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Abstract

This paper examines how liquidity affects market efficiency in a market environment where securities' true values are revealed at a predetermined point in time. We employ differences in minimum tick sizes at the betting exchange *Betfair* as a source of exogenous variation in liquidity. The results show that liquidity significantly decreases market efficiency for bets on weekend matches but not for bets on weekday matches. Because uninformed noise bettors are more likely to bet on weekends than on weekdays, our results indicate that the type of liquidity matters for market efficiency.

JEL Classification: G12, G14

Keywords: Liquidity, Market Efficiency, Noise Trading, Betting Market

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1 Introduction

To provide an optimal allocation of capital, financial markets have to be informationally efficient so that the prices of securities fully reflect all information available (Fama, 1991). This paper tests how liquidity affects informational market efficiency. An understanding of the impact of liquidity on market efficiency has important implications for policy makers and regulators in order to improve the design of markets.

However, the relationship between liquidity and efficiency is controversial. From a theoretical perspective, two competing hypotheses have evolved. On the one hand, liquidity facilitates the elimination of mispricings and thus increases market efficiency due to lower transaction costs (O'Hara, 1995). The theoretical model proposed by Kyle (1985) shows that with increasing liquidity, informed traders are able to trade more heavily on their information without impacting the prices. As such, liquidity providers camouflage the trading from informed traders, which allows them to increase their profits. Therefore, liquid markets reduce the transaction costs for arbitrageurs and encourage them to acquire information in those markets to correct mispricings. On the other hand, liquidity decreases market efficiency when liquidity is a proxy for uninformed or irrational noise trading. Noise traders' beliefs could deviate from the asset's fundamental value. These beliefs affect prices and lead to a loss for the arbitrageur if she has to liquidate her position before the price recovers. The fear of loss hinders the arbitrageur from entering a position and trading aggressively against noise traders in the first place. As a result, arbitrageurs start to predict the pseudosignals from noise traders, such as volume and price patterns or sentiment indices, rather than trading on fundamentals to correct mispricings (De Long, Shleifer, Summers, & Waldmann, 1990; Shleifer & Vishny, 1997).

Several empirical studies show that increasing liquidity results in enhanced market efficiency. Wurgler and Zhuravskaya (2002) test how prices respond to exogenous demand shocks of stocks that were added to the S&P 500 Index. The authors find that stocks without close substitutes, which thus have a higher arbitrage risk, exhibit less liquidity

and higher mispricing. Sadka and Scherbina (2007) investigate stocks with high analyst disagreement and find that less liquid stocks tend to be more severely overpriced due to higher trading costs. Chordia, Roll, and Subrahmanyam (2008) analyze the short horizon return predictability in connection with liquidity. The authors examine the return predictability of NYSE firms as an inverse measure of market efficiency and use the minimum tick size reductions as an exogenous increase in liquidity. Because return predictability declines across tick size regimes, liquidity is positively related to market efficiency. The studies of Chung and Hrazdil (2010a, 2010b) apply the method of Chordia et al. (2008) to a more comprehensive sample of NYSE firms and NASDAQ firms and also conclude that liquidity is positively related to market efficiency.

Other studies support the view that the prices of securities in liquid markets exhibit lower market efficiency. In an experimental market study, Bloomfield, OHara, and Saar (2009) form a group of informed traders who possess fundamental information and a group of uninformed traders who have no valuable fundamental information and examine how the uninformed traders affect market efficiency. As expected, uninformed noise traders increase market liquidity. However, at the same time, such traders harm market efficiency because their unwise contrarian strategies prevent market prices from adjusting to new information. A similar conclusion can be drawn from Linnainmaa (2010), who investigates limit orders using a detailed dataset of investor trading records. His data show that individual investors prefer to use limit orders to gain from the liquidity demand of impatient investors who place market orders. However, limit orders are only executed if the price moves against the order. Linnainmaa (2010) therefore considers such individual investors as uninformed traders who harm the process of adjustment to the intrinsic value.

Empirical financial studies face two major limitations when investigating the relation between liquidity and market efficiency. First, the fundamental values of traditional financial products are not observable. Therefore, all field studies must test market efficiency jointly with an equilibrium model (Fama, 1970). Second, the amount of liquidity is often

an endogenous function of the pricing accuracy. Before press releases, for example, liquidity tends to be low because limit order submitters worry that other traders who submit market orders possess superior information (Tetlock, 2008).

We use data from a major betting exchange to investigate the relation between liquidity and market efficiency. As in order-driven financial markets, betting exchanges facilitate a continuous double auction process. However, unlike with traditional financial securities, betting contracts have a clear endpoint at which their true value is revealed. Furthermore, the underlying outcome of such contracts, e.g., that the home team wins a match, is neither affected by the trader's expectations nor by macroeconomic factors. Thus, betting markets offer a unique setting for measuring the informational market efficiency of prices (Sauer, 1998; Verbeek, 2011).

To date, few studies have linked the market efficiency of betting markets to liquidity. Tetlock (2008) employs data of financial and sporting contracts from the *TradeSports* exchange. He concludes that higher liquidity increases mispricing and that prices of illiquid securities converge more quickly towards their fundamental value. To overcome the reverse causality problem between liquidity and efficiency, Tetlock (2008) employs exchange-wide trading activities as instrumental variables for changes in liquidity. However, because aggregated liquidity might be related to aggregated mispricing within the exchange, these instrumental variables may not be truly exogenous. Hartzmark and Solomon (2012) provide further evidence of the negative effect of liquidity on market efficiency in betting markets. They show that betting contracts from the *TradeSports* exchange on liquid Monday night NFL games exhibit greater mispricings than bets on less liquid games. However, they do not address the potential simultaneity of liquidity and market efficiency.

To estimate the causal effect of liquidity on market efficiency, we employ differences in minimum tick sizes that create exogenous variation in liquidity at the betting exchange *Betfair*. We use betting contracts on 2,227 soccer matches played in the *English Premier League* from 2006-2011 and in the *Spanish Primera División* from 2009-2011 traded at the

betting exchange *Betfair*. Using different liquidity and efficiency measures, the results from our simple t-tests and two-stage least squares model (2SLS) estimations show that market efficiency is negatively associated with liquidity.

Because previous theoretical studies argue that only liquidity due to uninformed or irrational noise traders decreases market efficiency (De Long et al., 1990; Shleifer & Vishny, 1997), the type of liquidity seems to matter for market efficiency. Therefore, this paper tests whether the fraction of noise traders moderates the negative relationship between liquidity and market efficiency in the betting industry by investigating the effect of liquidity on market efficiency for weekend and weekday matches separately.

Several earlier studies have shown that the betting activity at weekend matches is characterized by a higher share of irrational noise bettors than betting activity at weekday matches. Kopelman and Minkin (1991) state that weekend bettors at the racetrack are more casual and choose their bets based on irrelevant factors such as the name or color of the horses, whereas weekday bettors are highly knowledgeable about their pursuits and motivated by the desire for financial gain. Moreover, Sobel and Raines (2003) find that weekend bettors wager a significantly lower amount per person and that weekend bettors are less informed. Similarly, Sung and Johnson (2007) show that market efficiency is lower on weekends than on weekdays and explain this difference by the larger proportion of noise traders on weekends. Because all teams in a league play the same number of weekday matches, the allocation in weekend and weekday matches is neither correlated with certain teams nor with their objective winning probability. Even though the average liquidity is lower for weekend bets than for weekday bets in our sample, we find that the negative effect of liquidity on market efficiency is stronger for weekend matches and that the effect becomes insignificant for weekday matches.

Overall, our findings indicate that liquidity with a high fraction of noise bettors decreases market efficiency, whereas liquidity with a low fraction of noise bettors is not significantly related to market efficiency. A high fraction of noise bettors prevents prices

from adjusting to their true values. One reason for the persistence of mispricing is bettor sentiment, which causes noise bettors to prefer bets with particular characteristics. Similar to investor sentiment in financial markets (e.g., Barberis, Shleifer, & Vishny, 1998; Baker & Wurgler, 2006; De Long et al., 1990), bettor sentiment is found to bias prices in betting markets due to incorrect perceptions (e.g., Kuypers, 2000; Levitt, 2004) or loyalty towards certain teams (e.g., Forrest & Simmons, 2008; Franck, Verbeek, & Nüesch, 2011). Nevertheless, the persistence of mispricing in betting markets is surprising, as the true value of each bet is revealed at the end of the match, and therefore, informed bettors face less arbitrage risk. As the potential mispricing period in financial markets is unlimited, the negative influence of noise trader liquidity on market efficiency might be even more severe.

The remainder of this paper is organized as follows. Section 2 describes our data, introduces our liquidity and efficiency measures and discusses how we process our empirical analysis. Section 3 reports the main estimation results, and Section 4 concludes.

2 Data and Methods

2.1 Sample

We use betting data on professional soccer matches from the popular *winner* betting contracts on *home wins*, *draws* or *away wins* traded at *Betfair*, the most prominent betting exchange worldwide. *Betfair* provides an electronic platform on which bettors can directly trade bets with each other in a continuous double auction. Thus, as in the order-driven system of financial markets, individual bettors can post limit and/or market orders under which they are willing to place a bet on (buy order) or against (sell order) a given outcome of a match. The latent demand and supply in the form of limit orders is collected and displayed in the order book with a bid-ask spread between the best buying and selling orders. A transaction takes place whenever two parties agree on one price (Verbeek,

2011). This new form of sports betting has grown rapidly in the last several years. Its economic relevance is now considerable and in some cases comparable to common financial markets. *Betfair* had over 4 million registered customers and processed more than 7 million transactions on an average day in 2012 (Betfair, 2012b). The NYSE Group processed about 5.5 million trades on an average trading day in 2012 (NYSE, 2012).

Our sample consists of decimal betting odds information on 2,227 matches played in the *English Premier League* from 2006/07-2011/12 and in the *Spanish Primera Divisón* from 2010/11-2011/12. The dataset covers the last three hours before match start and is provided by *Fracsoft*, a vendor of historical *Betfair* data.[1] Decimal betting odds denote the payoff of a successful bet. For example, if the odds of a *home win* bet are 1.60, a one dollar wager pays \$1.60 if the home team wins the match.

For each event within a match, i.e., *a home win*, *a draw* and *an away win*, we have second-by-second information on the best back odds, which are the best odds offered to buy a bet, the best lay odds, which are the best odds to sell a bet, and the last odds to be matched. For the ease of interpretation, we convert the decimal odds into prices, defined as the reciprocal of the decimal odds (e.g., $p = \frac{1}{1.60} = 0.625$) ranging from zero to one. These prices indicate how much a bettor has to invest in order to collect \$1 in the event of a successful bet (Forrest & Simmons, 2008). Additionally, our dataset contains the current limit order volume available on both back and lay bets and the cumulative trading volume until time t before match start. Our main cross-sectional analysis is based on data taken 60 minutes before the match starts.

2.2 Liquidity Measures

The most commonly used measures of liquidity in the financial market microstructure literature are spread-related (e.g., Amihud & Mendelson, 1986; Chordia, Roll, & Sub-

[1]The completeness of the data increased continuously over time. The percentages of missing matches are 64% (Season 06/07), 52% (07/08), 20% (08/09), 13% (09/10), 13% (10/11) 12% (11/12) for the *English Premier League* and 21% (10/11), 19% (11/12) for the *Spanish Primera Divisón*. Because matches are missing due to technical reasons (Choi & Hui, 2012), sample selection should not affect our results.

rahmanyam, 2001; Hasbrouck & Seppi, 2001; Lin, Snager, & Booth, 1995). The spread approximates the costs incurred with trading. Thus, small spreads indicate high liquidity in the market (Von Wyss, 2004). We follow the approach of Chordia et al. (2008) and use the quoted spread, defined as the difference between the lowest ask price and the highest bid price, as an inverse measure of liquidity. For each match i, event $e \in \{home\ win, draw, away\ win\}$ and time t before match start, we calculated the quoted spread ($QSPR$) as

$$QSPR_{iet} = p_{iet}^{back} - p_{iet}^{lay} \tag{1}$$

where p^{back} refers to the best ask price and p^{lay} to the best bid price, respectively. The quoted spread is always positive, and its lower limit is at the minimum tick size (Von Wyss, 2004).

A unique feature of the *Betfair* trading platform is the increment rule that defines the minimum tick size. Table 1 depicts the odds increments over the possible odds range at *Betfair*. For short odds, e.g., between 1.01 and 1.99, the minimum odds increment

Table 1: Odds increments at *Betfair*

odds	]1;2[	[2;3[	[3;4[	[4;6[	[6;10[	[10;20[	[20;30[	[30;50[	[50;100[	[100;1000[
odds increment	0.01	0.02	0.05	0.1	0.2	0.5	1	2	5	10

Notes: The table presents the *acceptable* odds increments at the *Betfair* betting exchange as stated by Betfair (2012a).

is 0.01, whereas for long odds, e.g., between 10 and 19, the minimum odds increment increases to 0.5. The increment rule results in a discontinuous and non-linear minimum quoted spread ($MSPR$) function. Figure 1 depicts the minimum quoted spread function defined by *Betfair* and the actual quoted spread from our dataset for all possible midquote prices (p^M) calculated as the average between the best ask price and the best bid price. As expected, the correlation between the quoted spread and the minimum quoted spread seems to be highly positive, but the minimum quoted spread does not perfectly predict the

actual quoted spread. Moreover, there are clear drops in the quoted spreads at midquote price levels of 0.50 and 0.33, for example.

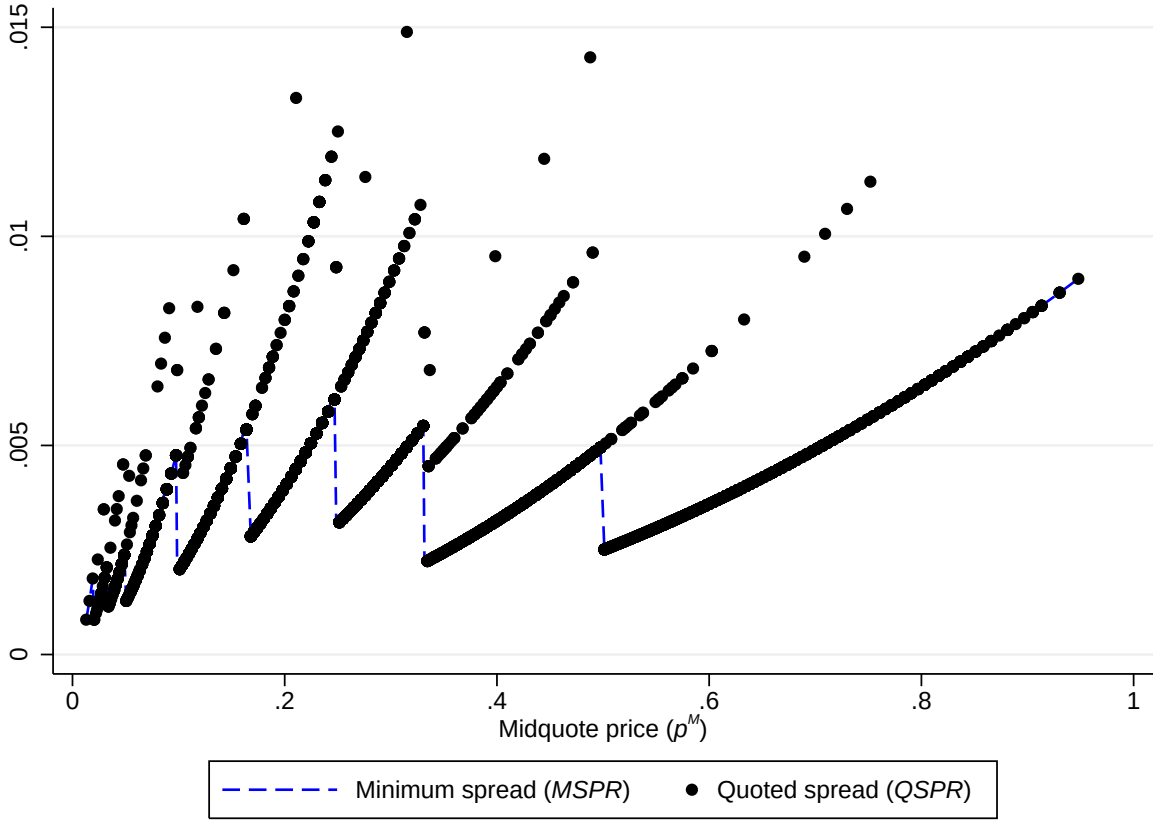


Figure 1: Minimum spread function and quoted spread

As a second measure of liquidity, we use the quote slope, which combines both price and quantity information (Hasbrouck & Seppi, 2001). If more volume is available at the best bid or ask price, the quote slope decreases and the market is more liquid. Similarly, if the bid and ask price are closer to each other, the quote slope decreases and the market is more liquid. Thus, a high quote slope indicates low liquidity. Formally, the quote slope in the betting exchange market is defined as

$$QSLP_{iet} = \frac{p_{iet}^{back} - p_{iet}^{lay}}{ln(vol_{iet}^{back}) + ln(vol_{iet}^{lay})} \tag{2}$$

where vol^{back} and vol^{lay} denote the best back and lay volume available in the limit order book for event e at time t.

Because several financial studies such as Chordia et al. (2001), Gervais, Kaniel, and Mingelgrin (2001) and Lee and Swaminathan (2000) incorporate volume-related liquidity measures, we use the logarithmized cumulative trading volume from the opening of the market until time t before match start ($LnVOL$) as a third liquidity measure.

Table 2 reports the summary statistics associated with our liquidity measures for the complete sample and for weekend/weekday matches separately. Based on the findings from the previous literature (Kopelman & Minkin, 1991; Sobel & Raines, 2003; Sung & Johnson, 2007), we expect liquidity on weekends to be more heavily affected by noise traders than liquidity on weekdays. As expected, the average quoted spread is higher

Table 2: Summary statistics of liquidity measures

	All (N=2,227)		Weekend (N=1,786)		Weekday (N=441)		Δ
	Mean	SD	Mean	SD	Mean	SD	t
$MSPR$	0.0040	0.0012	0.0040	0.0011	0.0039	0.0011	1.54
$QSPR$	0.0042	0.0014	0.0043	0.0015	0.0041	0.0014	2.23**
$QSLP$	0.0003	0.0001	0.00030	0.0001	0.00027	0.0001	4.88***
$LnVOL$	11.278	1.492	11.178	1.472	11.686	1.506	-6.48***

Notes: The table reports the summary statistics of liquidity measures 60 minutes before match start for the complete sample and for weekend and weekday matches separately. For each match, we randomly selected one event: (*a home win*, *a draw* or *an away win*). The last column reports the t-values from a t-test on the difference in liquidity for weekend and weekday matches. In all tests, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

than the average minimum quoted spread. The average cumulative volume traded for the complete sample is £246,000. Because the minimum quoted spread is given by the platform, there is no difference in means for weekend and weekday matches. By contrast, the $QSPR$ and the $QSLP$ are significantly higher and the $LnVOL$ is significantly lower on weekend matches than on weekday matches. The average cumulative volume traded on weekend matches is £213,000, whereas the average cumulative volume traded on weekdays is £380,000. Thus, the average liquidity is considerably lower for weekend matches.

2.3 Market Efficiency Measures

Our measures of market efficiency make use of the advantage that the fundamental value of each betting contract is observed after the match. Because the outcome of a bet is either 1 (win) or 0 (loss), the prices quoted at the betting exchange can be interpreted as the market's forecasting probability of an individual bet to win. Hence, we employ scoring rules that have been developed by the probabilistic forecasts verification literature to provide a summary measure for the efficiency of prices (Gneiting & Raftery, 2007). Scoring rules assess the ex post informativeness of the probabilities after the outcome is known (Jose, Nau, & Winkler, 2009).

The most common scoring rule is the Brier score (Brier, 1950). The Brier score is based on the squared error, defined as the squared difference between individual pairs of forecasts and observations. Because the Brier score captures both the resolution and the calibration of a forecast, it forms an attractive measure of market efficiency (Murphy & Winkler, 1987; Gneiting, Balabdaoui, & Raftery, 2007). The resolution refers to the ability of the forecast probability to discriminate between high- and low-probability events, whereas the calibration refers to the correspondence of the forecast probability and the true observed frequencies (I. Mason, 1982). To also take the difficulty of the forecasting problem into account, the Brier score is widely expressed as a skill score that measures the extent to which a forecast outperforms a reference forecast (S. Mason, 2004; Wilks, 1995). Formally, the Brier skill score (BSS) is defined as

$$BSS_{iet} = 1 - \frac{(Y_{ie} - p^{M}_{iet})^2}{(Y_{ie} - p^{ref}_{iet})^2} \tag{3}$$

where Y refers to the actual outcome, which is either a win (1) or a loss (0), and p^M refers to the quoted midpoint price as the market's valuation for the underlying value of the bet. The numerator of the ratio reflects the Brier score of the actual forecast, and the denominator reflects the Brier score of a reference forecast. A widely used reference forecast

is the empirical frequency of the occurrence of the the outcome (Jolliffe & Stephenson, 2003).[2] In our sample, the empirical frequency is 0.483 for *home win* events, 0.243 for the *draws* and 0.274 for *away win* events. The BSS ranges from one for a perfect forecast, to zero for a forecast that provides no improvement over the reference, to negative values for forecasts worse than the reference (S. Mason, 2004).

Our second measure of market efficiency is the absolute error skill score ($AESS$), which is more reliable than the Brier skill score in the presence of outliers (Armstrong, 2001). The $AESS$ is based on the ratio of the absolute error of the actual forecast and the absolute error of a reference forecast. We calculate the absolute error skill score as

$$AESS_{iet} = 1 - \frac{\mid Y_{ie} - p_{iet}^{M} \mid}{\mid Y_{ie} - p_{ite}^{ref} \mid} \tag{4}$$

The $AESS$ has a value of one for a perfect accuracy, a value of zero when the forecast contains no skill and a negative value when the accuracy is lower than the reference forecast equal to the empirical frequency.

Table 3 reports the summary statistics of our market efficiency measures for the complete sample and for weekend/weekday matches separately. The positive means show that

Table 3: Summary statistics of efficiency measures

	All (N=2,227)		Weekend (N=1,786)		Weekday (N=441)		Δ
	Mean	SD	Mean	SD	Mean	SD	t
BSS	0.0333	0.8250	0.0273	0.8311	0.0574	0.8000	-0.67
$AESS$	0.0939	0.3817	0.0908	0.3822	0.1064	0.3799	-0.77

Notes: The table reports the summary statistics of liquidity measures 60 minutes before match start for the complete sample and for weekend and weekday matches separately. For each match, we randomly selected one event (*home win*, *draw* or *away win*). The last column reports the t-values from a t-test on the difference in market efficiency for weekend and weekday matches. In all tests, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

betting exchange prices incorporate more information on average than the reference fore-

[2] An alternative reference forecast is the *climatological probability*, which corresponds to the noninformative price of 0.333 for each of the three events within a match. The use of this reference forecast does not change our results in any significant way.

cast. Both the BSS and the $AESS$ are higher for weekday matches than for weekend matches, but the difference is insignificant.

2.4 Identification Strategy

Our empirical analysis is divided into three parts. First, we make use of the discontinuity of the minimum quoted spread function displayed in Figure 1 by forming subsamples of observations which are ± 0.025 price units around the discontinuity area. This results in two groups with different inherent liquidity but similar prices. One group with observations below the discontinuity is considered as the *high-gap MSPR* group. The other group with observations above the discontinuity is considered as the *low-gap MSPR* group. We conduct parametric t-tests as well as nonparametric Wilcoxon rank-sum tests of the difference in market efficiency between the two liquidity groups.

In a second analysis, we use the predetermined minimum quoted spread function ($MSPR$) of *Betfair* as an identifying instrumental variable for our liquidity measures (L). The first-stage equation is

$$L_{ie} = \theta_0 + \theta_1 \cdot MSPR_{ie} + \theta_2 \cdot p_{ie}^M + \theta \cdot \Gamma_{ie} + u_{ie} \tag{5}$$

where p^M refers to the midquote price of the bet and Γ refers to a set of control variables such as dummy variables for the event e, seasons and leagues. As can be seen from Figure 1, the $MSPR$ is an increasing function of p^M, making the midquote price an important control variable (Angrist & Pischke, 2009). The second-stage equation is formulated as

$$E_{ie} = \beta_0 + \beta_1 \cdot \widehat{L_{ie}} + \beta_2 \cdot p_{ie}^M + \beta \cdot \Gamma_{ie} + \epsilon_{ie} \tag{6}$$

where E is the measure of market efficiency and $\widehat{L}$ is the fitted value of the first-stage regression estimated in Equation (5). The second-stage regression has the same set of control variables as the first-stage regression. Because we control for the midquote price

p^M, the favorite-longshot bias does not distort our results. The favorite-longshot bias refers to the empirical observation that favorite teams are often underpriced and longshots are overpriced (e.g., Snowberg & Wolfers, 2010; Thaler & Ziemba, 1988).

In a third step, we estimate Equations (5) and (6) for weekend and weekday matches separately to test whether the fraction of noise traders moderates the relationship between liquidity and market efficiency in the betting industry.

3 Results

Table 4 presents the means of market efficiency of the *low-gap MSPR* and the *high-gap MSPR* groups as well as the results of t-tests and Wilcoxon rank-sum tests on the differences between the groups. While Panel A uses BSS as a market efficiency measure, Panel B uses $AESS$ as an efficiency measure. Table 4 shows that market efficiency is

Table 4: Liquidity and market efficiency at a discontinuity area

Panel A: comparison of BSS

		t-test			Wilcoxon rank-sum test		
	N	Mean	SE	t	rank sum	expected	z
Low gap MSPR	419	0.1898	0.0300		153,893	174,094.5	
High gap MSPR	411	0.3701	0.0259		190,972	170,770.5	
Δ	830	-0.1803	0.0396	-6.450***			-5.850***

Panel B: comparison of $AESS$

		t-test			Wilcoxon rank-sum test		
	N	Mean	SE	t	rank sum	expected	z
Low gap MSPR	419	0.1769	0.0178		153,893	174,094.5	
High gap MSPR	411	0.2908	0.0176		190,972	170,770.5	
Δ	830	-0.1138	0.0250	-4.543***			-5.850***

Notes: The table presents the results of simple two-sided t-tests and Wilcoxon rank-sum tests based on the two groups *low-gap MSPR* and *high-gap MSPR*. The groups are formed from observations located ± 0.025 price units around the discontinuity gaps of the $MSPR$ function. When more than one observation per match is located in the discontinuity gap, we only include one randomly chosen observation from this match. Panel A displays the results for the differences in BSS, and Panel B displays the results for the differences in $AESS$. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

significantly higher in the *high-gap MSPR* group than in the *low-gap MSPR* group, independent of the efficiency measures and tests employed, which indicates that liquidity decreases market efficiency.[3]

Table 5 displays the results of the first-stage regressions that relate the minimum spread ($MSPR$) to the liquidity measures ($QSPR$, $QSLP$, and $LnVOL$). As expected,

Table 5: First-stage results of 2SLS model estimation

	$QSPR$	$QSLP$	$LnVOL$
	(1)	(2)	(3)
$MSPR$	1.019***	0.063***	-93.12***
	(0.022)	(0.002)	(16.41)
p^M	-0.0003***	-0.0002***	5.623***
	(0.0001)	(0.00001)	(0.112)
home	-0.00003	0.00000	0.692***
	(0.0001)	(0.00001)	(0.049)
away	0.00006	0.00002***	0.613***
	(0.0001)	(0.00001)	(0.041)
Primera División	0.0001*	0.00004***	-1.097***
	(0.0001)	(0.00001)	(0.045)
Season Dummies	Yes	Yes	Yes
N	2,227	2,227	2,227
partial R^2	52.68%	30.69%	1.33%
F-test of the excluded instrument	2,172***	806***	32.21***

Notes: The table presents the first-stage estimates for the quoted spread ($QSPR$), quote slope ($QSLP$) and the cumulative trading volume ($LnVOL$) from the *Betfair* minimum quoted spread ($MSPR$). The data are taken 60 minutes before each match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. The reference categories are the *draw* and the *English Premier League* for the event and league dummies, respectively. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

we find significantly positive effects of $MSPR$ on our spread-related liquidity measures and a significantly negative effect of $MSPR$ on the logarithm of betting volume. As the F-statistics of our identifying instrument are far beyond the critical threshold value of 8.96 (Stock, Wright, & Yogo, 2002), we do not have a weak instrument problem. Table

[3]This finding is robust to the use of the nonparametric relative operating characteristic curve (ROC) as an alternative measure of market efficiency (see Figure A.1 in Appendix A.1). Moreover, betting prices have significantly lower explanatory power in the *low-gap MSPR* group than in the *high-gap MSPR* group, which also confirms that liquidity decreases market efficiency (see Table A.1 in Appendix A.1)

5 also shows that the midquote price p^M positively affects liquidity, which indicates that bettors prefer betting on favorite teams over betting on longshot teams (see also Levitt, 2004). Additionally, matches played in the *Spanish Primera Divisón* are associated with less liquidity than matches played in the *English Premier League*. This result is not surprising, as sports betting is more popular in England than in Spain.

Table 6 reports the results of the second-stage regression. We find positive coefficients

Table 6: Second-stage results of 2SLS model estimation for BSS and $AESS$

	BSS			$AESS$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QSPR}$	70.95***			30.89***		
	(18.72)			(9.017)		
$\widehat{QSLP}$		1144.70***			498.38***	
		(306.22)			(148.71)	
$\widehat{LnVOL}$			-0.776***			-0.338***
			(0.235)			(0.111)
p^M	-2.144***	-1.935***	2.200*	-1.000***	-0.910***	0.891
	(0.222)	(0.231)	(1.312)	(0.085)	(0.091)	(0.625)
home	0.658***	0.651***	1.193***	0.372***	0.369***	0.605***
	(0.056)	(0.056)	(0.186)	(0.024)	(0.024)	(0.089)
away	0.141***	0.120***	0.622***	0.178***	0.169***	0.387***
	(0.037)	(0.037)	(0.158)	(0.016)	(0.017)	(0.074)
Primera División	0.0004	-0.048	-0.844***	0.007	-0.014	-0.361***
	(0.042)	(0.041)	(0.251)	(0.019)	(0.020)	(0.122)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	2,227	2,227	2,227	2,227	2,227	2,227
$F(10; 2{,}216)$	34.53***	32.93***	16.40***	48.51***	46.06***	26.46***

Notes: The table reports the second-stage estimates for the Brier skill score (BSS) and the absolute error skills score ($AESS$). The data are taken 60 minutes before each match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. The reference categories are the *draw* and the *English Premier League* for the event and league dummies, respectively. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

of the quoted spread and the quote slope and negative coefficients of the trading volume on BSS (Columns (1) - (3)) and on $AESS$, respectively (Columns (4) - (6)). Thus, liquidity is negatively related to market efficiency.[4] In all specifications, we include the midquote

[4]The results remain virtually the same if we use the effective spread as an alternative spread-related

price p^M, event dummies, a league dummy for the *Primera División* and seasonal dummies as control variables.[5] The midquote price p^M seems to have a negative effect on market efficiency, which might be due to the favorite-longshot bias. The prices of *home win* and *away win* events are more efficient than the prices of a *draw*, as a *draw* is typically very difficult to forecast. The efficiency of prices from matches played in the *Spanish Primera Divisón* do not seem to systematically differ from efficiency of prices from matches played in the *English Premier League*.

We also run separate regressions for each minute during the last three hours before match start. The resulting coefficient estimates for the quoted spread on the Brier skill score and on the absolute error skill score are displayed in Figure A.2 of Appendix A.2. The estimated coefficients are positive and remain relatively stable, which shows that the negative relation between liquidity and market efficiency is robust over time.

To test the moderating influence of noise trader liquidity, we estimate the effect of liquidity on market efficiency for weekday and weekend matches separately. Table 7 shows that the liquidity coefficients in the second-stage regressions are considerably larger on weekends than on weekdays. Whereas liquidity significantly decreases market efficiency on weekends, the relation is not statistically significant on weekdays. This result is robust to the use of different liquidity and efficiency measures (see also Table A.2 in the Appendix A.3).

measure. The effective spread is defined as twice the absolute difference of the last transaction price and the prevailing midquote price between the best bid and ask price (Bessembinder, 2003). Moreover, our results do not change if we use the absolute pricing error to measure market inefficiency, as employed by other studies such as Bloomfield et al. (2009), Wolfers and Zitzewitz (2004) or Snowberg and Wolfers (2010).

[5]The results are also robust to the inclusion of team dummies. Thus, time-constant team popularity does not seem to affect the relation between liquidity and market efficiency.

Table 7: Second-stage results of 2SLS model estimation for BSS for weekend and weekday matches

	BSS					
	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QSPR}$	87.03***	7.68				
	(19.89)	(53.29)				
$\widehat{QSLP}$			1372.15***	139.71		
			(320.81)	(968.09)		
$\widehat{LnVOL}$					-0.932***	-0.160
					(0.258)	(1.114)
p^M	-2.246***	-1.697***	-1.981***	-1.716***	2.954**	0.783
	(0.251)	(0.468)	(0.257)	(0.520)	(1.434)	(6.756)
home	0.699***	0.506***	0.691***	0.506***	1.346***	0.3620
	(0.064)	(0.115)	(0.063)	(0.114)	(0.209)	(0.816)
away	0.136***	0.150	0.110***	0.148	0.700***	0.272
	(0.040)	(0.094)	(0.042)	(0.089)	(0.678)	(0.901)
Primera División	0.002	0.026	-0.055	-0.032	-0.975***	-0.214
	(0.047)	(0.097)	(0.047)	(0.082)	(0.271)	(1.125)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1,786	441	1,786	441	1,786	441
$F(10; 1{,}775/430)$	29.77***	7.77***	27.78***	7.75***	12.84***	7.61***
F-test of excl. instr.	1,637***	683***	649***	192***	30.37***	1.71

Notes: The table reports the second-stage estimates for the Brier skill score (BSS) for weekend and weekday matches separately. The data are taken 60 minutes before each match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. The F-test of excluded instruments refers to the first stage. The reference categories are the *draw* and the *English Premier League* for the event and league dummies, respectively. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

4 Conclusion

This paper analyzes how liquidity affects market efficiency using data from simple betting contracts with observable fundamental values traded at the betting exchange *Betfair*. To isolate the causal effect of liquidity on market efficiency, we use the exogenously defined minimum spread function as an instrumental variable for liquidity. Nonparametric tests and the 2SLS results show that higher liquidity is associated with lower market efficiency.

Because irrational noise bettors are more likely to bet on weekend matches than on weekday matches, we conduct a subsample analysis for weekend and weekday matches. We find that liquidity significantly decreases market efficiency for weekend matches but not for weekday matches. On weekend matches, informed bettors seem to be unable to bet aggressively enough against the high fraction of uninformed and sentimental noise bettors to correct mispricings, even though the average liquidity is lower on weekends than on weekdays.

Our findings suggest that noise trader liquidity can destabilize prices and harm market efficiency, whereas other liquidity is not significantly associated with market efficiency. This result is striking, because betting contracts expire within a few hours, after which their true value is revealed and informed traders face no risk that mispricing will be persistent over long periods of time in the betting industry. In financial markets, noise trader liquidity might even more severely decrease market efficiency, as the potential mispricing period is unlimited.

A Appendix

A.1 ROC and probit estimation

A nonparametric ROC displays the relation between hit and false alarm rates, which indicates the degree of correct discrimination (I. Mason, 1982). The area under the ROC curve ranges between 0.5 and 1.0, where 0.5 reflects no discrimination skill and 1.0 reflects perfect discrimination skill. The ROC curves for both liquidity groups are displayed in Figure A.1. The ROC curve of the *high-gap MSPR* group lies mostly above the ROC curve of the *low-gap MSPR* group. Therefore, the area under the ROC curve is higher

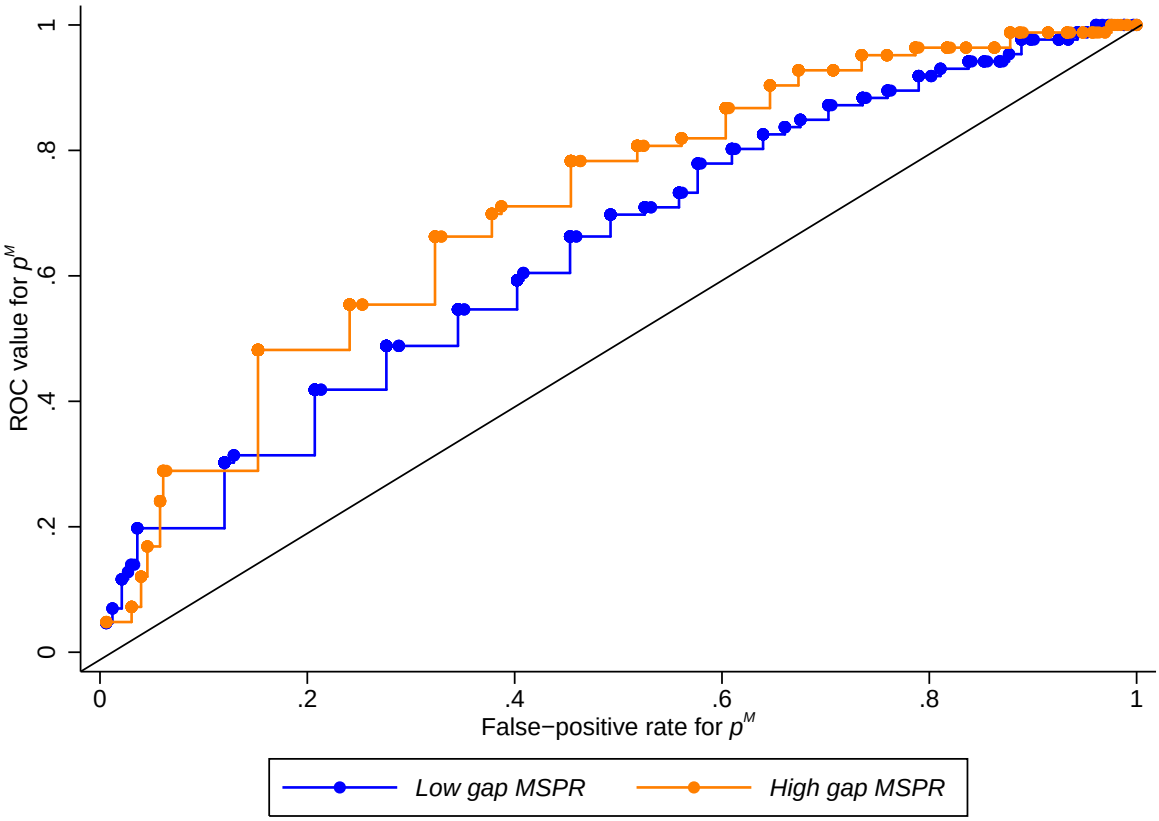


Figure A.1: Nonparametric ROC estimation

for the *high-gap MSPR* group (0.707) than the area for the *low-gap MSPR* group (0.639), indicating a superior discrimination ability of the forecasts from the *high-gap MSPR* group.

This finding is consistent with the results from the probit regression that relates the actual outcome Y (0/1) to the midquote prices for each liquidity group displayed in Table A.1. The R^2 from the *high-gap MSPR* group is 11.12% and thus higher than the R^2 from the *low-gap MSPR* group of 8.23%. Therefore, the midquote prices from the *high-gap MSPR* group predict the actual outcome better than the midquote prices from the *low-gap MSPR* group.

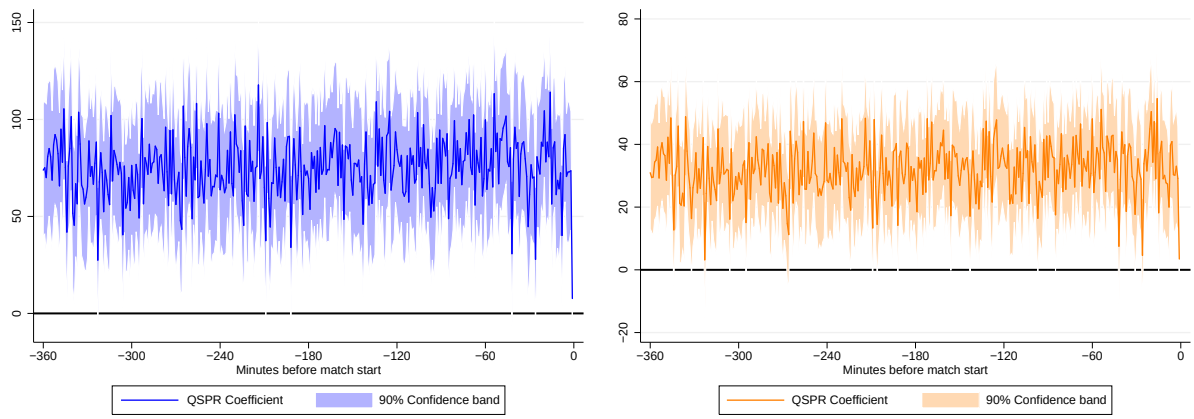
Table A.1: Results of the probit estimation

	Dependent variable: outcome Y (0/1)	
	Low-gap MSPR (1)	*High-gap MSPR* (2)
p^M	0.844***	1.090***
	(0.185)	(0.177)
home	0.142**	-0.047
	(0.062)	(0.053)
away	0.048	-0.006
	(0.049)	(0.046)
R^2	8.23%	11.12%
N	419	411

Notes: The table presents the marginal effects of a probit regression for the actual outcome of a bet (0/1) for the two groups *low-gap MSPR* and *high-gap MSPR*, separately. The groups are formed from observations located ±0.025 price units around the discontinuity gaps of the $MSPR$ function. The data are taken 60 minutes before each match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. The reference category for the event dummies is the *draw*. The standard errors are robust to heteroskedasticity and clustered at the match level. in all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

A.2 Estimated liquidity effect over time

Figure A.2 displays the coefficient estimates for the quoted spread on the Brier skill score and on the absolute error skill score over the last three hours before match start. The coefficient of $QSPR$ on BSS is always positive and seems to be stable around 70. However, there are cases in which the coefficient loses its significance. Nevertheless, over 98% of the p-values for the coefficients are smaller than 5%. For the coefficients of $QSPR$ on $AESS$, more than 94% of the p-values exhibit a value smaller than 5%. The results are qualitatively the same if we use $QSPL$ or $LnVOL$ as liquidity measures.



(a) Estimated coefficient of $QSPR$ on BSS

(b) Estimated coefficient of $QSPR$ on $AESS$

Figure A.2: Estimated liquidity coefficients over time

A.3 Estimates for *AESS* for weekend and weekday matches

Table A.2: Second-stage results of 2SLS model estimation for *AESS* for weekend and weekday matches

	AESS					
	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QSPR}$	37.94***	1.24				
	(9.89)	(21.55)				
$\widehat{QSLP}$			598.18***	22.55		
			(160.74)	(391.22)		
$\widehat{LnVOL}$					-0.406***	-0.026
					(0.125)	(0.448)
p^M	-1.017***	-0.921***	-0.901***	-0.918***	1.250*	-0.767
	(0.096)	(0.182)	(0.103)	(0.192)	(0.696)	(2.676)
home	0.381***	0.335***	0.377***	0.335***	0.663***	0.353
	(0.027)	(0.053)	(0.027)	(0.052)	(0.100)	(0.342)
away	0.174***	0.185***	0.162***	0.185***	0.420***	0.205
	(0.018)	(0.036)	(0.019)	(0.035)	(0.081)	(0.353)
Primera División	0.011	-0.016	-0.014	-0.017	-0.415**	-0.047
	(0.021)	(0.040)	(0.022)	(0.040)	(0.134)	(0.517)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1,786	441	1,786	441	1,786	441
$F(10; 1{,}775/430)$	39.89***	10.92***	37.12***	10.91***	19.41***	10.91***
F-test of excl. instr.	1,637***	683***	649***	192***	30.37***	1.71

Notes: The table reports the second-stage estimates for the absolute error skill score ($AESS$) for weekend and weekday matches separately. The data are taken 60 minutes before each match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. The F-test of excluded instruments refers to the first stage. The reference categories are the *draw* and the *English Premier League* for the event and league dummies, respectively. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

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