especially in online gambling, bettors can easily compare the odds of various bookmakers and identify the most favorable prices at low searching costs, for example on websites like betexplorer.com or oddschecker.com. Moreover, the assumptions do not take into account that

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1 In fact, Levitt (2004) analyzes the prices of a monopolistic bookmaker for NFL matches and finds evidence consistent with his theoretical predictions: Prices are less favorable for bets with comparably stronger demand – in his case, bets on favorites to win the game.
the bookmakers compete with bet exchanges, where prices are the result of matching a multitude of individuals with opposing opinions.

Our model relaxes the assumption of a closed-form demand structure. Instead of arbitrarily determining that the bettor’s decision to place a bet with a given bookmaker is already taken, we endogenize the overall betting volume as a function of the bookmaker’s price setting decision. We demonstrate that whether it is optimal to increase or decrease the price on more heavily demanded bets depends on the elasticity of demand an individual bookmaker is facing and how it is influenced by bettor sentiment. In the case of strong competition as in the European online betting market, bookmakers are likely to operate in the area of elastic individual demand. It is reasonable to assume that at least a fraction of the sentiment bettors do compare the terms offered by different bookmakers before placing their bets. The model shows that, under these conditions, it can be optimal for the bookmaker to decrease the price (improve the odds) for more heavily demanded bets rather than increasing it.

In the empirical part of the paper we investigate the price effect of team popularity as one source of sentimental betting. Because the betting volumes wagered at different bookmakers are a well-kept secret, we focus on sentiment betting that can be systematically linked to observable characteristics. This comes at the cost that we are only able to examine ‘the tip of the iceberg’. Bookmakers are expected to not only exploit systematic demand shifts but also unsystematic shifts, for they continuously observe the incoming demand and will, therefore, react to it in either case to maximize their profits. Yet the price impact we are after is predictable ex ante as a team’s popularity is readily available information. Therefore, the significance of any price effect found in our sample is even more striking as it represents a market inefficiency deliberately provoked by the bookmakers.

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2 The elasticity of a bookmaker’s individual demand is not infinite, however, as the betting market is found to be imperfectly competitive. This is supported by the fact that prices on the very same options vary across bookmakers (e.g., Pope and Peel, 1989; Vlastakis, Dotsis, and Markellos, 2009) and across market mechanisms (e.g., Smith, Paton, and Vaughan Williams, 2006; Smith, Paton, and Vaughan Williams, 2009; Franck, Verbeek, and Näesch, forthcoming).
The popularity of a team as a source of sentimental betting and market inefficiency has been documented in the recent literature (e.g., Avery and Chevalier, 1999; Forrest and Simmons, 2008; Braun and Kvasnicka, 2008). These studies argue that there might be some ‘committed’ bettors, who feel the urge to demonstrate their loyalty to a particular club by wagering their money on it. More glamorous teams have a larger fan base and are, therefore, more prone to attracting sentiment bets. In essence, there is 

\textit{ceteris paribus} an excessive proportion of stakes placed on the relatively more popular team winning. The empirical evidence on the direction to which bookmakers shade prices in the presence of sentiment betting is mixed. Avery and Chevalier (1999) show that winnings from backing prestigious teams in the \textit{National Football League (NFL)} were abnormally low. Forrest and Simmons (2008) find that in Spanish and Scottish soccer leagues not less but more favorable odds are offered for bets on more popular teams. Braun and Kvasnicka (2008) investigate the odds of different bookmakers for qualification games to the \textit{UEFA Euro 2008} and present evidence that some bookmakers shade prices in favor of the corresponding national team and others shade prices against it.

We analyze the price setting of eight well-known bookmakers for more than 16,000 English soccer matches played in the 2000/01 to 2007/08 seasons. We use the average home attendance as proxy for the amount of sentiment bets due to team popularity. In line with the predictions of our theoretical model and given the assumptions about the nature of demand in the English football betting market, we find evidence that bookmakers offer more favourable prices for bets on more popular teams.

But this result could yet have an alternative explanation. Shin (1991, 1992, 1993) has pointed out that bookmakers may shade the odds in order to hedge against the threat of bettors endowed with superior information. According to this theory, bookmakers lower the high odds on underdog teams where the risk of insider knowledge is particularly harmful. The empirical consequence of this reasoning is the favorite-longshot bias (see, e.g., the re-

\footnote{Even though behaving as if they had misperceptions, sentiment bettors might be capable of assessing win probabilities objectively. They are only biased in the sense that they exhibit a preference for betting on a particular outcome. Whether this behavior implies irrationality depends on the prices sentiment bettors are willing to accept when they place their bets.}
view of Coleman, 2003), which describes the well-documented empirical regularity that bookmaker odds tend to underestimate (overestimate) the frequency of high (low) probability outcomes. Since more popular teams are mainly the ones with stronger playing talent, the positive correlation between the fan-base and the expected betting return could be driven by aspects related to the longshot bias. In order to rule out the longshot bias as an alternative explanation, we distinguish between weekday and weekend games. Since every team in a league is randomly assigned the same number of weekday matches, this third variable is independent of which teams are involved in the match. Within the Shin framework, only the match composition should determine to what extent the bookmaker shades his prices because bettors endowed with superior information are as likely on weekdays as on weekends. Casual bettors who are susceptible to different kinds of sentiment, however, are more likely to place bets on weekends compared to weekdays (Kopelman and Minkin, 1991; Sobel and Raines, 2003; Sung and Johnson, 2009). Consistent with the theoretical prediction, we find clear evidence that more favorable prices are extended to bets on more popular clubs winning and that this effect is amplified on weekend games when the fraction of sentiment-driven bettors is expected to be higher.

Our results indicate that bookmakers actively shade prices in order to exploit sentimental preferences of the betting audience; they offer competitive odds where demand is relatively strong. We argue that, at least partly, it is due to the active pricing policy illustrated here that bookmakers have been able to remain profitable against rival order-driven structures that passively match supply and demand and operate at lower cost levels.

The remainder of the paper is structured as follows. The next section provides the theoretical model of the bookmaker's price setting decision in the presence of sentiment betting. Section two presents the empirical findings and section three concludes.

The theoretical model

Our model explores the price setting behavior of a risk-neutral profit maximizing bookmaker. In a soccer match there are three possible outcomes $e \in \{H,D,A\}$, a home win, a draw and an away win. The bookmaker posts the
decimal odds $o_e$, which represent the payout ratio for a winning bet. We refer to $\hat{p}_e = 1/o_e$ as the bookmaker's probability odd offered to the betting audience.\(^4\) By $\varphi_e$, we denote the true probability for an outcome $e$ happening.\(^5\)

The bookmaker’s per match profit is given by the volume wagered on the outcomes $v_e$ minus the corresponding expected payout to the bettors:

$$E[\Omega] = v_H \left[ 1 - \frac{\varphi_H}{\hat{p}_H} \right] + v_D \left[ 1 - \frac{\varphi_D}{\hat{p}_D} \right] + v_A \left[ 1 - \frac{\varphi_A}{\hat{p}_A} \right] \quad (1)$$

In other words, we sum up the amount of money wagered times the expected profit margin (denoted by the expression in brackets) for each outcome of a match.

The bettor’s average return on a one unit bet is given by $\varphi_e/\hat{p}_e$. The bookmaker’s probability odds of a match $\hat{p}_e$ sum to greater than one because of the inherent overround $s$, so that $\hat{p}_H + \hat{p}_D + \hat{p}_A = 1 + s$. Hence, the bettor’s payout ratio on a randomly chosen bet is $E\left[ \frac{\varphi_e}{\hat{p}_e} \right] = 1 - s$.\(^6\)

On average, the bookmaker’s profit margin $\left[ 1 - \frac{\varphi_e}{\hat{p}_e} \right]$ equals $s$. In the following, we assume that the bookmaker prices draw bets such that $\left[ 1 - \frac{\varphi_D}{\hat{p}_D} \right] = s$. Draws appear to be almost random events (Dobson and Goddard, 2001). To keep the model simple, we assume that $s$ is fixed across matches. Hence, the bookmaker is left with only the decision of how to price bets on home wins against away wins. To simplify matters, we can thus drop draw bets and equation (1) reduces to

$$E[\Omega] = v_H[s - ds] + v_A[s + ds] \quad (2)$$

\(^4\) From the bettor’s point of view, a bet is profitable in expectation whenever he estimates the outcome to occur more often than the reciprocal of the odd.

\(^5\) We state that the bookmaker is likely to be more skilled in predicting than any other party. Thus, any deviation from average pricing can be seen as an intentional act from the bookmaker’s side rather than a failure in processing relevant information into the odds.

\(^6\) The bettor earns the same return if he wagers on all three outcomes of the match, spreading the stake relative to the bookmaker’s probabilities.
The bookmaker can either increase the price of bets on the home team winning and decrease the price of the away win bets or vice versa. Recall that the price \( s_e = [s \pm ds] \) refers to the bookmaker’s decision of how to choose the odd \( a_e = \frac{1}{\varphi_e} \) relative to the true outcome probability \( \varphi_e \). If he deviates from the average price \( s \) by \((ds)\), he offers less favorable terms on this bet. At the same time, he then has to lower the price for the opposite wager by the same amount \((-ds)\).

We assume that betting volume on a particular outcome - at least within a range of \( S_e = [(s + ds), (s - ds)] \) - is given by the following linear demand function

\[
S_e = \alpha - \beta V. \tag{3}
\]

The bookmaker can attract betting volume \( V \) on the different outcomes by lowering his price \( S_e \). This relation is moderated by the parameters \( \alpha \) and \( \beta \) describing the shape of the (individual) demand function the bookmaker is facing.

We now introduce biased betting behavior. In a very simple way, biased bettor preferences can be understood as a shift of the demand function to the upper right at the given price level \( s \) for one of the outcomes relative to the other outcome. So, for a given profit margin asked by the bookmaker, there is more volume wagered by the betting audience on one of the outcomes compared to the other outcome. In our context, if the away team has a larger fan base than the home team, the demand for bets on the away team winning is increased due to a larger amount of sentimental betting.\(^7\)

The optimal price setting behavior in the presence of biased bettor preferences depends on the nature of the demand shift. The shift of demand can be induced by an increase of the intercept \( \alpha + ds \), by a decrease of the slope \( \beta - d\beta \), or by a combination of the two. Hence, if there is sentiment betting, the demand function for bets on the team attracting more sentiment bettors takes the form

\(^7\) The demand for the opposite bet on the match, which attracts fewer sentiment bettors, remains at the original level.
where \( da \in [0, \infty[ \) and \( d\beta \in [0, \infty[ \). An increase of the intercept \( \alpha + da \) means that the additional demand is constant across different levels of prices. We will refer to this situation as the influence of price-insensitive sentiment bettors. These bettors may wager on ‘their’ team independent of the odds offered. They neither have a reservation price nor do they seek more favorable odds by comparing the prices of different bookmakers.

The influence of price-sensitive sentiment bettors is modeled by a decrease in slope \( \beta - d\beta \) of the demand function.\(^8\) The interpretation of sentiment betting induced by \( d\beta \) is the following: Some bettors may - on the basis of sentiment - choose a team on which to place a bet. In a second step, they decide whether, the odd on that team meets their reservation price. If they do not agree with the bookmaker’s price, they may either not bet at all or switch to another bookmaker offering more favorable terms.

We now calculate the bookmaker’s profit \( \Omega_{da, d\beta} \) for the case where the bookmaker sets a price \( (s + ds) \) for the sentiment bet and \( (s - ds) \) for the opposite bet. According to equation (2), the bookmaker’s profit is given by the volume wagered times the corresponding price summed up for the two bets.

We then derive the optimal deviation from the average price. The bookmaker’s profit is maximized by an optimal price deviation \( ds_{a, \beta} \) which solves

\[
\max_{ds} \Omega_{da, d\beta} (s + ds) \\
= \left[ \frac{1}{\beta + \frac{s}{d\beta}} + \frac{1}{\beta - d\beta} \right] s(\alpha - s) + \left[ \frac{1}{\beta + \frac{s}{d\beta}} - \frac{1}{\beta - d\beta} \right] ads \\
- \left[ \frac{1}{\beta + \frac{s}{d\beta}} + \frac{1}{\beta - d\beta} \right] 2sds + \frac{1}{\beta - d\beta} s\alpha + \frac{1}{\beta - d\beta} dads \\
- \left[ \frac{1}{\beta + \frac{s}{d\beta}} + \frac{1}{\beta - d\beta} \right] ds^2 
\]  

(5)

The first-order condition regarding \( ds \) is

\(^8\) Note that price elasticity of demand does not change at a given reference price as the result of an increase of only price-sensitive sentiment bettors.
\[
\frac{\partial \Omega_{dg}}{\partial ds} = \left[ -\frac{1}{\beta} + \frac{1}{\beta - d\beta} \right] \alpha - \left[ -\frac{1}{\beta} + \frac{1}{\beta - d\beta} \right] 2s + \frac{1}{\beta - d\beta} d\alpha \\
- 2 \left[ \frac{1}{\beta} + \frac{1}{\beta - d\beta} \right] ds = 0
\] (6)

Thus, the bookmaker’s optimal price adjustment is given by

\[
ds_{da,db}^* = \frac{1}{2} \left[ -\frac{1}{\beta} + \frac{1}{\beta - d\beta} \right] (\alpha - 2s) + \frac{1}{2} \left[ \frac{1}{\beta} + \frac{1}{\beta - d\beta} \right] d\alpha
\] (7)

If \( da = 0 \) and \( db = 0 \), there is no sentiment towards any of the playing teams so that demand for home bets is equal to demand for away bets. In this case, equation (7) reduces to

\[
ds^* = 0
\] (8)

Thus, in this case the bookmaker should not deviate from the average price.

If \( da > 0 \) and \( db = 0 \), sentiment is exclusively caused by price-insensitive bettors. Here, equation (7) can be rearranged to

\[
ds_{da}^* = \frac{1}{4} da
\] (9)

Not surprisingly, the bookmaker should increase the price in the presence of only price-insensitive sentiment bettors.

If \( da = 0 \) and \( db > 0 \), sentiment betting is exclusively caused by price-sensitive bettors. In that case, equation (7) reduces to

\[
ds_{db}^* = \frac{1}{2} \left[ \frac{1}{\beta} + \frac{1}{\beta - d\beta} \right] (\alpha - 2s)
\] (10)

Since the fraction is strictly positive, the direction to which the bookmak-er should shade prices depends on the value of \((\alpha - 2s)\). The condition for a negative price deviation \(ds_{db}^*\) to be the optimal choice is \((\alpha - 2s) < 0\). This
inequality can be rearranged to \( \frac{s}{a-s} > 1 \). In the case of a linear demand function, the term on the left side is the absolute value of price elasticity of demand at the given price level \( s \), defined as \( |\varepsilon| = \frac{s}{a-s} \).

The condition for a negative price deviation \( ds_{da,\beta}^* \) to be optimal therefore reduces to

\[
d s_{da,\beta}^* < 0 \Leftrightarrow |\varepsilon| > 1
\]

Hence, if sentiment betting is exclusively caused by price-sensitive bettors, the price should be decreased if the absolute value of elasticity of demand exceeds one. However, the bookmaker should increase the price if demand at the given reference price is inelastic, and the bookmaker should not deviate at all if demand is unit elastic.

Finally, we examine the case of both price-insensitive sentiment bettors and price-sensitive sentiment bettors in the market. The optimal price deviation \( ds_{da,\alpha,\beta}^* \) is negative if the condition

\[
(-1) \left[ \frac{1}{\beta - d\beta} \right] da > (\alpha - 2s)
\]

is fulfilled. We can rearrange this inequality analogously to the above case. The condition for a negative price deviation \( ds_{da,\alpha,\beta}^* \) to be the optimal choice is then

\[
d s_{da,\alpha,\beta}^* < 0 \Leftrightarrow |\varepsilon| > 1 + \left[ \frac{1}{\frac{1}{\beta - d\beta}} - \frac{1}{\frac{1}{\beta} + \frac{1}{\beta - d\beta}} \right] \frac{1}{\alpha - s} da
\]

From equation (13) we see that the optimal price adjustment depends on two characteristics of the demand function: the price elasticity of demand and the amount of price-sensitive sentiment bettors compared to price-insensitive sentiment bettors. Figure 1 illustrates the situation.
The shaded area represents the cases where it is optimal for the bookmaker to lower the price for sentiment bets. Given an elasticity of demand \(|\varepsilon|\) below unity, it is always optimal to increase the price for the sentiment bet. However, if the demand function is elastic, the optimal price setting decision depends on \(d\alpha\) and \(d\beta\). From equation (13) we can derive that additional price-insensitive bettors \((d\alpha > 0)\) increase the threshold level of elasticity beyond which a price reduction maximizes the bookmaker’s profit. Additional price-sensitive sentiment bettors \((d\beta > 0)\) decrease the threshold level of elasticity. The function \(f(d\alpha)\) in Figure 1 illustrates this relationship: the strictly positive slope of the function decreases in \(d\beta\), which means that the ‘window’ for lower prices on sentiment bets to be the optimal strategy opens up with an increase of \(d\beta\). When decreasing the price, the bookmaker faces a trade-off between the gain of more betting volume from price-sensitive bettors and the loss of potential profit from price-insensitive sentiment bettors.

Our model implies that the bookmaker’s best reaction to sentiment betting depends on the nature of the demand. If the additional demand is due to
price-insensitive bettors, we expect less favorable odds relative to the true winning probability for these bets. On the other hand, if the additional demand is mainly caused by price-sensitive sentimental bettors and overall price elasticity is sufficiently large, we predict the opposite effect: more favorable terms extended to sentiment bets.

**Empirical evidence from the English bookmaker market**

In this section we examine the price effect of team popularity as one source of sentimental betting. The logic behind this kind of sentimental bettor preference is the idea that fans are unlikely to wager against the team they support due to loyalty towards ‘their’ club. Thus, teams with comparatively larger fan bases are expected to attract more sentimental betting volume than less popular teams (see also Avery and Chevalier, 1999, or Forrest and Simmons, 2008).

To test the influence of sentimental betting on the bookmaker’s price setting decision we analyze the odds on games in the upper four English soccer leagues played over eight seasons from 2000/01 to 2007/08. For each match, online-betting odds from eight different bookmakers were collected from the webpage www.football-data.co.uk. The bookmakers are B365, Bet&Win, Gamebookers, Interwetten, Ladbrokes, William Hill, Stan James and VC Bet. This list includes the two largest bookmakers in the UK, namely William Hill and Ladbrokes, but also smaller bookmakers like VC Bet. Since not all eight bookmakers offer odds on all soccer games of the upper four English leagues, the sample size varies between 6,107 and 16,024 matches.

As a proxy for the amount of sentiment bets we use the average home attendance of a team during the previous season. Home attendance characterizes the active fan base - people who are willing to buy access to home matches. This figure is likely to correlate with the number of passive fans and, thus, potential sentiment bettors (Forrest and Simmons, 2008). We collected the average home attendance figures during the preceding season from the database www.european-football-statistics.co.uk. The numbers are then standardized by season and league.

Following our model, we concentrate on home and away win bets and ignore draw bets because they are not influenced by sentimental betting. We
convert the listed ‘decimal odds’ (e.g., 1.8) into ‘probability odds’, which are
the reciprocal of the decimal odds (1/1.8=0.56). The sum of the ‘probability
odds’ exceeds 1 by the bookmaker’s overround. Some studies like Forrest and
Simmons (2008) therefore multiply the probability odds by 1/(1+overround)
to obtain the ‘implicit probabilities’ which in turn sum up to one. The under-
lying assumption that the overround is equally distributed over the three bets
of a game seems questionable, however. In our model, we argue that it is the
posted odds, rather than the implicit, margin corrected probabilities, on which
bettors base their decision whether to place a bet or not. For the punters, it
does not matter if odds are low due to the inherent overround, or as a result
of distorted implicit probabilities.⁹

In the theoretical model we have shown that the optimal price reaction of
a profit-maximizing bookmaker depends on the elasticity of demand the indi-
vidual bookmaker is facing and how it is influenced by bettor sentiment. Since
the European online betting market in general and the English betting market
in particular is highly competitive with numerous bookmakers and bet ex-
change platforms offering odds on the very same events, we postulate that
any additional sentimental demand is highly price-sensitive. Bettors can easily
compare the odds listed by several different bookmakers through a number of
websites such as betexplorer.com or oddschecker.com and find the best odds.
Price transparency is high and switching costs are low. Thus, in line with the
theoretical model we conjecture that English bookmakers decrease prices, i.e.,
increase the odds of bets likely to attract a comparatively high sentimental
betting volume. This implies that the posted odds of bets on very popular
teams are underestimated and no longer reflect the expected true winning
probabilities. Hence, we test this hypothesis by examining whether our proxy
of potential sentimental betting renders some explanatory power to the true
winning probabilities which lies beyond the bookmaker’s probability odds. If
this is the case, the posted odds deviate from the efficient level at which each
bet would be equally profitable on average.

In particular, we test a binary model that explains the actual outcome
(win or loss) of a certain bet \( Y_i \in \{0,1\} \) in terms of the probability odds \( \text{PROB}_i \)

⁹ Our results react insensitively, however, if we estimate the model with margin corrected,
implicit probabilities.
and a proxy for the relative volumes of sentimental betting placed on the two teams competing on the field, namely \( DATT_i \), which is defined as the difference in the standardized mean home attendance of the respective team and its opponent in the previous season. In order to control for potential distortion of the probability odds related to home team factors rather than to the relative amounts of sentimental betting volume, we additionally include a control variable for home team bets \( HOME_i \) into the model. As the independence assumption is likely to be violated for the two observations of the same match, we compute standard errors that are robust with respect to correlation of the error terms between the home win bet and the away win bet. In addition, we experimented with a random selection of either a home or an away win bet per match and separate regressions for only home or only away win bets to address the issue of non-independence between observations within the same game. All three estimation procedures lead to virtually the same results. Table 1 illustrates the variables’ summary statistics and the Pearson correlation coefficients.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>SD</th>
<th>Max</th>
<th>Min</th>
<th>1</th>
<th>2</th>
<th>3</th>
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<td>Y_i</td>
<td>Actual outcome of bet / (0/1)</td>
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<td>0.481</td>
<td>1.000</td>
<td>1.000</td>
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<td>PROB_i</td>
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<td>1.000</td>
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<td>0.132</td>
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<td>Home game dummy (0/1)</td>
<td>0.500</td>
<td>0.500</td>
<td>1.000</td>
<td>1.000</td>
<td>0.179</td>
<td>0.626</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Notes: This table shows the probability odds of the bookmaker William Hill, who is the largest bookmaker in the UK. The figures would not change much if any other of the eight bookmakers was chosen, because the correlations between sets of odds for each possible pair of bookmakers range from 0.98 to 0.99. The variable DATT_i is calculated using the difference of the home attendance figures of the previous season standardized by season and league.

We test the hypothesis that bookmakers decrease the price, i.e. reduce the probability odds of bets on comparatively more popular teams by estimating a probit model that explains the actual outcome (win or loss) of a certain bet \( Y_i \in \{0,1\} \) in terms of the probability odds \( PROB_i \), our proxy for relative amounts of sentimental betting \( DATT_i \), and a dummy variable \( HOME_i \) for home team bets:

\[
Y_i = G(\beta_1 \text{PROB}_i + \beta_2 \text{DATT}_i + \beta_3 \text{HOME}_i + \epsilon_i) \tag{14}
\]
The probit model assumes a standard normal cumulative distribution of \( G(.) \). The estimated marginal effects of the probit model, the levels of significance and the standard errors are displayed in Table 2.

### Table 2
Probit estimates of the sentiment bias

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>B365</th>
<th>B&amp;W</th>
<th>GB</th>
<th>IW</th>
<th>LB</th>
<th>WH</th>
<th>SJ</th>
<th>VC</th>
</tr>
</thead>
<tbody>
<tr>
<td>PROB_(i)</td>
<td>0.972***</td>
<td>0.941***</td>
<td>0.986***</td>
<td>0.991***</td>
<td>0.947***</td>
<td>0.959***</td>
<td>1.013***</td>
<td>0.966***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.059)</td>
<td>(0.036)</td>
<td>(0.037)</td>
<td>(0.035)</td>
<td>(0.035)</td>
<td>(0.061)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>DATT_(i)</td>
<td>0.020**</td>
<td>0.029**</td>
<td>0.018**</td>
<td>0.027***</td>
<td>0.021***</td>
<td>0.022***</td>
<td>0.025*</td>
<td>0.026*</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>HOME_(i)</td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.001</td>
<td>0.008</td>
<td>0.004</td>
<td>0.007</td>
<td>-0.018</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.015)</td>
<td>(0.015)</td>
</tr>
</tbody>
</table>

Notes: The table presents the marginal effects of the multivariate probit regressions that explain the outcome of the bet with the probability implied by the odds of the bookmakers, the sentiment proxy and the home team dummy. The standard errors are given in parentheses. In order to account for the non-independence of observations of the same game, we compute standard errors that are robust with respect to correlation of error terms between the home win bet and the away win bet of the same game. ***, **, * denote significance at the 0.1%, 1% and 5% level, respectively.

The results in Table 2 reveal that, controlling for the probability odds, the variable \( DATT_\(i\) \) significantly increases the likelihood that a bet will win. This implies that the probability odds \( PROB_\(i\) \) underestimate the probability for wins by prestigious teams and overestimate the probability for wins by less popular teams. Thus, more (less) favorable odds are offered to bettors of teams with a comparatively larger (lower) number of supporters. The null hypothesis of market efficiency is clearly rejected.

As a team’s playing strength and popularity are correlated (the correlation between \( PROB_\(i\) \) and \( DATT_\(i\) \) is 0.393, see Table 1), we have to be clear about the relationship between the sentiment bias and the well-known favorite-longshot bias that refers to the observation that bookmaker odds underestimate high probability outcomes and overestimate low probability outcomes (for a review of the longshot bias literature, see Coleman, 2004). So far, we cannot rule out that our results are driven by Shin’s longshot bias explanation. Shin (1991; 1992; 1993) pointed out that bookmakers tend to hedge

\[ 10 \] Alternatively, we also tested the logit model or the linear probability model (LPM). The logit model assumes a logistic distribution and is, like the probit model, a non-linear model, whereas the LPM is based on ordinary least squares and constant marginal effects. All three estimation procedures lead to virtually the same results.
against potential insiders with superior knowledge by increasing the prices (relative to true probabilities) where the risk is high, namely bets with high odds (longshot odds). Thus, a bookmaker may either increase the odds of the more popular teams in order to attract sentimental betting volume or, alternatively, the bookmaker may decrease the odds of the weaker team in order to secure against the risk of insider trading. Both lines of reasoning would yield similar empirical outcomes.

Since the sentiment variable $DATT_i$ is related to the probability odds $PROB_i$, we first test whether the sentiment variable only picks up potential non-linearity of the effect of $PROB_i$. In doing so, we experiment with a partly non-parametric estimation approach to test the robustness of the sentiment bias in Table 2. We define dummies for each probability category of a 10% quantile of $PROB_i$ and then replace the continuous variable $PROB_i$ by these quantile dummies. Employing this partly non-parametric approach we find that the effect of the sentiment proxy remains statistically significant (results not shown).\(^{11}\) Thus, our sentiment variable $DATT_i$ does not just capture potential nonlinear effects of the relationship between the bookmakers’ probability odds and the actual outcomes.

Secondly, we use information whether a game was played on a weekend rather than on weekdays to distinguish the sentiment bias from the longshot bias. The incidence of insider trading is likely to be uniformly distributed over the games and is therefore unrelated to the date of the game. Since teams are randomly assigned to play on weekdays,\(^{12}\) the risk of potential insider trading associated with the level of the posted odds is not correlated with the weekend dummy either. Thus, the effect of playing on weekends is orthogonal to the longshot bias explanation of Shin (1991, 1992, 1993). The amount of sentimental betting, however, is expected to be more pronounced on weekends than on weekdays as the casual bettors face lower opportunity costs to place bets on weekends (Kopelman and Minkin, 1991; Sobel and Raines, 2003; Sung and Johnson, 2009). Analyzing greyhound betting, Sobel and Raines (2003) show, that Friday and Saturday night races attract a larger share of casual

\(^{11}\) The estimation results are available from the authors upon request.

\(^{12}\) The correlation between the weekend dummy and the probability odds is zero in our sample.
bettors compared to weekday nights. On weekend races the average betting volume per person is much lower than on weekday races. Sung and Johnson (2009) argue that weekday bettors are more serious as they tend to have clear financial ambitions and invest more time, effort and money in analyzing the investment decisions than the casual bettors on the weekends. The latter typically consider betting and watching the games or races as a leisure pursuit. As Kopelman and Minkin (1991) put it:

“Weekday bettors tended to be serious: they apparently were importantly motivated by the desire for financial gain; and many appeared to be highly knowledgeable about their pursuits. In contrast, weekend bettors tended to be more casual; many apparently attended the track for entertainment or for social reasons: and many seemed to lack knowledge, making bets based on such (presumably) irrelevant factors as names, colours, and birthdates” (p. 701).

Hence, we argue that the casual bettors who are susceptible to all kind of biases mostly wager on weekends when the opportunity costs are lower than on weekdays, whereas potential insider trading is unrelated to the day of the match. We therefore predict that the positive influence of the variable \( DATT_i \) on the likelihood of winning the bet is more pronounced on weekends than on weekdays. In Table 3 we first estimate the probit models for weekend games and weekday matches separately. To economize space, we only show the results of the four bookmakers with the highest coverage, including William Hill and Ladbrokes, the two biggest bookmakers in the UK.\(^\text{13}\)

\(^{13}\) The results of the other four bookmakers not shown in Table 3 do not differ in any significant way, however.
Whereas the proxy of a team's relative fan-base does not affect the likelihood of winning the bet on weekdays, we find a strong and statistically significant positive influence for weekend games, holding the probability odds constant. In the next step we use the whole sample again but include a dummy marking weekend games as well as an interaction term between the proxy of sentimental betting and the weekend dummy. The interaction term allows us to test the statistical significance of the moderating influence of the weekend dummy. As the interaction effects in non-linear models are not directly interpretable (Ai and Norton, 2003; Norton, Wang, and Ai, 2004), we estimate a linear probability model (LPM). In linear models, the size and statistical significance of the interaction effect is not conditional on the explanatory variables in contrast to non-linear models.

### Table 3
Separate probit estimates of the sentiment bias for weekday and weekend games

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Bookmaker</th>
<th>Actual outcome of bet (0/1)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gamebooker</td>
<td>Interwetten</td>
</tr>
<tr>
<td></td>
<td>Weekday</td>
<td>Weekend</td>
</tr>
<tr>
<td>PROB,</td>
<td>1.010***</td>
<td>0.978***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>DATT,</td>
<td>-0.006</td>
<td>0.027**</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>HOME,</td>
<td>-0.011</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>observations</td>
<td>8,510</td>
<td>22,212</td>
</tr>
<tr>
<td>McFadden's $R^2$</td>
<td>0.061</td>
<td>0.061</td>
</tr>
</tbody>
</table>

Notes: The table presents the marginal effects of the multivariate probit regressions that explain the outcome of the bet with the probability implied by the odds of the bookmakers, the sentiment proxy and the home team dummy separately for weekday and weekend games. The standard errors are given in parentheses. In order to account for the non-independence of observations of the same game, we compute standard errors that are robust with respect to correlation of error terms between the home win bet and the away win bet of the same game. ***, **, * denote significance at the 0.1%, 1% and 5% level, respectively.
Table 4 reveals that the interaction effect is significantly positive for all bookmakers. Bookmakers decrease prices, i.e. increase the odds of bets on more popular teams on the weekends when the sentimental bettors face lower opportunity costs to wager. This positive weekend effect is not compatible with Shin’s explanation of the longshot bias, but it is perfectly in line with our prediction concerning the optimal bookmaker’s reaction to price-sensitive sentimental betting demand.

In the following, we demonstrate the economic relevance of our results. We calculate the average returns of a betting strategy that takes advantage of the bookmakers’ price reaction due to sentimental betting volume. In line with our previous findings, we expect a positive relation between the return and the variable $DATT_i$ and the average observed returns. To investigate this

Of course, we cannot rebut any other explanation why the bookmaker odds underestimate the frequency of high probability outcomes. Some other explanations argue with risk-loving (Ali, 1977; Quandt, 1986) and/or skewness-loving bettor preferences (Golec and Tamarkin, 1998). Such sentimental bettor preferences raise the demand of high odds (low probability outcomes), which increases the price of the high odds, and thus causes a longshot bias in parimutual betting markets, but not necessarily in the bookmaker market. Given the high price-elasticity of demand in English betting, our model predicts that bookmakers would actually not increase but reduce the price of longshot odds to attract the sentimental betting volume of risk-loving bettors, which we do not see in our data, however.
relation by means of our data, we rank all bets according to $DATT_i$. We then plot the observed mean returns of the bets against different categories of $DATT_i$. The categories are specified by a bandwidth of 0.05 of $DATT_i$ and at least 50 observations per group are required. In addition, we run a locally weighted polynomial regression (Fan, 1992; Fan and Gijbels, 1996). This non-parametric procedure offers the advantage that we do not have to make any assumption about the functional form of the relationship between the returns and $DATT_i$. Figure 2 shows the results of this procedure for bets on weekday matches, whereas Figure 3 illustrates the results for weekend bets. We use the odds of the bookmaker with the highest coverage, namely Intertetten. The illustrations are very similar, however, using the odds of other bookmakers.

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15 Local polynomial regression involves fitting the dependent variable, here the observed returns, to a polynomial form of the regressor $DATT_i$ 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 at 0.2.
Figure 2: Observed mean return as a function the sentiment proxy for weekday games

The lines are for zero return (solid horizontal line) and the expected return under random betting (broken line). The mean returns for the different categories of DATT (dots) and the local polynomial smoothing (solid line) with 95% confidence intervals (dotted lines) are given.
Figure 3: Observed mean return as a function the sentiment proxy for weekend games

The lines are for zero return (solid horizontal line) and the expected return under random betting (broken line). The mean returns for the different categories of DATT (dots) and the local polynomial smoothing (solid line) with 95% confidence intervals (dotted lines) are given.

Figures 2 and 3 show that the mean returns for the different categories of DATT (the dots) as well as the local polynomial smoothing (the solid line) increase with DATT. For weekend games this relation is steeper than for weekday games. Moreover, the figures reveal that positive average returns are possible for some restricted levels of DATT.

Conclusion

Betting markets are characterized by the coexistence of different organizational settings: customers can choose between the quote-driven setting and place a bet at a bookmaker or, alternatively, they can choose the order-driven setting and place a bet at the exchange market. Since bookmakers are exposed to substantial risk and incur significant transaction costs in calculating their quotes, the question arises why they are still able to survive against
competition from exchange markets operating as mere platforms between bettors.

Among the more recent explanations of this puzzle is the general idea that the business model of bookmakers is based on actively managing quotes to exploit sentimental bettor preferences. The theoretical model presented in this paper predicts that the pricing behavior of a profit-maximizing bookmaker depends on both the occurrence of bettor sentiment and the elasticity of demand he is facing. In particular the bookmaker will increase the price (i.e. decrease the odds) in the presence of price-insensitive sentiment bettors. If, however, the sentiment bettors are predominantly price-sensitive, the bookmakers can increase profits by lowering the price of bets on prestigious teams. As the English betting market is highly competitive with several bookmakers and bet exchanges offering odds on the same events, sentimental bettors are likely to be price-sensitive.

Using odds on more than 16,000 games in English soccer, we test the bookmaker's price reaction to the sentiment betting demand evoked by team popularity. Indeed, we find that bookmakers significantly decrease the price of odds on team winnings with a large supporter base. In addition, we find that this effect is amplified on weekends when sentimental bettors have lower opportunity costs to observe the games and place a wager. On weekend games, the bookmaker offered significantly more favorable odds for bets on more heavily supported teams. Thus, bookmakers offer favorable prices to attract a larger share of the price-sensitive sentiment bettors.

By taking a more in-depth look at the microeconomics of price-setting decisions, our paper supports the general idea that economizing on the sentimental preferences of bettors plays an important role in the business model of bookmakers. Bet exchanges have not crowded out bookmakers precisely because the latter, instead of just matching demand and supply, shade odds where demand is high.
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References


