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The liquidity advantage of the quote-driven market: Evidence from the betting industry

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ABSTRACT

Even though betting exchanges are considered to be the superior business model in the betting industry due to less operational risk and lower information costs, bookmakers continue to be successful. We explain the puzzling coexistence of these two market structures with the advantage of guaranteed liquidity in the bookmaker market. Using matched panel data of over 1.8 million bookmaker and betting exchange odds for 17,410 soccer matches played worldwide, we find that the bookmaker offers higher odds and bettor returns than the betting exchange when liquidity at the betting exchange is low.

1. Introduction

Since the beginning of the 2000s, the betting industry has been characterized by the coexistence of quote-driven and order-driven markets. Similar to intermediary market makers in quote-driven financial markets, bookmakers operate on their own account and quote betting odds at which bettors can place their bets (Croxson & Reade, 2011). In the order-driven market, betting exchanges serve as a marketplace in which buy and sell orders are directly matched between bettors in a continuous double auction without intermediaries (De Jong & Rindi, 2009).

This coexistence of market structures is puzzling. Betting exchanges face less operational risk (Koning & van Velzen, 2009), have lower information costs (Davies, Pitt, Shapiro, & Watson, 2005) and exhibit higher prediction accuracy in their odds (Franck, Verbeek, & Nüesch, 2010; Smith, Paton, & Vaughan Williams, 2006, 2009). Nevertheless, bookmakers continue to be successful. Bookmakers have not only managed to survive but have also generated considerable growth in net revenues. For example, *William Hill* and *Ladbrokes*, two major bookmakers in the United Kingdom, increased their net sportsbook revenues between 2008 and 2012 from £ 42 million to £ 166.7 million (+297%) and from £ 61.7 million to £ 77.8 million (+26%), respectively.

This paper explains the coexistence of both market structures with the liquidity advantage of the quote-driven bookmaker market. Liquidity provision is an important task of market makers in a quote-driven financial market (Demsetz, 1968). By guaranteeing market liquidity at the odds quoted, the market maker fills the gap that arises from the asynchronous order arrival of buyers and sellers. Hence, the market maker facilitates the rapidity of exchange by offering narrow bid-ask spreads. In order-driven markets, however, liquidity is provided by the flow of orders from market participants (De Jong & Rindi, 2009). An absence of a two-sided trading interest results in bid and ask prices that are far apart, which increases transaction costs. Therefore, order-driven markets are expected to perform poorly if liquidity is low (Demsetz, 1968).

De Jong, Nijman, and Roell (1995) and Huang and Stoll (1996, 2001) compare pure quote- and order-driven financial markets and conclude that transaction costs are generally lower in order-driven markets. Madhavan and Sofianos (1998), Friederich and Payne (2007) and Venkataraman and Waisburd (2007) analyze hybrid financial markets in which elements from order- and quote-driven

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markets are combined. They find that market makers can improve the terms of trade when the liquidity offered by public limit orders is low.

This paper uses the betting industry to compare the quote- and the order-driven market structures. The betting industry offers the unique setting that identical betting contracts are traded on both market structures simultaneously, i.e., besides the market structure, everything else is equal. In related financial studies, differences in market structures are often accompanied by differences in underlying assets and/or differences in macroeconomic conditions across pure market structures (e.g., De Jong et al., 1995; Huang & Stoll, 1996, 2001) or by complex interactions within hybrid market structures (e.g., Friederich & Payne, 2007; Madhavan & Sofianos, 1998; Venkataraman & Waisburd, 2007).

Using matched panel data of over 1.8 million bookmaker and betting exchange odds for 17,410 soccer matches played worldwide, we find that bookmaker odds are higher than betting exchange odds if market liquidity at the betting exchange is low and that bookmaker odds are lower than betting exchange odds if market liquidity at the betting exchange is high. Bettors obtain higher odds and returns when using the quote-driven bookmaker market if the cumulative trading volume at the betting exchange is less than £ 23,400 and/or if the quoted spread at the betting exchange is higher than 0.044 on average. However, as bettor returns are still negative on average, bookmakers are able to generate positive profits even when offering higher odds than the betting exchange.

The comparative advantage of the guaranteed liquidity in the quote-driven bookmaker market is found both in cross-sectional analyses that use across-match differences, in panel analyses that use within-match differences and in dynamic panel analyses that include a lagged dependent variable. Our results also hold in a subsample analysis in which odds from up to 42 different bookmakers are compared to the betting exchange odds.

While Croxson and Reade (2011) argue that betting exchanges generally offer higher odds and bettor returns than bookmakers, we show that the opposite is true in illiquid markets. The liquidity advantage of the quote-driven bookmaker market rationalizes the decision of *Betfair* to start offering quoted odds in addition to the exchange-based odds as of February 2013 (Betfair, 2013a). Our findings also help to explain the recent shift in financial market structures from pure quote-driven or pure order-driven structures to hybrid structures that combine the advantages of both markets.

The remainder of this paper is organized as follows. In Section 2, we discuss the two market structures in more detail and review the relevant theoretical and empirical literature. In Section 3, we describe our data sets, which consist of bookmaker and betting exchange odds from soccer matches. Section 4 presents the empirical analysis of the guaranteed liquidity supply as a competitive advantage of the quote-driven bookmaker market compared to the order-driven betting exchange market. Section 5 concludes.

2. Quote-driven and order-driven markets

The organizational structure of a market comprises the trading rules for instruments (De Jong & Rindi, 2009). In the betting market, the instruments traded are bets. Similar to conventional assets and derivatives in financial markets, a bet is a state-contingent contractual claim on a future cash flow. This cash flow is determined by two parameters: (i) the outcome of the underlying event, such as a horse race, a soccer match or a political election, and (ii) the price of the contract, i.e., the posted odds (Sauer, 1998). A common betting type is fixed-odds betting, where the cash flow of a successful bet is determined ex-ante. For example, if the decimal odds on the home team of a soccer match are 1.40, a one-dollar wager pays \$1.40 and yields a return of 40% if the home team wins. Therefore, higher odds imply a higher bettor return in the case of success but an accordingly lower winning probability.

Financial markets are classified as either quote-driven, where trades must be fulfilled through intermediaries, or order-driven, where trading is based on the direct interaction of market participants (De Jong & Rindi, 2009). Similar to market makers in quote-driven financial markets, bookmakers in the betting industry serve as intermediaries between buyers (bettors willing to place a bet on a particular outcome) and sellers (bettors willing to place a bet on the opposite outcome). The bookmakers unilaterally determine the odds for a given betting contract at which they are willing to accept bets (Harris, 2003). In this market, the bookmakers guarantee sufficient liquidity. The odds quoted by the bookmakers already contain a commission (i.e., the 'overround') that compensates them for providing liquidity and bearing the risk of unfavourable outcomes. Examples of well-established bookmakers are *Bwin*, *Ladbrokes*, *Tipico* and *William Hill*.

Since 2000, betting exchanges have evolved in the betting industry. They operate as order-driven markets in which buyers and sellers trade directly with each other in a continuous double auction without the intermediation of market makers. In this market structure, bettors can provide or take liquidity. Bettors who provide liquidity post a limit order that indicates the terms at which they will trade. A transaction only takes place if there is a corresponding order on the opposite side of the market. Otherwise, the order is placed in the limit order book until it is either executed or cancelled. Bettors who take liquidity submit a market order that is immediately executed at the best odds available (De Jong & Rindi, 2009; Harris, 2003). Betting exchanges facilitate trading activity by providing an electronic platform on which supply and demand are matched and collect a commission on the net winnings of successful bets (Franck, Verbeek, & Nüesch, 2013). Examples of larger betting exchanges are *Betfair*, *BETDAQ* and *Matchbook*.

Previous studies that compare the two market structures within the betting industry suggest that the betting exchange market is superior to the traditional bookmaking market in several ways. Koning and van Velzen (2009) argue that a fundamental advantage of betting exchanges is that they do not take any trading position. Because betting exchanges simply charge the winners a certain commission, a steady flow of income independent from the match outcomes is guaranteed. This exposes betting exchanges to minimal risk. In contrast, traditional bookmakers are continuously exposed to risk, as they can lose substantial amounts of money when they misjudge the probabilities or when they are overexposed to an event that occurs (Davies et al., 2005). Furthermore, bookmakers need informed specialists who monitor the market and actively manage the odds. The information costs of bookmakers are therefore considerably higher than those of betting exchanges that simply provide a trading platform (Davies et al., 2005).

Empirical studies have found that prediction accuracy is higher in the order-driven betting exchange market than in the quote-driven bookmaker market (Franck et al., 2010; Smith et al., 2006, 2009). Moreover, Croxson and Reade (2011) and Ozgit (2005) show that bettors obtain higher net returns in the betting exchange market than in the bookmaker market. Given these advantages of the order-driven market, the ongoing success of the quote-driven bookmaker market is surprising.

In this paper, we investigate a distinct source of competitive advantage of the quote-driven market: the benefit that arises from the continuous provision of liquidity by the bookmaker. According to the theoretical work of Demsetz (1968), a key function of market makers in financial markets is the supply of immediacy by continuously quoting prices and by providing liquidity to the asynchronous arrival of orders from investors. The models of Garbade and Silber (1979) and Grossman and Miller (1988) show that the liquidity supply of market makers reduces temporal imbalances in order flow and increases the rapidity of exchange. By contrast, a lack of liquidity at the order-driven market leads to high bid quotations and low ask quotations, which increases both transaction and waiting costs.

De Jong et al. (1995) and Huang and Stoll (1996, 2001) compare pure quote- and order-driven financial markets and conclude that transaction costs are generally lower in order-driven markets. Other financial studies investigate hybrid markets in which liquidity is provided by market makers and by limit orders submitted by market participants simultaneously (De Jong & Rindi, 2009). Madhavan and Sofianos (1998) analyze market makers in the hybrid NYSE market. Because market makers participate more when bid-ask spreads are high, Madhavan and Sofianos (1998) conclude that the market maker is a liquidity provider of last resort. Friederich and Payne (2007) analyze the order flow in the London Stock Exchange (LSE) at which investors are free to choose between the order-driven or the quote-driven execution modes. Their results demonstrate that the liquidity supplied by intermediaries is increasingly utilized when execution risk is high. Furthermore, the authors show that the share of order flow migrates to the market maker segment when the bid-ask spreads of the limit order book are high. Venkataraman and Waisburd (2007) investigate firms that have chosen a designated market maker at the otherwise order-driven Paris Bourse. Their results suggest that the market maker resolves temporal imbalances in order flow by selectively providing liquidity when the public supply is insufficient. Thus, by maintaining a market presence, the market maker can improve the terms of trade offered by public limit orders.

However, comparative investigations of financial market structures are limited in two ways. First, comparisons of pure quote-driven and order-driven structures are often accompanied by differences in underlying assets and/or differences in macroeconomic conditions. Thus, a clear benchmark of market quality is missing (Madhavan, 2000). Second, hybrid structures combine both elements of order- and quote-driven markets with complex interactions and trading rules. For example, the liquidity supply of the market maker at the NYSE is constrained in a number of ways, and at the Paris Bourse, only large trades can be executed with the market maker (Friederich & Payne, 2007).

In the betting industry, by contrast, identical betting contracts are traded simultaneously on well-distinct market structures, which allows a proper comparison of market structures and a clean investigation of the liquidity advantage of the quote-driven market.

3. Sample and data

Our main data set consists of decimal betting odds from the bookmaker *Tipico* and the betting exchange *Betfair* on the *winner* betting contracts on *home win*, *draw* and *away win* of soccer matches. Soccer is by far the most important sports betting market, accounting for about 70% of the estimated $700bn generated by the betting industry each year (BBC, 2013). The bookmaker *Tipico* is one of the leading bookmakers in Europe. Through its on-line portal and more than 1,000 betting shops across Europe, the company offered odds on 1.76 million betting contracts and handled over 790 million bets from customers in 2012 (Tipico Co. Ltd., 2013). *Betfair* is the largest and most liquid betting exchange. In 2012, the betting exchange had over 4 million registered customers and processed more than 7 million transactions on an average day, which is more than the transactions of all European stock exchanges combined (Betfair, 2012).

The data set is provided by *Tipico* and covers 17,410 matches from over 400 leagues across more than 60 countries played between March 2012 and October 2012. Within each country, we observe matches from different divisions. For example, the data from England include matches from the *Premier League* (level 1), *Championship League* (level 2), *League One* (level 3), *League Two* (level 4), *Conference National* (level 5) and *Conference North/South* (level 6). Additionally, the data set also covers transnational tournaments such as the UEFA Champions League or Europa League, World Cup qualification matches and international friendlies. The lion's share of matches were played in European leagues, accounting for over 12,000 matches.

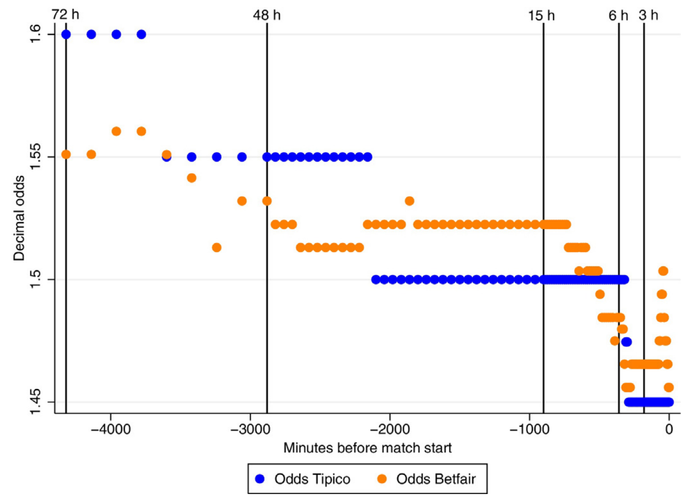


Fig. 1. Example decimal odds on *home win* for Chelsea FC vs. Newcastle United, May 2, 2012.

For each match and event, the data include the pre-play history of bookmaker and betting exchange odds, which were simultaneously recorded and thus have a time-stamp accurate to the second.[1] The order book of betting exchanges usually displays both *back* and *lay* odds, where *back* odds refer to the odds of a bet *on* a certain outcome, whereas *lay* odds refer to the odds of a bet *against* a certain outcome. We use the best, i.e., the highest, *back* odds from the exchange order book at each time point in our analyses, because these odds correspond to the bookmakers' (*back*) odds.[2]

As an example, Fig. 1 shows the decimal odds information available for the *home win* event bet from the match of *Chelsea FC* vs. *Newcastle United* played on May 2, 2012.

The bookmaker changed his quoted odds only four times, whereas the odds available at *Betfair* exhibited a higher variation over time. This pattern is typical for many matches in our data set: while the bookmaker odds changed about twice on average, the betting exchange odds changed about 31 times on average.

In total, we observed 1,873,831 pairs of odds from the bookmaker and the betting exchange for each of the three events *home win*, *draw* and *away win*. The data set also contains the cumulative trading volume at the betting exchange for each match and time point of the odds collection. The cumulative trading volume is the amount of money that has been matched since the beginning of the pre-play period.

Whereas our betting exchange *Betfair* is by far the largest betting exchange and thus likely to be representative for the betting exchange market, the bookmaker *Tipico* is smaller than other major

[1] The frequency at which the odds were collected depended on the time remaining until match start, ranging from every 3 h between 72 and 48 h before match start to every 5 min during the final 3 h before match start. Matches with a pre-play history of less than 1 h have been deleted from the data set.

[2] One could argue that the betting exchange market equilibrium odds are neither the *back* nor the *lay* odds but the matched odds. However, a fair comparison between market structures should take the best available market order odds into account, i.e., the highest *back* odds at the betting exchange and the odds quoted by the bookmaker.

bookmakers such as *William Hill* or *Ladbrokes* and may therefore not be representative for the bookmaker market. To test the robustness of our results, we collected closing bookmaker odds, i.e., the last odds before match start, from up to 42 different bookmakers for a random subsample of 20% of the 17,410 matches from www.oddsportal.com.[3]

4. Empirical analysis

As identical betting contracts are offered on both market structures simultaneously, we simply relate the odds of both market structures to each other. Thereby, higher odds are more attractive for bettors. For the ease of interpretation, we convert the odds into prices, which are the reciprocal of the odds (e.g., $p = \frac{1}{1.40} \approx 0.714$). These prices represent the amount of money a bettor has to invest in order to collect $1 for a winning bet (Forrest & Simmons, 2008).

For each match i, event $e \in \{home\ win, draw, away\ win\}$ and time t before match start, the price offered by the bookmaker is defined as

$$p_{iet,BM} = \frac{1}{odds_{iet,BM}} \tag{1}$$

where $odds_{BM}$ refers to the decimal odds quoted by the bookmaker. The bookmaker odds already include a commission. Betting exchanges usually charge a commission on net winnings that is not included in the odds offered. Hence, the net price at the betting exchange is calculated as

$$p_{iet,BE} = \frac{1}{[\underbrace{(odds^{back}_{iet,BE} - 1)}_{\text{net winnings}} \cdot (1-c)] + 1} \tag{2}$$

where $odds^{back}_{BE}$ refers to the best decimal back odds and c refers to the commission. The commission at *Betfair* varies between 2% and 5% on net winnings, contingent on the betting activity of a bettor. Thereby, the commission decreases the more money a bettor has wagered in the past (Betfair, 2013b). In this paper, we employ the standard commission of 5% to compute an upper (lower) bound for the prices (net bettor returns) from *Betfair*.[4]

Liquidity is an important characteristic of well-functioning markets and permits the trading of large quantities quickly at low costs (Harris, 2003). While liquidity in the quote-driven market is guaranteed by the bookmaker,[5] liquidity in the order-driven market depends on the order flow from market participants (De Jong & Rindi, 2009).

A common measure of liquidity in financial studies is the quoted spread (e.g., Amihud & Mendelson, 1986). The quoted spread is the difference between the lowest ask price and the highest bid price (Chordia, Roll, & Subrahmanyam, 2008). A small quoted spread indicates high market liquidity because the transaction costs are lower. We calculate the quoted spread (*QSPR*) as

$$QSPR_{iet,BE} = \frac{1}{odds^{back}_{iet,BE}} - \frac{1}{odds^{lay}_{iet,BE}} \tag{3}$$

where $odds^{back}$ refers to the best ask price, and $odds^{lay}$ refers to the best bid price available at the betting exchange.

A second common measure of liquidity in financial studies is the trading volume (e.g., Chordia, Roll, & Subrahmanyam, 2001; Elyasiani, Hauser, & Lauterbach, 2000; Hasbrouck & Seppi, 2001). We therefore use the cumulative trading volume, i.e., the amount of money that has been matched since the beginning of the pre-play period at the betting exchange, as a second measure of liquidity.

Fig. 2a displays the average bookmaker and betting exchange prices as a function of the average quoted spread for *home win* events at the betting exchange, and Fig. 2b displays the prices as a function of the cumulative trading volume for *home win* events at the betting exchange. Both figures show that liquidity at the betting exchange increases the average price at the bookmaker market and decreases the average price at the betting exchange. If the betting exchange market is illiquid (i.e., high quoted spread, low cumulative trading volume), the bookmaker market offers significantly lower prices than the betting exchange. However, if the betting exchange market is liquid (i.e., low quoted spread, high cumulative trading volume), the betting exchange offers significantly lower prices than the bookmaker market. If the quoted spread is 0.044 and the cumulative trading volume is £ 23,438 at the betting exchange, both markets offer the same prices on average. If liquidity at the betting exchange exceeds these threshold values, the betting exchange offers lower prices. Otherwise, the bookmaker market offers lower prices for bettors. Similarly, Fig. 2c and d show that bettor returns are significantly higher at the bookmaker market when liquidity is low at the betting exchange. However, as bettor returns are still negative on average, bookmakers are able to generate positive profits.

Taken together, Fig. 2 indicates that the bookmaker and the betting exchange prices and bettor returns both but differently react to the liquidity at the betting exchange. The following econometric models examine the influence of liquidity at the betting exchange on the bookmaker and betting exchange prices and on bettor returns in more detail.

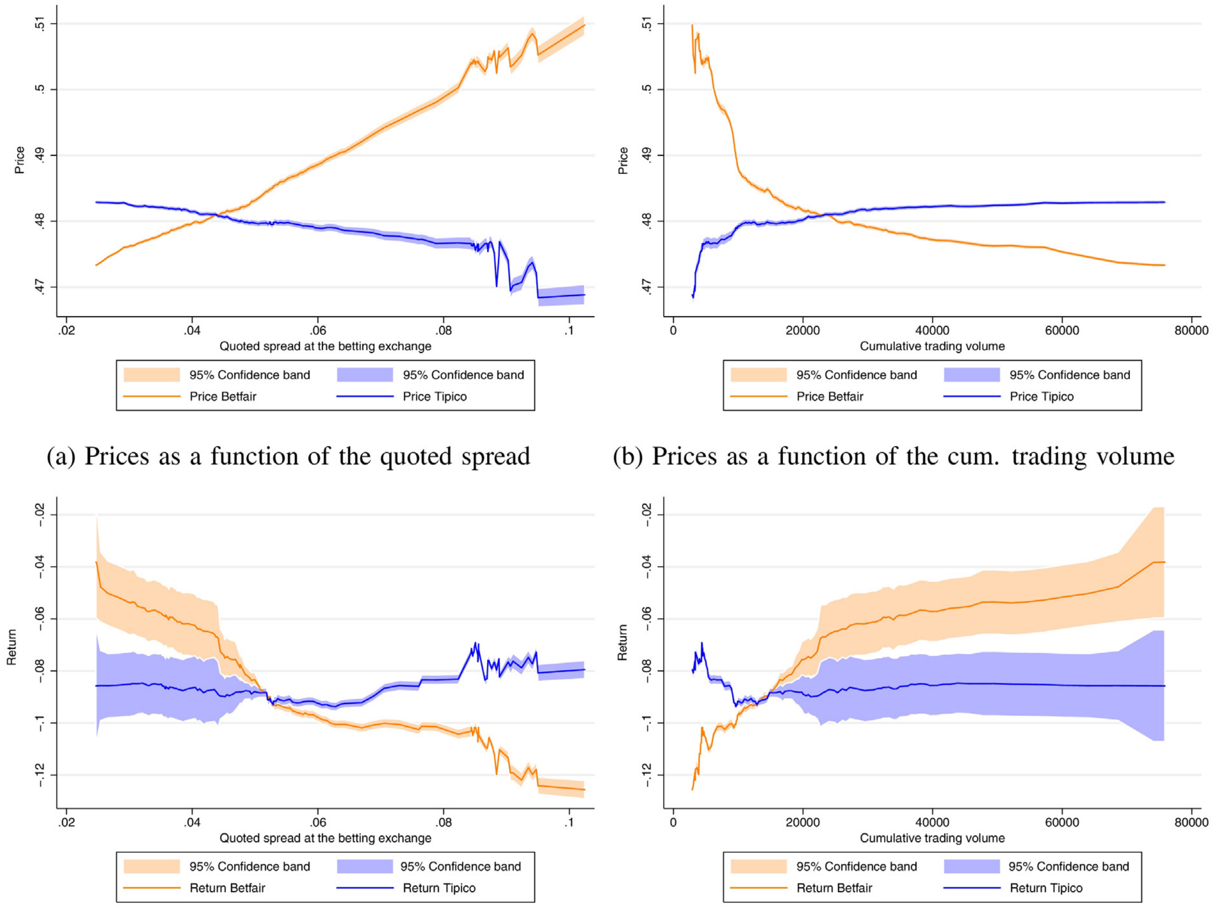
As a dependent variable, we use an indicator variable *LOW_BM* that equals 1 if the bookmaker offers a lower price than the betting exchange and 0 otherwise. Thus, when *LOW_BM* equals 1, the bookmaker market provides higher bettor returns if the event occurs. Our main independent variable is the liquidity at the betting exchange, measured by either the quoted spread (*QSPR*) or the log cumulative trading volume (*LnVOL*). As we have longitudinal data on matched bookmaker-betting exchange prices, we run four different regressions: (i) a pooled LPM, (ii) a LPM with one randomly chosen observation per match, (iii) a fixed-effects LPM, and (iv) an Arellano-Bond dynamic panel GMM model.[6]

[3] 94 matches were missing on oddsportal.com. The subsample therefore consists of 3388 matches. As oddsportal.com does not provide a pre-play history of bookmaker odds, we test the robustness of the across-match analysis. The subsample includes odds from the following bookmakers: *10Bet, 12Bet, 188BET, 5Dimes, 888sport, Bestbet, Bet365, Bet-at-home, Betclic, Betfred, BetGun, BetOnline, Betsafe, Betsson, BetVictor, Betway, BoyleSports, Bwin, Coral, Dafabet, DOXXbet, Expekt, Intertops, Interwetten, Island Casino, Jetbull, Ladbrokes, Leonbets, Luxbet, Marathonbet, Mybet, NordicBet, Noxwin, Pinnacle, SBOBET, Sportingbet, Tipico, Titanbet, TonyBet, Unibe, William Hill and Youwin.*

[4] It is reasonable to assume that most of the bettors betting at *Betfair* pay 5% in commission, as a discount in the commission requires very high betting activity. According to the *Betfair* commission rule, a bettor has to wager at least $112,500 per week in order to reach the 2% commission rate (Betfair, 2013b). Nevertheless, all our results are robust to the use of any *Betfair* commission between 2% and 5%.

[5] One might worry that liquidity at the bookmaker is restricted by maximum stake limits. Indeed, bookmakers limit the maximal winning amount per betting contract. For example, the maximum winning amount per bet is £ 500,000, £ 100,000 and € 100,000 for the bookmakers *William Hill*, *Ladbrokes* and *Tipico*, respectively. For an average bettor, these limits are sufficiently high. According to the on-line betting survey from Merrion Stockbrokers (2010), over 95% of the bettors stake less than $250 on average, and 75% of the bettors stake less than $25 on average.

[6] Our results are robust to the use of (fixed-effects) logit models. We prefer the linear model as a main specification because observations with no within-group variation in the dependent variable are dropped from fixed-effects logit models, which changes the interpretation and the generalization of the results. In addition, unlike with linear models, pooled logit estimates cannot be directly compared with those from a fixed-effects model because including fixed effects in a non-linear



(a) Prices as a function of the quoted spread (b) Prices as a function of the cum. trading volume

(c) Returns as a function of the quoted spread (d) Returns as a function of the cum. trading volume

Fig. 2. Prices and bettor returns as a function of liquidity measures.

The pooled LPM and the LPM with one randomly chosen observation per match analyze the relationship between liquidity and bookmakers versus betting exchange pricing using across-match variation, whereas the fixed-effects LPM and the Arellano-Bond model analyze this relationship using within-match variation. Because liquidity at the betting exchange tends to increase in the pre-play period and because incoming match-relevant information may differently influence the bookmakers and betting exchange's pricing, we include a full set of dummies for each hour in the pre-play period of a match as controls in all of our models. In the across-match analyses, we additionally include league dummies to control for unobserved league-level factors that may correlate with the liquidity at the betting exchange and differential pricing at the bookmaker and the betting exchange market. To take into account that the liquidity at the betting exchange at t could be influenced by the relative prices at $t-1$, the Arellano-Bond model additionally includes a lagged dependent variable as a control variable.

Table 1 shows the coefficient estimates and heteroskedasticity-consistent standard errors clustered at the match level in parentheses for *home win* bets. Panel A displays the across-match results and Panel B the within-match results. The results for *away win* and *draw* bets are virtually the same (see Tables A.1 and A.2 in the Appendix).

The results in Panel A show that illiquidity at the betting exchange significantly increases the probability that the bookmaker price is lower than the betting exchange price. The bookmaker tends to offer lower prices in matches with a high quoted spread and a low cumulative trading volume. Whereas we pool all observations in Columns (1) and (2), we only use a randomly chosen observation per match in Columns (3) and (4). The magnitudes of the estimates are virtually the same, and all liquidity coefficients are still statistically significant at the 1% level. Thus, we find that when liquidity is low, bookmakers offer lower prices than betting exchanges.

Panel B of Table 1 shows the results of the within-match analyses that no longer use liquidity and price differences across matches to identify the effects. In the fixed-effects LPM models in Columns (1) and (2), we control for all time-constant match heterogeneity and test how the relative pricing at the bookmaker and the betting exchange market changes if liquidity changes. The results suggest that an increase in liquidity at the betting exchange reduces the probability that the bookmaker offers a lower price.

As the relative prices in the recent past are likely to influence the liquidity at the betting exchange, Columns (3) and (4) of Panel B show the estimates of an Arellano-Bond dynamic-panel GMM model that includes the lagged dependent variable as additional control variable. Here again, liquidity at the betting exchange

model would change the estimates even if the fixed effects were independent of the variables of interest (Norton, 2012).

Table 1
Analysis of prices for *home win* events.

Panel A: Across-match analysis

	Dependent variable: *LOW_BM* (1/0)			
	Pooled LPM		Random time point LPM	
	(1)	(2)	(3)	(4)
QSPR	0.964***		0.964***	
	(0.017)		(0.030)	
LnVOL		−0.046***		−0.046***
		(0.001)		(0.002)
Hourly dummies	Yes	Yes	Yes	Yes
League dummies	Yes	Yes	Yes	Yes
R^2	19.68%	18.91%	22.01%	21.21%
N	1,873,831	1,873,831	17,410	17,410
N of groups	17,410	17,410		

Panel B: Within-match analysis

	Dependent variable: *LOW_BM* (1/0)			
	Fixed-effects LPM		Arellano-Bond GMM	
	(1)	(2)	(3)	(4)
QSPR	0.808***		1.050***	
	(0.019)		(0.007)	
LnVOL		−0.043***		−0.020***
		(0.001)		(0.001)
LOW_BM_{t-1}			0.727***	0.791***
			(0.001)	(0.001)
Hourly dummies	Yes	Yes	Yes	Yes
R^2 overall	11.19%	12.12%		
N	1,873,831	1,873,831	1,839,011	1,839,011
N of groups	17,410	17,410	17,410	17,410

Notes: Panel A: Columns (1) and (2) report the coefficients estimated from a pooled LPM with heteroscedasticity-consistent standard errors clustered at the match level in parentheses. Columns (3) and (4) report the results from a pooled LPM with one randomly chosen observation per match. Panel B: Columns (1) and (2) report the coefficients estimated from a fixed-effects LPM with robust standard errors. Columns (3) and (4) report the results from a Arellano-Bond dynamic panel GMM model. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

market decreases the probability that the bookmaker offers a lower price than the betting exchange.

To investigate the liquidity advantage of the quote-driven market further, we use the net bettor returns from a one-unit wager placed at both the bookmaker market and the betting exchange market as a dependent variable. As independent variables, we include an indicator variable *BM* that equals 1 if the return corresponds to the bookmaker market and 0 if the return corresponds to the betting exchange market, the centred liquidity variables $QSPR_c$ or $LnVOL_c$, and the interaction terms $BM \times QSPR_c$ or $BM \times LnVOL_c$, respectively.[7] Here again, we use hourly dummies to control for time trends and league dummies to control for time-constant league heterogeneity.

Table 2 shows the coefficient estimates for *home win* events from a pooled OLS model, an OLS model with a randomly chosen pair of returns per match and a fixed-effects OLS model.[8] The insignificant *BM* dummy shows that bettor returns are not generally lower at the bookmaker market than at the betting exchange market. The significantly negative effect of the quoted spread ($QSPR_c$) and the significantly positive effect of cumulative trading volume ($LnVOL_c$) indicate that liquidity at the betting exchange increases bettor returns in general. The main variable of interest in Table 2 is the interaction term. The interaction effects are significantly positive when using the quoted spread as an illiquidity measure and significantly negative when using the cumulative trading volume as an liquidity measure. Thus, bettor returns at the bookmaker market are higher than at the betting exchange market if liquidity at the betting exchange is low. This finding is consistent across all three regression specifications as well as for *away win* and *draw* bets (see Tables A.3 and A.4 in the Appendix). Moreover, the results are robust to the use of net bettor returns based on a 2% betting exchange commission and to the use of a Tobit model.[9]

In the following we test whether the results in Tables 1 and 2 based on prices from the bookmaker *Tipico* are representative for the entire bookmaker market. To do so, we compare the betting exchange prices to the prices from the five major bookmakers *Bet365*, *Ladbrokes*, *William Hill*, *Pinnacle*, and *Bwin* and to an average bookmaker price from up to 42 different bookmakers, using a random subsample of 20% of all matches in the main data set. As the bookmakers do not offer odds on all matches in our subsample the number of observations varies between 2088 (*Pinnacle*) and 3334 (*Bwin*).

As in the main analysis, we first investigate the effect of liquidity on the difference in prices by using the indicator variable *LOW_BM* as the dependent variable and our liquidity measures as the main independent variables.[10] Panel A of Table 3 shows that the coefficient of *QSPR* is significantly positive for all bookmakers and that the coefficient value for *Tipico* prices, though its best fit is

[7] We mean-centre the variables *QSPR* and *LnVOL* to get a meaningful interpretation of the coefficients when an interaction term is included (Wooldridge, 2012).

[8] Unfortunately, the estimation of an Arellano-Bond dynamic-panel GMM model is not suitable here, as we have two return observations per time unit.

[9] The fixed-effects Tobit specification is not feasible as there is no sufficient statistic allowing the fixed-effects to be conditioned out of the likelihood (StataCorp., 2015).

[10] As in the main analysis, we include league dummies. Because the subsample only considers closing bookmaker odds, i.e., the last odds before match start, we do not need to include time dummies.

Table 2
Analysis of bettor returns for *home win* events.

	Dependent variable: *bettor return*					
	Pooled OLS		Random time point OLS		Fixed-effects OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
BM	−0.006	−0.006	−0.011	−0.011	−0.006	−0.006
	(0.006)	(0.006)	(0.012)	(0.013)	(0.006)	(0.006)
$QSPR_c$	−0.656***		−0.739***		−0.602***	
	(0.052)		(0.083)		(0.029)	
$BM \times QSPR_c$	0.602***		0.584***		0.605***	
	(0.036)		(0.062)		(0.036)	
$LnVOL_c$		0.017***		0.018**		0.010***
		(0.004)		(0.007)		(0.001)
$BM \times LnVOL_c$		−0.013***		−0.015***		−0.013***
		(0.007)		(0.004)		(0.001)
Hourly dummies	Yes	Yes	Yes	Yes	Yes	Yes
League dummies	Yes	Yes	Yes	Yes		
R^2	4.25%	4.17%	5.77%	5.68%	0.17%	0.06%
N	3,747,662	3,747,662	34,820	34,820	3,747,662	3,747,662
N of groups	17,410	17,410			17,410	17,410

Notes: Columns (1) and (2) report the coefficients estimated from a pooled OLS model. Columns (3) and (4) report the results from a pooled OLS model with one randomly chosen observation per match. Columns (5) and (6) report the coefficients estimated from a fixed-effects OLS model. All standard errors reported in parentheses are heteroscedasticity-consistent and clustered at the match level. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 3
Subsample analysis of prices for *home win* events.

Panel A: *QSPR*							
	Dependent variable: *LOW_BM* (1/0)						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
QSPR	2.385***	2.207***	2.972***	2.868***	2.630***	2.594***	2.729***
	(0.319)	(0.329)	(0.498)	(0.766)	(0.650)	(0.369)	(0.376)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	18.90%	22.13%	25.02%	17.71%	14.77%	21.38%	27.29%
N	3388	3329	2822	2310	2088	3334	3388
Panel B: *LnVOL*							
	Dependent variable: *LOW_BM* (1/0)						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
LnVOL	−0.031***	−0.024***	−0.021***	−0.019**	−0.017*	−0.036***	−0.042***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.010)	(0.005)	(0.005)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	16.64%	19.91%	21.96%	16.66%	14.23%	18.84%	24.12%
N	3388	3329	2822	2310	2088	3334	3388

Notes: The table shows the coefficients for *QSPR* (Panel A) and *LnVOL* (Panel B) estimated from an LPM for different major bookmakers and the average bookmaker (*Avg. BM*), which uses the average of prices from up to 42 different bookmakers. Heteroscedasticity-consistent standard errors are displayed in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

lower than those for the average bookmaker and four of the five major bookmakers, is consistent with all these within one standard deviation. Thus, illiquidity at the betting exchange significantly increases the probability that the bookmaker price is lower than the betting exchange price for bookmakers in general, not just for *Tipico*.

Panel B of Table 3 uses the cumulative trading volume *LnVOL* at the betting exchange as liquidity measure. Here again, we find that liquidity at the betting exchange affects the probability that the bookmaker price is lower than the betting exchange price. The coefficients of *LnVOL* are negative and statistically significant when using the prices of the five major bookmakers and when using an average of the prices from up to 42 different bookmakers. Moreover, magnitudes of the coefficients are similar across the different models. The results of Table 3 are robust to the use of logit models and are virtually the same for *away win* and *draw* bets (see Tables A.5 and A.6 in the Appendix).

Next, we replicate the regression specifications of the bettor return for our subsample and display the results in Table 4. In Panel A, the interaction effects of $BM \times QSPR_c$ are significantly positive, independent of whether the bettor returns of *Tipico*, the returns of other major bookmakers or the average returns from up to 42 different bookmakers are considered. Thus, the bettor returns are higher at the bookmaker market when illiquidity at the betting exchange is high. In Panel B, the interaction effects of $BM \times LnVol_c$ are negative and statistically significant when using the average bettor returns from up to 42 bookmakers and when using the bettor returns of any of the major bookmakers, with the exception of *William Hill*. In the case of *William Hill*, the interaction effect is also negative and only marginally insignificant (p-value = 0.126). The results for *away win* and *draw* bets are virtually the same (see Tables A.7 and A.8 in the Appendix).

To sum up, not only *Tipico* but all other major bookmakers benefit from a liquidity advantage and offer lower prices and higher

Table 4
Subsample analysis of bettor returns for *home win* events.

Panel A: *QSPR*

	Dependent variable: *bettor return*						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
BM	−0.028***	−0.023***	−0.046***	−0.035***	0.008	−0.033***	−0.031***
	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
$QSPR_c$	−1.037**	−1.000*	0.050	0.005	0.029	−1.163**	−1.034**
	(0.515)	(0.534)	(0.811)	(1.332)	(1.670)	(0.544)	(0.511)
$BM \times QSPR_c$	0.778***	0.738***	0.876***	0.555***	0.422*	0.754**	0.744***
	(0.190)	(0.180)	(0.303)	(0.153)	(0.234)	(0.218)	(0.175)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	10.62%	10.74%	11.13%	10.83%	11.40%	10.66%	10.64%
N	6776	6658	5644	4620	4176	6668	6776

Panel B: *LnVOL*

	Dependent variable: *bettor return*						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
BM	−0.028***	−0.023***	−0.049***	−0.037***	0.008**	−0.033***	−0.031***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
$LnVOL_c$	0.002	0.001	0.003	0.011	0.018	0.004	0.002
	(0.014)	(0.014)	(0.018)	(0.019)	(0.024)	(0.014)	(0.014)
$BM \times LnVOL_c$	−0.006***	−0.006***	−0.006***	−0.003	−0.004*	−0.007***	−0.006***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	10.57%	10.70%	11.11%	10.83%	11.40%	10.59%	10.59%
N	6776	6658	5644	4620	4176	6668	6776

Notes: The table shows the coefficients for estimated from an OLS regression model for different major bookmakers and the average bookmaker (*Avg. BM*), which uses the average of bettor returns from up to 42 different bookmakers. Heteroscedasticity-consistent standard errors clustered at the match level are displayed in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

bettor returns than the betting exchange when the liquidity at the betting exchange is low.

5. Conclusion

Due to less operational risk, lower information costs and higher prediction accuracy, betting exchanges are considered to be a superior business model to traditional bookmaking (e.g., Davies et al., 2005; Koning & van Velzen, 2009). Nevertheless, bookmakers continue to be successful. This paper argues that the liquidity advantage of the bookmaker market helps to explain the puzzling co-existence of bookmakers and betting exchanges in the betting industry.

Both across- and within-match analyses demonstrate that the liquidity at the betting exchange significantly influences the bookmaker's and the betting exchange's prices. We find that bookmaker odds are higher than those of the betting exchange if the cumulative trading volume at the betting exchange is less than £ 23,400 and/or the quoted spread at the betting exchange is higher than 0.044 on average. Our results imply that a lack of liquidity at the betting exchange causes large gaps between bid and ask prices and thus higher betting exchange prices than bookmaker prices. Analyses of bettor returns confirm that bettors obtain higher returns at the bookmaker market than at the betting exchange market if liquidity at the betting exchange is low. Thus, the guaranteed liquidity provision at the bookmaker market is particularly valuable in periods in which liquidity is low at the betting exchange. Altogether, our paper shows that the order-driven betting exchange structure is not generally superior to the quote-driven bookmaker structure, as the active management of the sportsbook offers a distinct liquidity advantage, which helps to explain the ongoing coexistence of the two market structures.

Of course, the liquidity advantage is only one explanation for the coexistence of the market structures in the betting industry. Another advantage of the bookmaker is rooted in his profit-maximizing response to incoming betting demand. When the incoming volume demand is asymmetrically distributed due to the sentimental preferences of bettors, bookmakers can increase their profits by distorting their odds (Forrest & Simmons, 2008; Franck, Verbeek, & Nüesch, 2011; Levitt, 2004). Croxson and Reade (2011) hypothesize that bookmakers continue to be successful because bettors face learning costs when switching to the betting exchange structure. The exchange interface, with its limit order book, different odds and the options to back or lay a bet, may discourage bettors from switching the market structure. Bookmakers also offer incentives such as free bets to dissuade customers from leaving. Franck et al. (2013) show that bookmakers tend to offer higher odds than the betting exchange as an element of their promotional activities to attract new customers. Once bettors have opened an account, switching costs cause them to stick with the given bookmaker, even under unfavourable conditions.

Our analysis sheds some light on the recent shift of financial markets into hybrid structures. The London Stock Exchange (LSE) and the Nasdaq market, for example, moved from quote-driven systems to a hybrid market structure, at which the order book is supplemented by market makers (Friederich & Payne, 2007). Furthermore, the New York Stock Exchange (NYSE) is characterized by elements of both market structures (Madhavan, 2000). Empirical financial studies suggest that market makers are particularly valuable in hybrid structures when liquidity at the order book is low (e.g., Friederich & Payne, 2007; Madhavan & Sofianos, 1998; Venkataraman & Waisburd, 2007). As such, the hybrid market structure combines the advantages of both the quote-driven and order-driven structures. This might be one of the reasons why *Betfair* has started a sportsbook offering quoted fixed odds in addition to the exchange-based odds as of February 2013 (Betfair, 2013a), essentially moving to a hybrid market structure.

Appendix A.

Tables A.1–A.8

Table A.1
Analysis of prices for *away win* events.

Panel A: Across-match analysis

	Dependent variable: *LOW_BM* (1/0)			
	Pooled LPM		Random time point LPM	
	(1)	(2)	(3)	(4)
QSPR	0.939***		0.958***	
	(0.016)		(0.039)	
LnVOL		−0.052***		−0.054***
		(0.001)		(0.002)
Hourly dummies	Yes	Yes	Yes	Yes
League dummies	Yes	Yes	Yes	Yes
R^2	23.16%	23.34%	25.23%	25.58%
N	1,873,831	1,873,831	17,410	17,410
N of groups	17,410	17,410		

Panel B: Within-match analysis

	Dependent variable: *LOW_BM* (1/0)			
	Fixed-effects LPM		Arellano-Bond GMM	
	(1)	(2)	(3)	(4)
QSPR	0.794***		1.025***	
	(0.018)		(0.006)	
LnVOL		−0.049***		−0.026***
		(0.001)		(0.0005)
LOW_BM_{t-1}			0.714***	0.780***
			(0.001)	(0.001)
Hourly dummies	Yes	Yes	Yes	Yes
R^2 overall	11.50%	15.05%		
N	1,873,831	1,873,831	1,839,011	1,839,011
N of groups	17,410	17,410	17,410	17,410

Notes: Panel A: Columns (1) and (2) report the coefficients estimated from a pooled LPM with heteroscedasticity-consistent standard errors clustered at the match level in parentheses. Columns (3) and (4) report the results from a pooled LPM with one randomly chosen observation per match. Panel B: Columns (1) and (2) report the coefficients estimated from a fixed-effects LPM with robust standard errors. Columns (3) and (4) report the results from a Arellano-Bond dynamic panel GMM model. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.2
Analysis of prices for *draw* events.

Panel A: Across-match analysis

	Dependent variable: *LOW_BM* (1/0)			
	Pooled LPM		Random time point LPM	
	(1)	(2)	(3)	(4)
QSPR	1.058***		1.166***	
	(0.018)		(0.034)	
LnVOL		−0.068***		−0.072***
		(0.001)		(0.002)
Hourly dummies	Yes	Yes	Yes	Yes
League dummies	Yes	Yes	Yes	Yes
R^2	29.89%	32.41%	31.69%	34.39%
N	1,873,831	1,873,831	17,410	17,410
N of groups	17,410	17,410		

Panel B: Within-match analysis

	Dependent variable: *LOW_BM* (1/0)			
	Fixed-effects LPM		Arellano-Bond GMM	
	(1)	(2)	(3)	(4)
QSPR	0.844***		1.124***	
	(0.020)		(0.003)	
LnVOL		−0.064***		−0.009***
		(0.001)		(0.001)
LOW_BM_{t-1}			0.705***	0.932***
			(0.001)	(0.003)
Hourly dummies	Yes	Yes	Yes	Yes
R^2 overall	13.76%	20.60%		
N	1,873,831	1,873,831	1,839,011	1,839,011
N of groups	17,410	17,410	17,410	17,410

Notes: Panel A: Columns (1) and (2) report the coefficients estimated from a pooled LPM with heteroscedasticity-consistent standard errors clustered at the match level in parentheses. Columns (3) and (4) report the results from a pooled LPM with one randomly chosen observation per match. Panel B: Columns (1) and (2) report the coefficients estimated from a fixed-effects LPM with robust standard errors. Columns (3) and (4) report the results from a Arellano-Bond dynamic panel GMM model. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.3
Analysis of bettor returns for *away win* events.

	Dependent variable: bettor return					
	Pooled OLS		Random time point OLS		Fixed-effects OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
BM	−0.004**	−0.004**	−0.006**	−0.005*	−0.004**	−0.004**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$QSPR_c$	−0.750***		−0.747***		−0.819***	
	(0.045)		(0.069)		(0.040)	
$BM \times QSPR_c$	0.829***		0.824***		0.829***	
	(0.036)		(0.055)		(0.039)	
$LnVOL_c$		0.002***		0.009		0.015***
		(0.001)		(0.007)		(0.001)
$BM \times LnVOL_c$		−0.017***		−0.018***		−0.017***
		(0.0004)		(0.001)		(0.001)
Hourly dummies	Yes	Yes	Yes	Yes	Yes	Yes
League dummies	Yes	Yes	Yes	Yes		
R^2	2.78%	2.69%	3.33%	3.22%	0.15%	0.03%
N	3,747,662	3,747,662	34,820	34,820	3,747,662	3,747,662
N of groups	17,410	17,410			17,410	17,410

Notes: Columns (1) and (2) report the coefficients estimated from a pooled OLS. Columns (3) and (4) report the results from a pooled OLS with one randomly chosen observation per match. Columns (5) and (6) report the coefficients estimated from a fixed-effects OLS. All standard errors reported in parentheses are heteroscedasticity-consistent and clustered at the match level. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.4
Analysis of bettor returns for *draw* events.

	Dependent variable: bettor return					
	Pooled OLS		Random time point OLS		Fixed-effects OLS	
	(1)	(2)	(3)	(4)	(5)	(6)
BM	0.001	0.001	−0.002	−0.002	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
$QSPR_c$	−0.870***		−0.890***		−0.829***	
	(0.049)		(0.076)		(0.036)	
$BM \times QSPR_c$	0.847***		0.819***		0.847***	
	(0.039)		(0.054)		(0.039)	
$LnVOL_c$		0.013***		0.022***		0.015***
		(0.0005)		(0.006)		(0.001)
$BM \times LnVOL_c$		−0.016***		−0.017***		−0.016***
		(0.0004)		(0.001)		(0.001)
Hourly dummies	Yes	Yes	Yes	Yes	Yes	Yes
League dummies	Yes	Yes	Yes	Yes		
R^2	3.01%	2.88%	3.54%	3.43%	0.22%	0.06%
N	3,747,662	3,747,662	34,820	34,820	3,747,662	3,747,662
N of groups	17,410	17,410			17,410	17,410

Notes: Columns (1) and (2) report the coefficients estimated from a pooled OLS. Columns (3) and (4) report the results from a pooled OLS with one randomly chosen observation per match. Columns (5) and (6) report the coefficients estimated from a fixed-effects OLS. All standard errors reported in parentheses are heteroscedasticity-consistent and clustered at the match level. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.5
Subsample analysis of prices for *away win* events.

Panel A: *QSPR*

	Dependent variable: *LOW_BM* (1/0)						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
QSPR	2.350***	2.322***	2.675***	3.825***	2.164***	2.417***	2.813***
	(0.376)	(0.351)	(0.596)	(0.571)	(0.514)	(0.414)	(0.443)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	21.19%	19.95%	23.11%	17.96%	14.59%	22.51%	31.86%
N	3388	3329	2822	2310	2088	3334	3388

Panel B: *LnVOL*

	Dependent variable: *LOW_BM* (1/0)						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
LnVOL	−0.043***	−0.037***	−0.037***	−0.028***	−0.038***	−0.042***	−0.044***
	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)	(0.005)	(0.005)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	19.78%	18.27%	20.84%	15.46%	14.82%	20.81%	28.09%
N	3388	3329	2822	2310	2088	3334	3388

Notes: The table shows the coefficients for *QSPR* (Panel A) and *LnVOL* (Panel B) estimated from an LPM for different major bookmakers and the average bookmaker (*Avg. BM*), which uses the average of prices from up to 42 different bookmakers. Heteroscedasticity-consistent standard errors are displayed in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.6
Subsample analysis of prices for *draw* events.

Panel A: *QSPR*

	Dependent variable: *LOW_BM* (1/0)						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
QSPR	2.735***	2.500***	3.396***	4.653***	2.072**	2.697***	2.835***
	(0.343)	(0.345)	(0.500)	(1.305)	(1.017)	(0.333)	(0.443)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	27.90%	22.68%	29.13%	22.67%	17.45%	34.45%	36.79%
N	3388	3329	2822	2310	2088	3334	3388

Panel B: *LnVOL*

	Dependent variable: *LOW_BM* (1/0)						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
LnVOL	−0.057***	−0.063***	−0.047***	−0.035***	−0.046***	−0.050***	−0.060***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)	(0.005)	(0.005)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	26.06%	22.73%	25.50%	19.22%	18.37%	31.13%	34.11%
N	3388	3329	2822	2310	2088	3334	3388

Notes: The table shows the coefficients for *QSPR* (Panel A) and *LnVOL* (Panel B) estimated from an LPM for different major bookmakers and the average bookmaker (*Avg. BM*), which uses the average of prices from up to 42 different bookmakers. Heteroscedasticity-consistent standard errors are displayed in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.7
Subsample analysis of bettor returns for *away win* events

Panel A: *QSPR*

	Dependent variable: *bettor return*						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
BM	−0.039***	−0.028***	−0.072***	−0.070***	0.024***	−0.050***	−0.052***
	(0.006)	(0.005)	(0.007)	(0.009)	(0.006)	(0.006)	(0.005)
$QSPR_c$	−1.514***	−1.538***	−2.532***	−3.726***	−2.08	−1.497***	−1.034**
	(0.552)	(0.564)	(0.767)	(1.181)	(1.311)	(0.557)	(0.547)
$BM \times QSPR_c$	0.728***	0.512***	0.607***	0.955***	0.356	0.686***	0.646***
	(0.171)	(0.125)	(0.175)	(0.260)	(0.238)	(0.140)	(0.128)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	8.65%	8.90%	8.58%	8.80%	9.76%	8.71%	8.66%
N	6776	6658	5644	4620	4176	6668	6776

Panel B: *LnVOL*

	Dependent variable: *bettor return*						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
BM	−0.039***	−0.028***	−0.071***	−0.072***	0.025***	−0.051***	−0.052***
	(0.006)	(0.005)	(0.007)	(0.008)	(0.004)	(0.006)	(0.006)
$LnVOL_c$	0.005	0.002	0.018	0.017	−0.017	0.007	0.005
	(0.017)	(0.018)	(0.022)	(0.024)	(0.030)	(0.017)	(0.017)
$BM \times LnVOL_c$	−0.010***	−0.008***	−0.009***	−0.008***	−0.005*	−0.011***	−0.010***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	8.58%	8.83%	8.45%	8.67%	9.74%	8.66%	8.60%
N	6776	6658	5644	4620	4176	6668	6776

Notes: The table shows the coefficients estimated from an OLS regression model for different major bookmakers and the average bookmaker (*Avg. BM*), which uses the average of bettor returns from up to 42 different bookmakers. Heteroscedasticity-consistent standard errors clustered at the match level are displayed in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A.8
Subsample analysis of bettor returns for *draw* events.

Panel A: *QSPR*

	Dependent variable: *bettor return*						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
BM	−0.040***	−0.015***	−0.058***	−0.030**	0.080***	−0.054***	−0.047***
	(0.004)	(0.004)	(0.006)	(0.013)	(0.018)	(0.005)	(0.004)
$QSPR_c$	−1.492***	−1.032***	−1.635*	0.029	−1.383	−1.447***	−1.524***
	(0.545)	(0.586)	(0.884)	(1.559)	(2.330)	(0.548)	(0.547)
$BM \times QSPR_c$	1.020***	1.032***	1.109**	2.219**	4.150***	1.083***	1.043***
	(0.299)	(0.363)	(0.543)	(0.260)	(1.255)	(0.307)	(0.302)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	11.11%	10.65%	11.49%	11.35%	11.07%	10.93%	11.01%
N	6776	6658	5644	4620	4176	6668	6776

Panel B: *LnVOL*

	Dependent variable: *bettor return*						
	Tipico	*Bet365*	*Ladbrokes*	*W. Hill*	*Pinnacle*	*Bwin*	*Avg. BM*
BM	−0.040***	−0.015***	−0.062***	−0.047***	0.030***	−0.055***	−0.047***
	(0.004)	(0.004)	(0.004)	(0.015)	(0.006)	(0.005)	(0.004)
$LnVOL_c$	0.018	0.022	0.002	−0.014	−0.013	0.014	0.019
	(0.019)	(0.019)	(0.022)	(0.026)	(0.031)	(0.019)	(0.019)
$BM \times LnVOL_c$	−0.007***	−0.008***	−0.007***	−0.007***	−0.006**	−0.009***	−0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
League dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	11.06%	10.61%	11.45%	11.33%	11.02%	10.88%	10.95%
N	6776	6658	5644	4620	4176	6668	6776

Notes: The table shows the coefficients estimated from an OLS regression model for different major bookmakers and the average bookmaker (*Avg. BM*), which uses the average consisting of bettor returns from up to 42 different bookmakers. Heteroscedasticity-consistent standard errors clustered at the match level are displayed in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

References

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, *17*, 223–249.

BBC. (2013). *Football betting – The global gambling industry worth billions*. Retrieved from http://www.bbc.com/sport/0/football/24354124.

Betfair. (2012). *FY12 results announcement*. Betfair Corporate. Retrieved from http://corporate.betfair.com/media/press-releases/2012/29-06-2012.aspx.

Betfair. (2013a). *Annual report and accounts*. Betfair Corporate. Retrieved from http://corporate.betfair.com/~media/Files/B/Betfair-V2/pdf/annual-report-2013.pdf.

Betfair. (2013b). *How is my commission calculated?* Betfair Corporate. Retrieved from http://en.learning.betfair.com/app/answers/detail/a_id/2486.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *Journal of Finance*, *56*, 501–530.

Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics*, *87*, 249–268.

Croxson, K., & Reade, J. (2011). Exchange vs. dealers: A high-frequency analysis of in-play betting prices. *Working Paper, University of Oxford*.

Davies, M., Pitt, L., Shapiro, D., & Watson, R. (2005). Betfair.com: Five technology forces revolutionize worldwide wagering. *European Management Journal*, *23*, 533–541.

De Jong, F., Nijman, T., & Roell, A. (1995). A comparison of the cost of trading French shares on the Paris bourse and on SEAQ international. *European Economic Review*, *39*, 1277–1301.

De Jong, F., & Rindi, B. (2009). *The microstructure of financial markets*. New York: Cambridge University Press.

Demsetz, H. (1968). The cost of transacting. *Quarterly Journal of Economics*, *82*, 33–53.

Elyasiani, E., Hauser, S., & Lauterbach, B. (2000). Market response to liquidity improvements: Evidence from exchange listings. *Financial Review*, *35*, 1–14.

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

Franck, E., Verbeek, E., & Nüesch, S. (2010). Prediction accuracy of different market structures - bookmakers versus a betting exchange. *International Journal of Forecasting*, *26*, 448–459.

Franck, E., Verbeek, E., & Nüesch, S. (2011). Sentimental preferences and the organizational regime of betting markets. *Southern Economic Journal*, *78*, 502–518.

Franck, E., Verbeek, E., & Nüesch, S. (2013). Inter-market arbitrage in betting. *Economica*, *80*, 300–325.

Friederich, S., & Payne, R. (2007). Dealer liquidity in an auction market: Evidence from the London Stock Exchange. *Economic Journal*, *117*, 1168–1191.

Garbade, K., & Silber, W. (1979). Structural organization of secondary markets: Clearing frequency, dealer activity, and liquidity risk. *Journal of Finance*, *34*, 577–593.

Grossman, S., & Miller, M. (1988). Liquidity and market structure. *Journal of Finance*, *43*, 617–633.

Harris, L. (2003). *Trading and exchanges: Market microstructure for practitioners*. Oxford University Press, Inc.

Hasbrouck, J., & Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics*, *59*, 383–411.

Huang, R., & Stoll, H. (1996). Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. *Journal of Financial Economics*, *41*, 313–357.

Huang, R., & Stoll, H. (2001). Tick size, bid-ask spreads, and the market structure. *Journal of Financial and Quantitative Analysis*, *36*, 503–522.

Koning, R., & van Velzen, B. (2009). Betting exchanges: The future of sports betting? *International Journal of Sports Finance*, *4*, 42–62.

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

Madhavan, A. (2000). Market microstructure: a survey. *Journal of Financial Markets*, *3*, 205–258.

Madhavan, A., & Sofianos, G. (1998). An empirical analysis of NYSE specialist trading. *Journal of Financial Economics*, *48*, 189–210.

Merrion Stockbrokers. (2010). *Merrion online betting survey*.. Retrieved from http://www.merrion-capital.com/research/paddy-power-merrion-online-betting-survey.html.

Norton, E. (2012). Log odds and ends. In *Working Paper, National Bureau of Economic Research*.

Ozgit, A. (2005). The bookie puzzle: Auction versus dealer markets in online sports betting. In *Working Paper, University of California*.

Sauer, R. (1998). The economics of wagering markets. *Journal of Economic Literature*, *36*, 2021–2064.

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

Smith, M., Paton, D., & Vaughan Williams, L. (2009). Do bookmakers possess superior skills to bettors in predicting outcomes? *Journal of Economic Behavior & Organization*, *71*, 539–549.

StataCorp. (2015). *Stata 14 Base Reference Manual*. College Station, TX: Stata Press.

Tipico Co. Ltd. (2013). *Jedes Spiel ein Endspiel*.. Retrieved from http://www.tipico-group.com/download/1407/Tipico2013.pdf.

Venkataraman, K., & Waisburd, A. (2007). The value of the designated market maker. *Journal of Financial and Quantitative Analysis*, *42*, 735–758.

Wooldridge, J. (2012). *Introductory econometrics: A modern approach* (5th ed.). Cengage Learning.