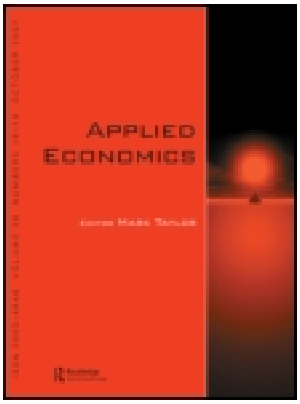

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Evidence of in-play insider trading on a UK betting exchange

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Evidence of in-play insider trading on a UK betting exchange

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An open question in market microstructure is whether 'informed' traders have an advantage due to access to private, inside, information; or due to a superior ability to process public information. In this article we attempt to answer this question with data from a sports betting exchange taken during play. Uniquely, this allows us to time-stamp information events to the nearest second, and to ensure we are observing all relevant information regarding the value of an asset. We find evidence of inside information but not of a superior ability to process public information. The first finding suggests that a subset of the betting population are observing the action before the wider public (possibly due to delays in the television signal), and betting using this informational advantage.

I. Introduction

There is a rich history of empirical betting market studies to explore financial market theories. In particular, betting markets have proved a popular setting for tests of market efficiency, and interest has been focused on a persistent anomaly: the favourite/long-shot bias, where returns on favourites exceed those on long-shots.[1] In this article we use betting market data to test two hypotheses from market microstructure.

The initial motivation for market microstructure research was a realization that Walrasian equilibrium was a poor characterization of the type of trade carried out on major stock exchanges.[2] In a continuous time trading environment an intermediary is either contracted to, or can extract profits from, the provision of liquidity. The costs of this intermediation distort the quoted bid and ask prices from the asset's fundamental value. Analysis of the formation of price, which had previously focused on the fundamentals of the asset, now needed to include the payoffs and preferences of the intermediary.

In the Glosten and Milgrom (1985) model, the specialist market-maker trades an asset with a population composed of informed traders, who have private, inside, information on the fundamental value of the asset, and liquidity traders, who trade randomly. A bid–ask spread is charged in order to offset losses to the informed with gains from liquidity traders. This is the adverse selection component of the bid–ask spread. Extrapolating this result, if a subset of the trading population has private information on the contents of a forthcoming public announcement, then the bid–ask spread will increase prior to, and during, the announcement.

Kim and Verrecchia (1994) endogenize the acquisition of private information by adding a trading

[1] The first observation of the bias, in Griffith (1949), predated the market efficiency literature. Ottaviani and Sørensen (2008) survey the technical explanations of the bias. For a more general survey of market efficiency in betting markets, see Vaughan Williams (2005).

[2] Garman (1976) was the author to coin the term 'market microstructure'. For a review of the market microstructure literature, see O'Hara (1995), Madhavan (2000), Biais *et al*. (2005) and, for empirical work, Hasbrouck (2007).

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group which processes information. Their information advantage materializes after information on the asset is publicly announced, as they are able to create private information via their analysis. The specialist market-maker will therefore increase the bid–ask spread after a public announcement to offset losses to the information processors. This model interestingly proposes that information disclosure can increase, rather than limit, adverse selection if the signal received from information is noisy.

In the context of information arrival, the two models lead to the following noncompeting hypotheses:

Hypothesis 1: The adverse selection component of the bid–ask spread arises due to asymmetric information prior to public information arrival.

Hypothesis 2: The adverse selection component of the bid–ask spread arises due to asymmetric abilities to process symmetric information after public information arrival.

A number of authors have examined the bid–ask spread in financial markets around significant information events in order to distinguish between the two hypotheses. Lee *et al*. (1993) find that spreads widen both before and after earnings announcements, although the effect after an announcement is short-lived. Krinsky and Lee (1996) decompose the bid–ask spread into its adverse selection, transaction cost and inventory-control components, and find that the adverse selection component of the bid–ask spread increases both prior to and after an earnings announcement. Gajewski (1999), in a study of earnings announcements on the Bourse de Paris, finds greater support for Hypothesis 2.

In our study we examine bid–ask spreads on a betting exchange, both before a sporting event, when information arrival is infrequent, and during an event, when information arrival is highly frequent. The advantage of such a setting is that information arrival can be time-stamped to the nearest second. Previously, information arrival in this context was identified only to the nearest minute (Gajewski, 1999). In addition, while the announcement of information in a financial market does not preclude the prior existence, or subsequent arrival, of private information not observed by the public, in a sporting environment, once play has begun, all information relevant to the value of a betting asset is observable. This allows us to correctly isolate the effects of information arrival. A final advantage lies in the fact that betting market assets have a reasonable probability of default. The importance of new information for the value of a betting asset is greater than new information in a financial market, where the probabilility of default, regardless of the information content, is minimal. Adverse selection in a betting market should therefore be more pronounced.

The betting price data we use in this article is taken from a tennis match. Tennis is chosen because information events are of sufficient length and can be foreseen. For example, a tie-break is often important in determining the outcome of a match and takes place over a sufficient period of time for bettors to realize the importance of the play whilst it occurs.[3] In contrast, a goal is important in determining the outcome of a football match but is short lived and cannot necessarily be foreseen. In our study, information periods are separated into four, with a *low-information period* prior to play and during rain breaks; an *intermediate information period* whilst the match is in play; a *high-information period* during tie-breaks and a *post-high information period* immediately following a tie-break. We find that the adverse selection component of the bid–ask spread increases during our high-information period, but decreases, even relative to our intermediate information period, immediately after the high-information period. This lends support to Hypothesis 1, but not Hypothesis 2.

This brings us to the question of the nature of inside information on a betting market. Prior to play this could take the form of information on the wellbeing, fitness or determination of the athlete. Once the match has begun, such information is typically revealed to the public in the early stages of play. However, we observe that inside information increases during a match, and, further, appears to spike during moments of importance, such as tie-breaks. In other words, inside information is being created during a match. We therefore propose that informed bettors derive their advantage from observing the action before the rest of the public. Television pictures typically transmit with a few seconds delay and therefore bettors with a faster transmission, or present at the game, are able to trade on an informational advantage.[4] To capitalize on this fleeting advantage, bettors would need to feed this information into a computer and initiate bets via an algorithm. In these circumstances, a high-frequency trading strategy (e.g. trading after each point) would generate significant returns.

This article is organized as follows. In Section II we describe the data and present some

[3] A tie-break is played at the end of a set if the players are tied on six games each. The winner of the tie-break wins the set.
[4] As we discuss in Section III, the betting exchange in question does take steps to limit this advantage.

descriptive statistics. In Section III we outline the methodology and provide results. Section IV concludes.

II. Data

The focus of our betting study is the Men's 2008 Wimbledon Tennis Final, between Roger Federer and Rafael Nadal. Described afterwards as 'one of the greatest finals of a grand-slam tournament' (*The Times*, 8th July 2008), this match attracted a lot of attention as it pitted the number one ranked player in the world (Federer) against the number two (Nadal), in the most prestigious of the grand-slam events. As an indication of the betting interest, Betfair, a betting exchange, matched GBP 28 334 894 on Nadal to win and GBP 20 802 434 on Federer to win.

We obtained Betfair betting price data for this match from Fracsoft, a company contracted to market historical pricing data for Betfair. The data available includes the quoted odds and respective volumes for each player to win, for 211 minutes and 48 seconds before the match begins, and also the 400 minutes and 44 seconds from the beginning of the match until the end. This gives us 36 752 seconds of pricing data for this match. The match itself lasted for 4 hours and 48 minutes but there were two rain delays, during which betting could continue. Bets on an exchange can be traded in the form of a back bet (where the bettor receives the stake plus the odds if the event occurs) or a lay bet (where a bettor receives the stake if the event does not occur but is liable for the odds if it does occur). From these quoted odds we calculated the back-lay (bid–ask) spread.

As well as a bet on a player to win, bets were traded on the score, in sets, by which a player would win. We used this data to identify the timing of tie-breaks. After a set ends (e.g. after a tie-break) and a particular set score is no longer possible, bets cease to be traded. This allowed us to time-stamp the end of the tie-break. We then calculated the length of the tie-break with video footage of the match. As a result we were able to identify the *low-information periods* (prior to play or during a rain break), the *intermediate information periods* (during play including tie-breaks), the *high-information periods* (during a tie-break), and finally the *post-high information periods* (immediately following a tie break).[5]

As well as this match, we carried out similar analysis on three matches at an earlier stage of this tournament. In these cases we did not have video footage, and so estimated the duration of tie-breaks as 5 minutes. Our statistical results for these matches were similar to those we report here, but because we were not able to cross-check the data with video footage, we limit the results we report to the 2008 Final.

This best of five set match finished three sets to two to Nadal. The third and fourth sets both went to a tie-break, with Federer winning both to stay in the match. The *high-information period* consists of the third set tie-break, which lasted 456 seconds, and the fourth set tie-break, which lasted 816 seconds. The *post-high information period* is defined in our study as the 5 minutes (300 seconds) that immediately follow each of those tie-breaks.[6]

The criteria of a relevant betting asset for our study is as follows. The asset must have been traded during at least two periods which qualify as *high-information periods* and two periods which qualify as *post-high information periods*. By this criteria, we analysed four bets: Federer to win, Nadal to win, Nadal to win 3-2 and Federer to win 3-2. All other set betting outcomes fell short of that criteria.

Table 1 outlines the descriptive statistics for the spreads quoted on the four assets. Spreads are converted into implied probability form. For example, if a back bet is quoted at 3-1, then the implied probability is $1/(3+1) = 0.25$. If the lay bet is quoted at 4-1, then the implied probability is $1/(4+1) = 0.2$, which results in a spread of $0.25 - 0.2 = 0.05$.

More generally, our measure of the bid–ask spread is

$$S = \frac{1}{O_b + 1} - \frac{1}{O_l + 1} \quad (1)$$

where O_b is the best back odds offered and O_l is the best lay odds offered.

The average spread is higher, and displays a greater SD, in the *high-information period* for all four assets. The difference is understandably most pronounced in assets 3 and 4, the set betting assets, which have the greatest variance in payoff. The average spread in the *post-high information period* is lower than the average spread in the *intermediate information period* for all four assets. This appears to suggest that spreads increase around important information arrival, but fall quickly once information has been revealed.

[5] There are undoubtedly times, other than during a tie-break, which could be classified as *high-information periods*. We could also include break-points, set-points and match points. However, these periods are shorter than tie-breaks which may not give the liquidity providers sufficient time to react to their existence.

[6] We also classified the *post-high information period* as 1 minute following the tie-break and the results were unaffected.

Table 1. The mean bid–ask spread (Equation 1, to 4 d.p.) for asset 1 (Nadal to win), 2 (Federer to win), 3 (Nadal to win 3-2) and 4 (Federer to win 3-2) as measured in all, low-, intermediate, high- and post-high information periods

Information period	1	2	3	4
All	0.0053 (0.0043)	0.0052 (0.0057)	0.0189 (0.0440)	0.0201 (0.0650)
Low	0.0038 (0.0000)	0.0032 (0.0000)	0.0053 (0.0011)	0.0055 (0.0013)
Intermediate	0.0061 (0.0051)	0.0062 (0.0068)	0.0261 (0.0530)	0.0278 (0.0793)
High	0.0098 (0.0084)	0.0131 (0.0168)	0.0910 (0.1636)	0.1170 (0.2200)
Post-high	0.0052 (0.0032)	0.0046 (0.0033)	0.0243 (0.0235)	0.0233 (0.0297)

Note: SDs are given in parentheses.

This lends support to the Glosten and Milgrom (1985)-based Hypothesis 1.

Figure 1 illustrates the evolution of the bid–ask spread from before play to during play. This figure represents the bid–ask spread in asset 1. The match begins at time 12 708 and the bid–ask spread is on average higher and more volatile after this time. In the next section we present our empirical model.

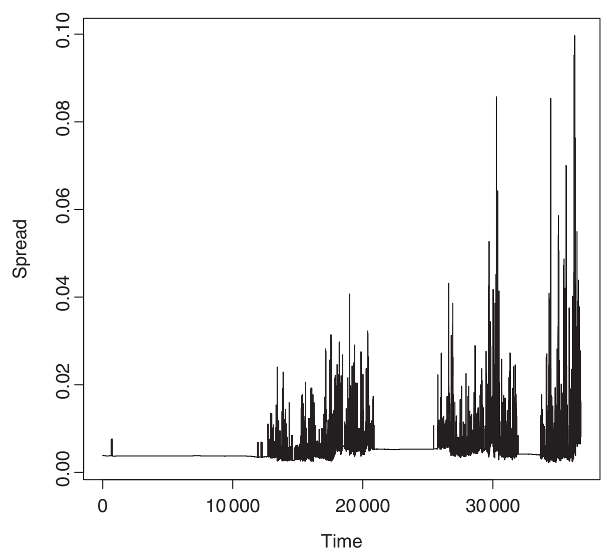

Fig. 1. The bid–ask spread, as defined in Equation 1, for asset 1 (Nadal to win). The match began at Time = 12 708

III. Methodology and Results

Our aim in this section is to control for the elements of the bid–ask spread which could be ascribed to transaction costs, inventory-control effects or a lack of competition in liquidity provision, and therefore isolate the adverse selection component. In addition, we need to control for autocorrelation in the spreads as the spreads at nearby time periods are not independent.

To test our two hypotheses, we considered the following regression model for each of the four assets:

$$S_t = \beta_0 + \beta_1 S_{t-1} + \beta_2 V_t + \beta_3 D_t + \beta_4 B_t + \beta_5 P_t + \epsilon_t \tag{2}$$

At time t, S_t is the spread as defined in Equation 1, S_{t-1} the spread at the previous time point, V_t is the sum of the volume available at the best three back and lay odds and D_t, B_t and P_t are indicator variables, determining if t is during a *intermediate period* (during the match), a *high-information period* (during a tie-break) or a *post-high information period* (in the 300 seconds following a tie break), respectively. β_0, β_1, β_2, β_3, β_4, β_5 are fixed coefficients and ϵ_t is an error term with the usual Ordinary Least Squares (OLS) assumptions.

We include the spread at the previous time point to control for temporal dependencies between spreads, and a measure of volume to control for illiquidity which can cause spreads to widen irrespective of adverse selection. We also expect that our measure of volume controls for inventory-control effects, as the impact of a liquidity provider's inventory considerations would be limited in a liquid market.[7]

In this model β_0 has an economic interpretation. This is the component of the bid–ask spread which arises regardless of the informational considerations. This is a positive fixed transaction cost to cover the

[7] The inventory-control literature largely assumes that liquidity is provided by a contracted specialist who is obligated to provide liquidity continuously (Stoll, 1978; Amihud and Mendelson, 1980; O'Hara and Oldfield, 1986). When the liquidity provider does not have an obligation to trade continuously, as would be the case with a betting limit order trader, they can maintain a desired exposure to the event by placing market orders. In addition, the effect of inventory on price is transient and, particularly in a liquid market, should therefore be negligible.

Table 2. The results of the OLS estimation of Equation 2 for assets 1 to 4

	1	2	3	4
β_0	1.117e−03*** (<2e−16)	1.318e−03*** (<2e−16)	4.380e−04 (0.12576)	1.084e−03** (0.001255)
β_1	7.236e−01*** (<2e−16)	7.691e−01*** (<2e−16)	9.303e−01*** (<2e−16)	9.355e−01*** (<2e−16)
β_2	−7.112e−10*** (2.62e−06)	−3.128e−09*** (<2e−16)	−1.084e−08 (0.42213)	−1.541e−07** (0.00769)
β_3	5.796e−04*** (<2e−16)	1.509e−04** (0.007)	1.131e−03** (0.001205)	5.640e−04* (0.045465)
β_4	1.067e−03*** (<2e−16)	1.584e−03*** (<2e−16)	4.809e−03*** (<2e−16)	6.035e−03*** (<2e−16)
β_5	−2.751e−04** (0.0087)	−2.817e−04* (0.0218)	−8.338e−05 (0.446775)	−3.459e−05 (0.4847)
Adj.R^2	0.5714	0.6457	0.8831	0.8876

Notes: One-sided p-values are given in parentheses.
*, ** and *** signals significance at the 5, 1 and 0.1% levels, respectively.

labour and computing resources involved in providing liquidity. We also require that $\beta_2 < 0$ as the bid–ask spread increases as competition, proxied by volume, decreases.

By Hypothesis 1, we expect that $\beta_3 > 0$ and $\beta_4 > 0$. When information is arriving, the liquidity providers should increase the bid–ask spread to guard against those with prior access to this information. For Hypothesis 2, we require that $\beta_5 > 0$. That is, the bid–ask spread is increased immediately after an important information event as a subset of the betting population has superior abilities to process this information and assess the fundamental value of the traded bet. In addition, Hypothesis 2 requires $\beta_3 > 0$ as those with superior analytical abilities can put them to work on smaller information events.

Table 2 reports our results for the estimation of Equation 2. Diagnostic plots suggest that the model assumptions are valid. In what follows, 'significant' indicates significance at the 5% level and 'highly significant' indicates significance at the 1% level. $B_0 > 0$ for all four assets and highly significant in three of them, and $\beta_2 < 0$ for all four assets and highly significant in three of them. As our rationale outlined above, there is evidence of a fixed transaction cost component of the bid–ask spread, and that the bid–ask spread decreases as volume increases.

We find that $\beta_3 > 0$ for all four assets and highly significant for three of them. This concurs with our assumption that the arrival of information creates an adverse selection problem for those providing liquidity. Whether that adverse selection problem is due to inside information or the ability of certain bettors to process public information is answered by β_4 and β_5. We find that β_4 is positive and highly significant for all four assets. In other words, liquidity providers increase the bid–ask spread during significant information events due to asymmetric information at these times. This lends support to Hypothesis 1.

On the other hand, we find little support for Hypothesis 2. $\beta_5 < 0$ for all four assets and significant for two of them. In other words, the adverse selection component of the bid–ask spread decreases after a significant information event. This supports the traditional view that information disclosure limits adverse selection by taking away the informational advantage of the informed.

If bettors are trading on the basis of inside information, then the question remains as to the source of such information. Inside information in a betting market has traditionally been related to the fitness and determination of the athletes. Once the match has begun, such information is typically revealed to the public in the early stages of play. If this type of inside information was carrying over into the match, then we would expect little variation in the adverse selection component of the bid–ask spread both before and during a match. However, we observe, via our β_3 and β_4 coefficients, that adverse selection increases during a match, and, further, appears to spike during moments of importance, such as tie-breaks. In other words, inside information is being created during a match, and we propose that this inside information accrues to traders observing the action before the rest of the public.

There is reason to believe that the pictures viewed on television are delayed with respect to viewing the action live. For television pictures to be transmitted, the images must be encoded, processed and then transmitted to the host broadcaster for further processing. They can then be transmitted to the home audience, or by satellite to other broadcasters around the world. Although information is not available on the delay in this particular instance, the delay may be significant even for those watching the event in the host country. If a bettor has a mobile device at the game, which would appear rather inconspicuous amongst the crowd, then information can be relayed to a computer instructed to trade algorithmically.

It must be acknowledged that our evidence for in-play insider trading is the fact that liquidity providers take mitigating actions to offset losses to such insiders. It may be argued that this evidence is circumstantial. Our approach, however, is in good company. In Shin (1993), the level of insider trading is inferred from the overround that a bookmaker charges on a series of horse races. The overround is the extent to which is the sum of the implied win probabilities of all the horses exceeds 100%. This is the margin that the bookmaker claims. This margin, much like the bid–ask spread charged on a betting exchange, is the action that an intermediary takes to offset losses to those with private information.

Another issue is that Betfair does attempt to nullify the private information that accrues to those with a viewing advantage. For in-play markets there is a 1–5 second window (after a bet is matched) during which a liquidity provider can cancel the offer.[8] The length of the window depends on the company's estimation of the delay in television transmission. The aim of this window is precisely to deter trading on private information during a match. Our results, however, suggest that this window is either insufficient to remove the viewing advantage, or at least is perceived by those providing liquidity to be insufficient.

Our general results on the nature of informed trading differ slightly from those carried out on financial markets. Lee *et al*. (1993), Krinsky and Lee (1996) and Gajewski (1999) find equal or greater support for Hypothesis 2, as for Hypothesis 1. A possible reason for this may lie in the different environment within which we test. There may be greater scope for detailed analysis of earnings announcements in a financial market than there is for the outcome of a tie-break in a tennis match. Although we would argue that a sophisticated bettor could calculate the conditional probability of a player winning, given the outcome of the last set, this does not correspond with our conversations with bookmakers. Although detailed statistical analysis is carried out prior to a match, in-play pricing is often determined by the bookmaker's 'feeling' on a game, whilst observing competitor's pricing to ensure that an arbitrage is not available. If a bookmaker believes that there is little to be gained from detailed statistical analysis, it is unlikely that those providing liquidity on a betting exchange will feel the need to guard against other bettors using such analysis.

The task confronting bettors may just be simpler than that confronting a stock market trader. The odds quoted on a player to win are easily interpreted as the implied probability of such an outcome. The efficient value of a stock, on the other hand, is the present value of all future returns, whether that be dividend payouts or capital gains. Analysing the effect of a company earnings announcement on such returns is therefore a complicated task.

A second possible explanation is the relative novelty of in-play betting exchanges. Although private information has been gathered, and sometimes created, on the outcome of sporting events for a long period, the possibility of trading in-play has only emerged in the last decade. As a result, returns from the possession of in-play inside information may be at an early and bountiful stage, if competition is low. Once the market develops, and opportunities diminish, it may be that informed bettors will follow financial market professionals and develop an alternative advantage via analytical techniques.

IV. Conclusion

In this article we have set out to answer a fundamental question in market microstructure: whether 'informed' traders derive their advantage from access to inside information, or due to a superior ability to process public information. For this purpose we took data from a sports betting exchange during play. Uniquely, this allowed us to time-stamp information events to the nearest second, and to ensure that we were observing all relevant information regarding the value of an asset. We found evidence of inside information but not of a superior ability to process public information. As traditional types of betting inside information (such as knowledge of the player's fitness) become stale once a match begins, our findings suggest that a subset of the betting population is creating its own inside information by observing the action before the wider public (possibly due to delays in the television signal), and betting using this informational advantage. To capitalize on this fleeting advantage, bettors would need to feed this information into a computer and initiate bets via an algorithm. In these circumstances,

[8] See http://help.betfair.com/contents/itemId/i65767339/index.en.html.

a high-frequency trading strategy (e.g. trading after each point) would generate significant returns.

In the UK, the speed of television transmission differs substantially between those channels transmitted terrestrially, and those transmitted by satellite. The terrestrial transmission is noticeably faster. In 2008, the Wimbledon Final was televized on BBC1 which is available on terrestrial television. Most of the tennis played during the year, however, is only available on satellite television. This creates the possibility that the effect we have observed here may be more pronounced elsewhere.

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