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Abstract

This paper examines how liquidity affects market efficiency in a market environment where securities' fundamental values are revealed at a predetermined point in time. We employ differences in minimum tick sizes at the betting exchange *Betfair* which induce 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. As uninformed noise bettors are more likely to bet on weekends than on weekdays, the type of liquidity seems to matter 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 prices of securities fully reflect all information available (Fama, 1991). This paper tests how liquidity affects informational market efficiency. The relation between liquidity and efficiency is controversial. On the one hand, liquidity lowers transaction costs and the impact of individual orders on prices (O'Hara, 1995). Thus, arbitrageurs have more incentive to acquire information and trade more aggressively on this information, which should force the prices to drift closer to their fundamental values (Kyle, 1985). Several empirical studies show that increasing liquidity results in enhanced market efficiency (e.g., Chordia, Roll, & Subrahmanyam, 2008; Chung & Hrazdil, 2010a; Sadka & Scherbina, 2007; Wurgler & Zhuravskaya, 2002). On the other hand, high liquidity due to irrational noise traders could prevent arbitrageurs from trading sufficiently against them and result in a higher mispricing relative to the prices in illiquid markets (Shleifer & Vishny, 1997; De Long, Shleifer, Summers, & Waldmann, 1990). Bloomfield, OHara, and Saar (2009) and Linnainmaa (2010) provide empirical evidence of greater mispricings in liquid markets.

Empirical financial studies face two major limitations when investigating the relation between liquidity and market efficiency. First, 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 an endogenous function of the pricing accuracy. In models of adverse selection, for example, a release of information about a security's fundamental values, i.e., an improvement in market efficiency, is associated with preceding periods of illiquidity 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, betting exchanges differ from financial markets in their informational environment. Betting contracts have a clear endpoint at which their fundamental value is revealed. Furthermore, the underlying outcome of such contracts, e.g., the home team to win a match, is affected neither by the trader's expectations nor by macroeconomic factors. By contrast, traditional financial securities are infinitely lived and have, unless the underlying firm goes bankrupt, no point in time where the true fundamental value is revealed. Thus, betting markets offer a unique setting for measuring the informational market efficiency of prices (Sauer, 1998; Verbeek, 2011).

So far, few studies link 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 the 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. Croxson and Reade (2011) use high-frequency in-play betting data on soccer matches from a betting exchange and do not find any significant relationship between liquidity and market efficiency. They do not address the endogeneity of liquidity.

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*. In combination with the observation of the fundamental value of the contracts traded at the betting exchange, this exogenous variation means that *Betfair* offers a quasi-experiment to investigate the influence of liquidity on market efficiency.

We use betting contracts on 2,227 soccer matches played in the *English Premier League* from 2006-2011 and in the *Spanish Primera Divisón* from 2009-2011 traded at the betting exchange *Betfair*. Using different liquidity and efficiency measures, the results from our

two-stage least squares model (2SLS) estimation show that market efficiency is negatively associated with liquidity.

Earlier studies (Kopelman & Minkin, 1991; Sobel & Raines, 2003; Sung & Johnson, 2007) 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. We find that the negative effect of liquidity is more pronounced for weekend matches whereas 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 fundamental 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).

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data and discusses how we process our empirical analysis. Section 4 reports the main estimation results and Section 5 concludes.

2 Literature Review

The relation between liquidity and market efficiency has important implications for policy makers and regulators. From a theoretical perspective, two competing hypotheses have evolved. On one side, liquidity facilitates the elimination of mispricings and thus increases market efficiency due to lower transaction costs (O'Hara, 1995). On the other side, liquidity due to uninformed or irrational noise trading decreases market efficiency because rational agents are unable to fully offset noise traders' biases (De Long et al., 1990).

Earlier studies within the market microstructure literature have also addressed the link between liquidity and market efficiency. However, the findings are widely inconsistent.

Several studies support the view that prices of securities in liquid markets exhibit higher market efficiency. 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.

Wurgler and Zhuravskaya (2002) provide indirect empirical evidence and 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 present a higher arbitrage risk, exhibit a steeper demand curve and higher mispricing. As steeper demand curves imply less liquidity, mispricing is greater in illiquid markets due to risk averse arbitrageurs who will trade less aggressively when arbitrage risk is high.

Sadka and Scherbina (2007) provide further evidence for a positive link between liquidity and market efficiency. They investigate stocks with high analyst disagreement. As the information about the earnings becomes publicly available at a certain point in time, mispricing of such stocks tends to be short-lived. Sadka and Scherbina (2007) find that less liquid stocks tend to be more severely overpriced due to higher trading costs. In an additional time series analysis, the authors show that increasing aggregated liquidity accelerates the convergence of prices to fundamentals.

The study of Chordia et al. (2008) is one of the first to analyze the short horizon return predictability in connection with liquidity. The authors examine the five-minute return predictability from lagged order flow of 193 NYSE firms as an inverse measure of market efficiency. Between 1993 and 2003, the minimum tick size in bid-ask spreads decreased, providing an exogenous increase in liquidity. Because return predictability declined across

the three tick size regimes, liquidity is found to be positively related to market efficiency. Chordia et al. (2008) conclude that higher liquidity facilitates efficiency via two distinct channels. First, arbitrageurs better absorb the asymmetric order flow in periods of high liquidity, which speeds up the convergence of prices to fundamental values. Second, the reduced minimum price change enables the correction of smaller mispricings.

Chung and Hrazdil (2010a) apply the methodology of Chordia et al. (2008) to a comprehensive sample of 4,222 NYSE firms between 1993 and 2004. Using the inverse adjusted R^2 from the estimation results of the short horizon return prediction as a proxy for market efficiency, the authors find that liquidity measured as the inverse effective bid-ask spread is positively related to market efficiency. This positive relation is amplified during periods of newly disclosed information. The findings of Chung and Hrazdil (2010a) are robust to potential confounding effects emerging from the trading frequency and the firm size. A further study by Chung and Hrazdil (2010b) investigates the return predictability of 11,073 NASDAQ firms across three minimum tick size regimes. As before, they observe that liquidity increases market efficiency.

One major concern of using the return predictability as an inverse indicator of market efficiency is that large deviations from fundamental values could be present without leaving statistically identifiable traces in the pattern of ex-post returns (Summers, 1986). Additionally, Chordia et al. (2008) and Chung and Hrazdil (2010a, 2010b) analyze the relation between liquidity and market efficiency during a time period in which large technical advances were made and access to information became less costly. Hence, contemporaneous confounders are very difficult to rule out.

Other studies support the view that prices of securities in liquid markets exhibit lower market efficiency. De Long et al. (1990) argue that noise traders' beliefs could deviate from the asset's fundamental value over long periods of time. 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.

Moreover, the model of Shleifer and Vishny (1997) challenges the view that a large number of tiny arbitragers with small stakes are the ones taking position against mispricings. In fact, the small traders are typically not the ones who are informed. Rather, arbitrage is conducted by a relatively small number of professionals who take large positions with funds from outside investors. When prices diverge far from fundamental values due to noise traders, arbitrageurs with their own funds would generally increase their positions. However, arbitrageurs who manage other people's money have to fear an early liquidation of the positions due to their investors' pressure. Hence, arbitrageurs tend to avoid such volatile positions, which makes them less effective in achieving market efficiency.

One explanation of the persistence of mispricing over longer periods of time is investor sentiment that results from psychological misperceptions in making forecasts. For example, Barberis et al. (1998) predict in their theoretical model that investors underreact to earnings announcements and similar events, and overreact to consistent patterns of good or bad news.

In an experimental market study, Bloomfield et al. (2009) examine how uninformed noise trading affects market efficiency. As expected, such traders increase the market liquidity dramatically. However, the presence of uniformed noise traders also harms 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. In his data set from Finland, 76.3% of individuals' orders are limit orders. One reason for individual traders to use limit orders is the potential gain from the liquidity demand of impatient investors who place

market orders. However, their limit orders only execute if the price moves against the order, for example around positive earnings announcements. As a result, such individual and uninformed traders can be interpreted as liquidity providers who harm the process of adjustment to the intrinsic value.

Studies that investigate the link of liquidity and market efficiency in prediction and/or betting markets are scarce. Tetlock (2008) investigates contracts on binary financial and sporting event outcomes from the *TradeSports* exchange, where the fundamental values of the contracts are revealed at a predetermined point in time. To overcome the reverse causality problem between liquidity and efficiency, Tetlock (2008) constructs instrumental variables based on the exchange-wide liquidity. However, if aggregated liquidity is related to aggregated mispricing, those instruments may not fully resolve the endogeneity problem. One likely scenario would be that the aggregated liquidity at the weekend is widely influenced by casual bettors who might also affect the market efficiency. The results of Tetlock (2008) indicate that liquidity increases the deviation of prices from the fundamental value of the contracts and thus harms market efficiency. Similar to Linnainmaa (2010), he explains this finding by naive and passive limit order traders who bet against market order traders in informative periods and thus decelerate the response of prices to information.

Hartzmark and Solomon (2012) provide further evidence for the negative effect of liquidity on market efficiency in betting markets. They examine NFL betting contracts from the *TradeSports* exchange and find that the more liquid Monday Night games exhibit greater mispricings than other games.

Croxson and Reade (2011) use high-frequency soccer betting market data from the betting exchange *Betfair*. Although the main focus lies on a general assessment of the market efficiency at the betting exchange, Croxson and Reade (2011) investigate whether liquidity affects mispricings. Using the squared difference between the efficient price drift estimated by a Poisson model and the actual price drift as efficiency measure, the authors

are unable to find any effect of liquidity on mispricings and conclude that the price drift is efficient. However, the study of Croxson and Reade (2011) does not address the potential simultaneity of liquidity and market efficiency.

Overall, previous findings are inconsistent with regard to the general effect of liquidity on market efficiency. However, there is wide consensus that *noise trader liquidity* decreases market efficiency.

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 are less informed. Finally, Sung and Johnson (2007) provide evidence that prices for weekend markets exhibit lower market efficiency than weekday markets because weekend markets are populated by a larger proportion of noise bettors.

This paper is the first to investigate the relation between liquidity and market efficiency in a setting where exogenous variation in liquidity is created by different minimum tick sizes and the fundamental values of securities are revealed at a predetermined point in time. By investigating the effect of liquidity on market efficiency for weekend and weekday matches separately, we are able to test the hypothesis that noise trader liquidity decreases market efficiency.

3 Data and Methodology

3.1 Sample

We use betting data on professional soccer matches from the popular *winner* betting contracts on *home win*, *draw* or *away win* 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 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 for an *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., *home win*, *draw* and *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 have been 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

[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.

the current limit order volume available on both back and lay bets and the cumulative trading volume until time t before match start.

3.2 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, & Subrahmanyam, 2001; Hasbrouck & Seppi, 2001; Lin, Snager, & Booth, 1995). The spread approximates the costs incurring 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 in 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 positive, but the minimum quoted spread does not predict the actual quoted spread perfectly. Moreover, there are clear drops in the quoted spreads at midquote price levels of 0.50 and 0.33, for example.

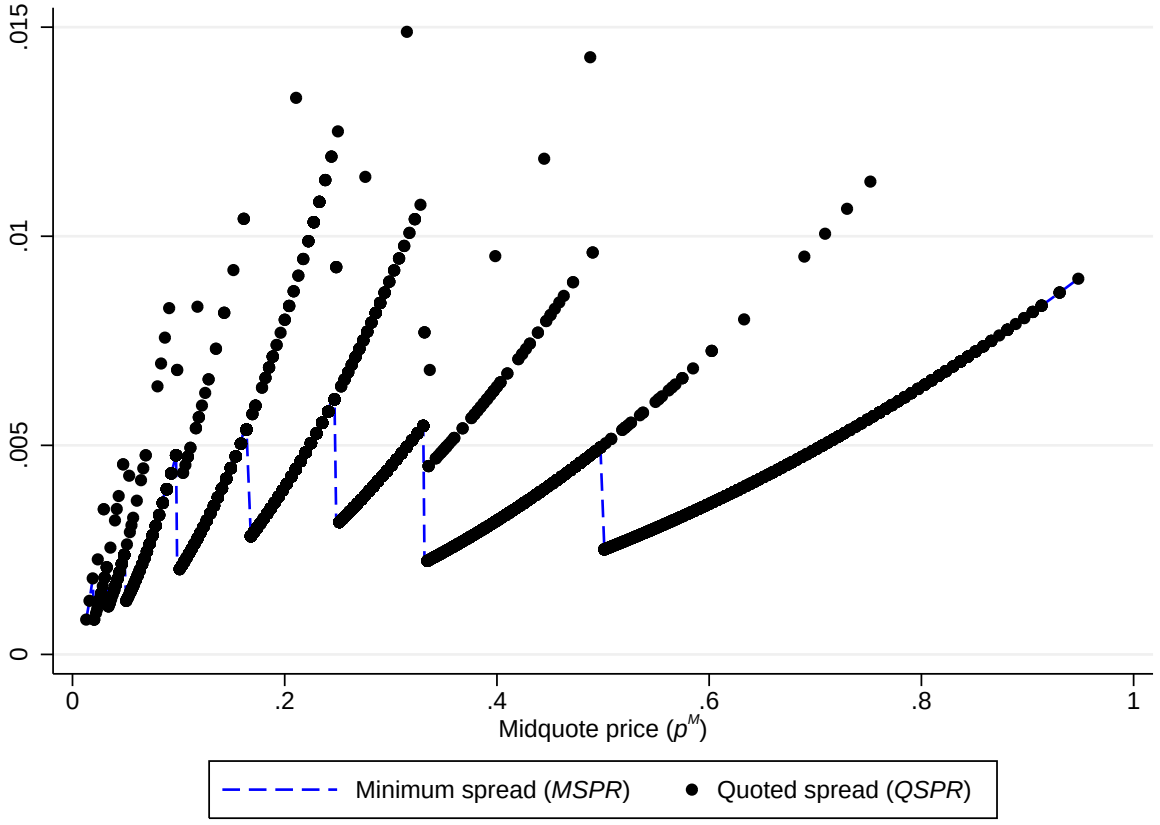


Figure 1: Minimum spread function and quoted spread

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.

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

Table 2 reports summary statistics associated with our liquidity measures 60 minutes before match start. Because each of the 2,227 matches consists of the three events *home win*, *draw* and *away win* the total number of observations is 6,681. As expected, the average quoted spread is higher than the average minimum quoted spread. The average cumulative volume traded is £248,000.

Table 2: Summary statistics of liquidity measures (60 minutes before match start)

Variable	Description	N	Mean	Std. Dev.	Min	Max
$MSPR$	Minimum quoted spread	6,681	0.0040	0.0010	0.0008	0.0090
$QSPR$	Quoted spread	6,681	0.0042	0.0014	0.0008	0.0149
$QSLP$	Quote slope	6,681	0.0003	0.0001	0.0001	0.0012
$LnVOL$	Log. cum. volume traded	6,681	11.261	1.5003	7.3708	15.541

Notes: The table reports the summary statistics of liquidity measures 60 minutes before match start. The data is obtained from *Fracsoft* and spans the seasons 2006/07-2011/12, including matches from the *English Premier League* and the *Spanish Primera Divisón*. The total number of matches is 2,227, with each match covering the three events *home win*, *draw* and *away win*.

3.3 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. One of the most widely

used reference forecasts is the *climatological probability* of the outcome to occur (Jolliffe & Stephenson, 2003). In our setting, the *climatological probability* is the noninformative price of 0.333 for each of the three events within a match. Thus, the denominator takes on the value 0.444 if the outcome occurs and 0.111 if the outcome does not occur. The BSS ranges from one for a perfect forecast, through 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 uninformed reference forecast of 0.333. Table 3 reports the summary statistics of our market efficiency

Table 3: Summary statistics of efficiency measures (60 minutes before match start)

Variable	Description	N	Mean	Std. Dev.	Min	Max
BSS	Brier skill score	6,681	0.1166	0.8724	-6.5064	0.9985
$AESS$	Absolute error skill score	6,681	0.1511	0.4035	-1.7398	0.9613

Notes: The table reports the summary statistics of efficiency measures 60 minutes before a match start. The data is obtained from *Fracsoft* and spans the seasons 2006/07-2011/12, including matches from the *English Premier League* and the *Spanish Primera Divisón*. The total number of matches is 2,227, with each match covering the three events *home win*, *draw* and *away win*.

measures 60 minutes before match start. The positive means show that betting exchange prices incorporate more information on average than the reference forecast.

3.4 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

$$L_{iet} = \theta_0 + \theta_1 \cdot MSPR_{iet} + \theta_2 \cdot p^M_{iet} + \theta \cdot \Gamma_{iet} + u_{iet} \tag{5}$$

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

$$E_{iet} = \beta_0 + \beta_1 \cdot \widehat{L_{iet}} + \beta_2 \cdot p^M_{iet} + \beta \cdot \Gamma_{iet} + \epsilon_{iet} \tag{6}$$

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).

Third, we split our sample into matches played on weekends and on weekdays and estimate Equations (5) and (6) for weekend and 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. Because all teams in the same league play the same number of weekday matches, this allocation is neither correlated with certain teams nor with their objective winning probability (Franck et al., 2011).

4 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 market efficiency measure, Panel B uses $AESS$ as efficiency measure. Table 4 shows that market efficiency is significantly higher in the *high gap MSPR* group than in the *low gap MSPR* group, independent of the efficiency measures and tests employed.[2]

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, 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 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 *English Premier League* are associated with

[2]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)

Table 4: Liquidity and market efficiency at discontinuity area

Panel A: comparison of BSS

		t-test			Wilcoxon rank sum test		
	N	Mean	SE	t	rank sum	expected	z
Low gap MSPR	1,353	0.3442	0.0151		1,584,839	1,730,487	
High gap MSPR	1,204	0.3887	0.0176		1,685,564	1,539,916	
Δ	2,557	-0.0445	0.0230	-1.932*			-7.817***

Panel B: comparison of $AESS$

		t-test			Wilcoxon rank sum test		
	N	Mean	SE	t	rank sum	expected	z
Low gap MSPR	1,353	0.2652	0.0093		1,584,839	1,730,487	
High gap MSPR	1,204	0.3149	0.0108		1,685,564	1,539,916	
Δ	2,557	-0.0498	0.0145	-3.507***			-7.817***

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. 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.

more liquidity than matches played in the *Spanish Primera Divisón*. This 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 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.[3] In all specifications we include the midquote price p^M, event dummies, a league dummy for the *Primera División* and seasonal dummies as control variables.[4]

We run the regressions separately for each minute during the last three hours before

[3]The results remain virtually the same if we use the effective spread as an alternative spread-related 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 employed by other studies such as Bloomfield et al. (2009), Wolfers and Zitzewitz (2004) or Snowberg and Wolfers (2010).

[4]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 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 is taken 60 minutes before the match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

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 suggests that the negative relation between liquidity and market efficiency is robust over time.

In the following, we test whether the negative effect of liquidity on market efficiency is more pronounced on weekends when the relative fraction of uninformed noise traders is larger than on weekdays. 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. Table 7 uses BSS as efficiency measure. However, the results are qualitatively the same if we use $AESS$ as efficiency measure (see Table A.2 in Appendix A.3).

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

	BSS			$AESS$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QSPR}$	52.45**			30.99***		
	(20.54)			(9.730)		
$\widehat{QSLP}$		846.23**			500.01***	
		(334.01)			(159.97)	
$\widehat{LnVOL}$			-0.574**			-0.339***
			(0.242)			(0.119)
p^M	-2.217***	-2.063***	0.994	-0.958***	-0.867***	0.939
	(0.186)	(0.213)	(1.410)	(0.079)	(0.091)	(0.680)
home	0.054	0.049	0.449**	0.090***	0.086***	0.323***
	(0.038)	(0.038)	(0.182)	(0.019)	(0.019)	(0.091)
away	0.029	0.013	0.384**	0.090***	0.081***	0.230***
	(0.027)	(0.027)	(0.159)	(0.015)	(0.015)	(0.080)
Primera División	0.051	0.015	-0.573**	0.031	0.010	-0.338**
	(0.047)	(0.049)	(0.269)	(0.021	(0.023)	(0.132)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	2,227	2,227	2,227	2,227	2,227	2,227
$F(10; 2{,}216)$	23.85***	23.70***	19.03***	25.77***	25.16***	17.56***

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

5 Conclusion

This paper analyses 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 weekend matches are expected to exhibit more irrational noise bettors than 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

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)
$\widehat{QSPR}$	61.28***	18.11				
	(23.032)	(46.68)				
$\widehat{QSLP}$			966.20***	328.84		
			(366.69)	(848.24)		
$\widehat{LnVOL}$					-0.656**	-0.377
					(0.267)	(1.035)
p^M	-2.266***	-1.962***	-2.080***	-1.914***	1.396	0.282
	(0.211)	(0.392)	(0.241)	(0.453)	(1.543)	(6.303)
home	0.051	0.069	0.045	0.067	0.506**	0.336
	(0.043)	(0.079)	(0.043)	(0.078)	(0.203)	(0.759)
away	0.024	0.032	0.006	0.029	0.422**	0.320
	(0.030)	(0.070)	(0.031)	(0.065)	(0.169)	(0.832)
Primera División	0.054	0.036	0.014	0.023	-0.634**	-0.405
	(0.053)	(0.101)	(0.056)	(0.101)	(0.288)	(1.207)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1,786	441	1,786	441	1,786	441
$F(10; 1{,}775/430)$	20.45***	4.28***	20.32***	4.27***	16.50***	3.61***
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 is taken 60 minutes before the 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. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

for weekday matches. On weekend matches, informed bettors seem to be unable to bet aggressively enough against uninformed and sentimental noise bettors to correct mispricings.

Our findings suggest that noise trader liquidity can destabilize prices and harm market efficiency. Whereas the mispricing period in betting markets is limited by the end of the match, mispricing periods due to noise trader liquidity can last much longer in financial markets.

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 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 for the *high*

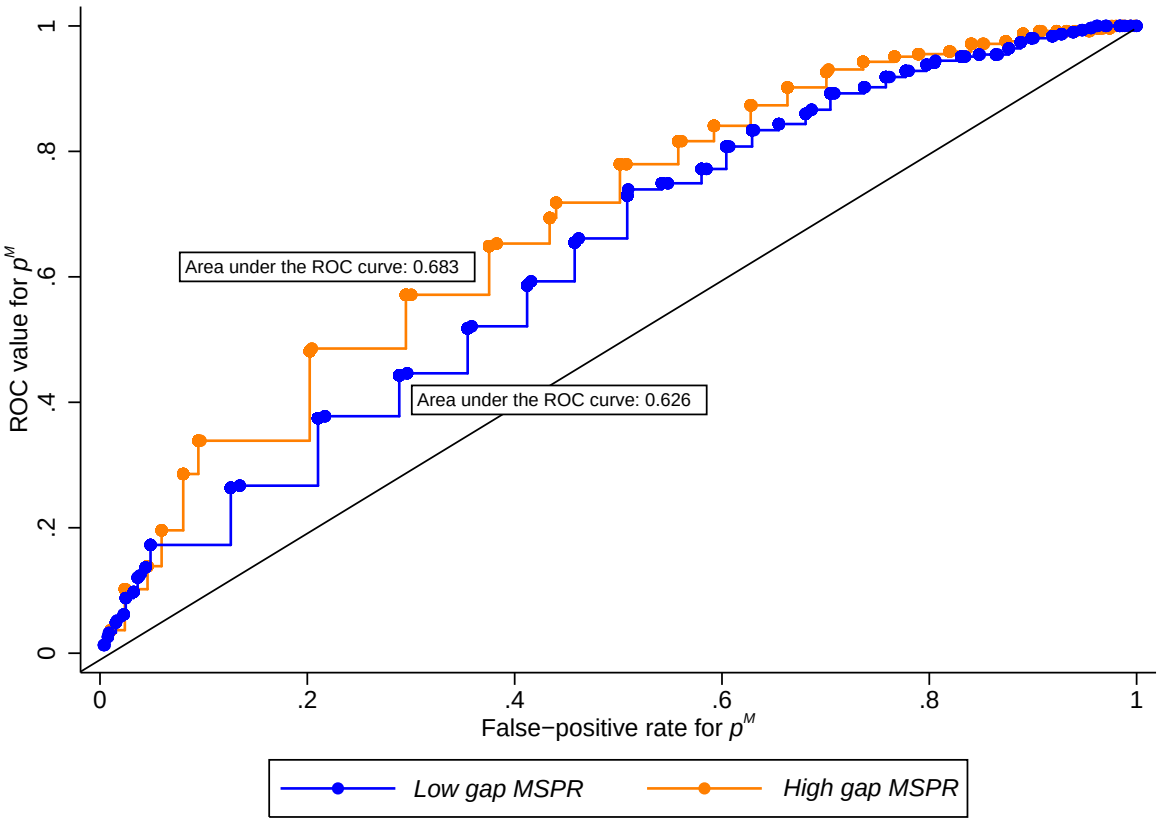


Figure A.1: Nonparametric ROC estimation

gap MSPR group (0.683) than the area for the *low gap MSPR* group (0.626), 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 9.43% and thus higher than the R^2 from the *low gap MSPR* group of 6.10%. 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.

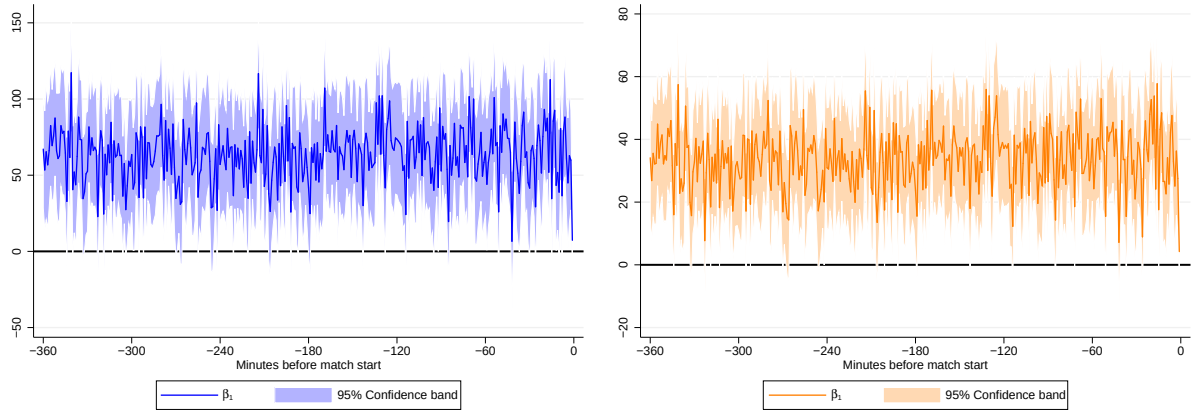
Table A.1: Results of probit estimation

	Dependent variable: outcome Y (0/1)	
	Low gap MSPR (1)	*High gap MSPR* (2)
p^M	0.841***	0.926***
	(0.100)	(0.096)
home	0.053	-0.027
	(0.035)	(0.035)
away	-0.024	-0.011
	(0.027)	(0.027)
R^2	6.10%	9.43%
N	1,353	1,204

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 standard errors are robust to heteroskedasticity and clustered at 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 50. However, there are cases in which the coefficient loses its significance. Nevertheless, over 88% of the p-values for the coefficients are smaller than 5%. For the coefficients of $QSPR$ on $AESS$, more than 92% 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 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)
$\widehat{QSPR}$	35.66***	10.96				
	(10.90)	(21.51)				
$\widehat{QSLP}$			562.18***	198.85		
			(175.78)	(392.30)		
$\widehat{LnVOL}$					-0.382***	-0.228
					(0.132)	(0.480)
p^M	-0.959***	-0.921***	-0.850***	-0.893***	1.172	0.435
	(0.090)	(0.169)	(0.104)	(0.189)	(0.750)	(2.882)
home	0.083***	0.110***	0.080***	0.109***	0.348***	0.272
	(0.022)	(0.041)	(0.022)	(0.040)	(0.102)	(0.358)
away	0.086***	0.097***	0.075***	0.095***	0.317***	0.271
	(0.017)	(0.034)	(0.017)	(0.033)	(0.085)	(0.383)
Primera División	0.036	0.008	0.013	-0.0005	-0.364**	-0.260
	(0.024)	(0.044)	(0.026)	(0.045)	(0.143)	(0.562)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1,786	441	1,786	441	1,786	441
$F(10; 1{,}775/430)$	21.61***	5.47***	20.98***	5.43***	14.65***	4.45***
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 is taken 60 minutes before the 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. 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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