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INFORMATION AND EFFICIENCY: GOAL ARRIVAL IN SOCCER BETTING*

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An efficient market incorporates news into prices immediately and fully. Tests for efficiency in financial markets have been undermined by information leakage. We test for efficiency in sports betting markets – real-world markets where news breaks remarkably cleanly. Applying a novel identification to high-frequency data, we investigate the reaction of prices to goals scored on the 'cusp' of half-time. This strategy allows us to separate the market's response to major news (a goal), from its reaction to the continual flow of minor game-time news. On our evidence, prices update swiftly and fully.

A matter of considerable importance in economics and finance is how relevant information becomes impounded in market prices. The significance of the topic derives partly from its theoretical pertinence: the efficient functioning of the price mechanism requires that a security's price at all times reflect its true fundamental value. It also has much to do with practical interests: traders with superior information may secure gains at the expense of the less well informed. The efficient markets hypothesis predicts that asset prices will incorporate relevant information, and in the simplest interpretation, will do so immediately and completely.

Applying efficiency tests in the real world, most investigations have centred on conventional financial markets.[1] Somewhat problematically considering the objective of such enquiries, it can be hard to tell when news actually breaks in financial markets – it is difficult to rule out information leakage not observed by the econometrician. Such investigations are also beset by the joint-hypothesis problem, which has led many investigators to the laboratory setting to investigate efficiency.

Sports betting markets offer a superior lens for efficiency studies, especially where news arrival is the focus. Unlike laboratory experiments, these are real markets with participants that are well motivated and often experienced. Contracts on sports outcomes (unlike equities and other financial securities) have well-defined terminal

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[1] Vaughan Williams (2005) offers a comprehensive review of the academic literature which has investigated information efficiency in financial markets.

values and converge to these over a short period of time. Moreover, and most importantly, major sports news often breaks remarkably cleanly. For instance, once a soccer game has kicked off the most significant innovation in information concerns the scoring of a goal, and this event becomes common knowledge at a single identifiable point in time. This is particularly so where a game is televised, as many now are. Until very recently, it was impractical to base efficiency studies around sports news; wagering was tightly controlled by traditional bookmakers (dealers), who posted prices, updated these infrequently, allowed betting only up until kick-off and, due to their business model (betting against their own customers) guarded data particularly fiercely. But from 2000, widespread Internet penetration facilitated a development in betting which would transform the industry landscape (and research possibilities): the emergence of online betting exchanges.

From an academic perspective, the success of betting exchanges, and in particular the dominant exchange Betfair, presents an attractive research opportunity. We exploit data extracted from the Betfair exchange at high frequency to conduct a novel and unusually clean test for semi-strong form efficiency. Our data comprise second-by-second snapshots of Betfair's live order book for 1,206 professional soccer matches from a wide range of competitions; domestic and international, club and national team matches.

The major news in a soccer match concerns the arrival of goals. Goals arrive infrequently and tend to be material to match outcomes. If the betting markets in our sample are semi-strong form efficient then prices should respond immediately and completely to such news. This article implements a complementary set of tests to investigate this.

In our main test, we introduce a new identification strategy which allows us to study the incorporation of major news in individual contracts whilst side-stepping the potential complication of 'efficient' drift. Our strategy involves exploiting the (virtually) newsless window provided by the half-time interval in play. Soccer games feature two periods of play – a first half and a second half, each lasting 45 minutes plus a few minutes of 'injury time' (added on by the referee to compensate for stoppages). Between these periods the match stops completely for 15 minutes but betting related to the match outcome continues. We exploit this window as an opportunity to identify potential inefficient goal-related drift simply and cleanly. We study the reaction to goals that arrive on the cusp of half-time. Our sample features 160 goals that arrive within 5 minutes of the exact end of the first half. Looking more closely at these 'cusp goals', 53 are scored in the final minute of first half play. These goals provide the basis for a particularly strong test for semi-strong form efficiency. Focusing on the reaction of half-time prices to these goals, we implement both a test for statistical efficiency, using regression methodology, and a test for economic efficiency. Our test for economic efficiency asks whether a hypothetical trader could make money during the half-time interval by exploiting goal-related price drift during the break. We are unable to reject the efficiency hypothesis that a cusp goal immediately shifts price but does not cause this to drift during the interval: prices update so swiftly and completely that the news of a goal is fully digested by the time the break commences, even where the goal occurs just moments before the end of play.

The key strengths of this test are simplicity and cleanness. A potential weakness relates to the potential for any efficiency finding to be specific to the half-time interval. One might suspect, for instance, that our inability to detect sluggishness in updating over the break could be due to a lull in trading during this time. We deal with this concern by tracking and reporting half-time trading activity. On average we find that betting interest remains healthy during the break, and we verify that half-time trading is strong in games with cusp goals.

The rest of our article is organised as follows. The next section introduces the literature surrounding market efficiency testing. Section 2 provides further background on the betting industry and discusses Betfair in more detail. In Section 3, we describe the data set used in this study. Section 4 discusses our testing strategy and presents the main findings regarding market efficiency. Concluding remarks are set out in Section 5. Section A.1 of Appendix A contains further robustness tests. Online Appendix B contains supplementary materials referred to in the main text.

1. Literature

The efficient markets hypothesis is most commonly associated with Fama (1965, 1970, 1998). Its early origins can be traced back to the work of Louis Bachelier, who in 1900 studied the dynamics of stock price behaviour (Bachelier, 1900). Extensive efforts have been made to put the efficiency of markets to the test. Fama (1970) popularised the idea of considering efficiency in relation to subsets of the totality of information, focusing on three differently stringent tests. The first and most lenient test is for weak form efficiency. It requires the current price to reflect all information contained in historical prices.[2] A second test deals with semi-strong form efficiency. In a market that is semi-strong form efficient prices update completely and immediately to new information, provided that this very obviously is publicly available.[3] Finally, and most stringently, there is the notion of strong form efficiency, according to which price must at all times reflect all available information, even where this is held privately.[4]

There have been many attempts to test market efficiency, most commonly in the context of financial markets. For instance, and regarding public information (the second form of test), several researchers have scrutinised the response of share prices to corporate events such as stock splits (Fama, *et al.*, 1969), the release of company results (Ball and Brown, 1968; Beaver, 1968), merger announcements (Asquith, 1983), as well as to announcements about economic variables such as the money supply (Waud, 1970; Chen *et al.*, 2003).

Some investigations find support for the view that prices update efficiently but a number of others have uncovered evidence of post-news price drift, indicative of an

[2] For illustration, weak-form efficiency rules out the possibility that technical analysis techniques could be used to produce excess returns, though analysis of fundamentals still might.

[3] This is the strictest interpretation of semi-strong efficiency. Less strict formulations exist whereby it is sufficient that it not be possible to trade upon the relevant subset of information in such a way as to earn above-normal profits. When semi-strong form efficiency holds neither technical analysis nor fundamental analysis will deliver abnormal returns.

[4] In a market that is efficient in the strong form sense it is not possible for traders to earn excess returns systematically, not even with privileged information.

inefficient market. This is described in the finance literature as 'the tendency of individual stocks' performances following major corporate news events to persist for long periods in the same direction as the return over a short window (Jackson and Johnson, 2006). For instance, in the study by Patell and Wolfson (1984), profitable trading opportunities arise following public announcements about dividend and earnings and take 5–10 minutes to dissipate. Meanwhile, Chan (2003) examines returns to a subset of stocks after public news about them is released and finds evidence of post-news drift.[5]

Somewhat problematically considering the objective of such enquiries, it can be hard to tell when news actually breaks in financial markets – it is difficult to rule out information leakage not observed by the econometrician.[6] There is also the difficulty of defining normal returns. It is hard to interpret cleanly the results of tests for efficiency in financial markets as any test must assume an equilibrium model that defines normal security returns. If efficiency is rejected, this could be because the market is inefficient or because the postulated equilibrium model is incorrect. This problem – known as the joint hypothesis problem – means that market efficiency as such can never be rejected. Responding to these complications, some investigators have preferred to analyse markets in the laboratory, where conditions such as the information structure can be tightly controlled (Chamberlain (1948) and, more recently, Plott and Sunder (1988); List (2004)). But while experimental settings can eliminate some concerns their artificiality raises others: what trading experience do subjects (typically students) have? Are they appropriately motivated?[7]

Some recent research has turned to sports betting markets in search of a cleaner, real-world context for tests of market efficiency. The vast majority of previous betting analyses are based on low frequency prices (typically bookmaker odds) sampled prior to the start of a live event. For instance, studies by Golec and Tamarkin (1991) and Gray and Gray (1997) both examine efficiency in the American football (NFL) betting markets using the closing spreads of Las Vegas sportsbooks. Closing spreads are the final prices quoted by the bookmakers shortly before game time. Vaughan Williams (2005) provides a recent and thorough review of previous work on betting and efficiency. In its exploitation of in-running betting exchange data, and its focus on goal arrival in soccer betting, our work is most closely related to a recent article by Gil and Levitt (2007). Gil and Levitt analyse data from the Intrade exchange (http://www.intrade.com), which until recently operated markets for sports-related bets. Considering 50 matches from the 2002 Soccer World Cup, the authors implement an event-study methodology to study updating to goals during minutes of play. They report that Intrade prices, though they respond strongly to a team scoring, trend for

[5] The literature contains ambiguous findings in terms of the sign of any inefficient reaction to news. De Bondt and Thaler (1985) find evidence that NYSE traders overreact to information due to a cognitive bias. Abarbanell and Bernard (1992) and Chan *et al.* (1996), meanwhile, argue that traders in financial markets adapt to new information slowly – they underreact. The literature contains several useful reviews of the evidence regarding post-event price drift (Kothari and Warner, 1997; Daniel *et al.*, 1998; Fama 1998).

[6] Some market participants may be party to the content of announcements (or some part of this content) before these 'go public' (Jarrell and Poulson, 1989). See Worrell *et al.* (1970) for an illustrative discussion of leakage in the context of layoff announcements.

[7] See Levitt and List (2007) for a recent consideration of factors affecting the generalisability of laboratory findings, including the extent to and manner in which subjects are scrutinised in their decision-making.

10–15 minutes after the goal is registered. Gil and Levitt (2007) interpret the drift they observe in Intrade's markets as evidence of informational inefficiency – prices, they suggest, update sluggishly to the news of a goal.

In addition to the sports betting literature, our work contributes to the growing literature on prediction markets, also called information markets, or virtual futures, which are essentially betting markets designed specifically to aggregate information for decision making (Wolfers and Zitzewitz, 2004; Hahn and Tetlock, 2006; Vaughan Williams, 2011 and references therein). The formal literature on prediction markets remains underdeveloped and has yet to investigate with sufficient rigour whether the information such markets generate can be relied on for decision making – in other words whether these markets are efficient. Whilst evidence from some existing studies is encouraging (Berg *et al.*, 2003, 2008; Spann and Skiera, 2003), and several researchers see great potential for these markets to improve decision-making and policy across a potentially wide range of settings (Hanson, 2002; Hahn and Tetlock, 2005; Sunstein, 2006, among others), many open questions surround the design of information markets and considerably more work is needed to explore their efficiency systematically in real-world settings (Croxson, 2011).

2. Betting and the Betfair Exchange

Traditionally, betting markets have been run by a closed community of licensed dealers, known as bookmakers. Bookmakers are similar to market makers in financial markets; they establish and maintain liquid markets by quoting prices at which they will deal. In betting, the prices are termed 'odds' and the most common type of bet is known as a fixed-odds bet. Suppose party *A* wishes to back (bet on) some outcome and party *B* wishes to lay (bet against) the same. Under a fixed-odds bet, *A* agrees to pay *B* a certain amount (the backer's 'stake') if the outcome fails to materialise, and *B* agrees to pay *A* the same stake multiplied by pre-agreed (hence 'fixed') odds if instead it does. For example, *A* might stake $100 at odds of 3:1 ('three to one') that Argentina will win the World Cup. In this case, he collects $300 from *B* if Argentina succeed, but otherwise *B* keeps his $100 stake. When betting with bookmakers, customers are restricted to backing outcomes only; the bookmaker plays the role of party *B*, taking the lay side to every bet.

Odds relate inversely to the probabilities associated with particular outcomes.[8] For instance, odds of 3:1 imply a view that Argentina is three times more likely to fail than to succeed (a 25% probability of Argentine victory).[9] Bookmakers rely on in-house gambling experts to assess the likelihood of different outcomes and to compile a set of odds accordingly. As the event draws closer the odds can be adjusted, reflecting the arrival of relevant information and the bookmaker's desire to maintain a balanced book. Odds are described as 'fair' when the implied probabilities sum to one. However,

[8] The interpretation of betting prices as probabilities is a somewhat debated area. The interested reader is referred to Wolfers and Zitzewitz (2006) and the articles cited therein, particularly Manski (2006).

[9] In this example, the odds are quoted in so-called fractional form. An alternative is to quote decimal odds, in which case the stake is included in the quoted multiple, so that 3:1 becomes 4. This is convenient because the implied probability is then obtained simply by inverting the decimal odds and normalising.

built into the set of prices offered by the bookmaker is a premium for liquidity services (known in betting circles as the 'overround' or 'vigourish') such that the sum of probabilities exceeds one. In 1999, this bookmaking model was the standard model of betting and bookmakers belonged to an exclusive and profitable club. In the UK, one of the world's key betting markets, it was illegal for anyone other than a licensed bookmaker to accept bets and a handful of major players (William Hill, Ladbrokes, Coral) dominated the market. The overround stood at a healthy 22%.[10]

The arrival of online betting exchanges in 2000 marked a revolution in the industry. The leading exchanges are essentially order-driven markets in fixed-odds bets. They allow individual customers to bet with each other directly, thereby disintermediating the bookmaker. This means that exchange bettors can and do lay individual outcomes, contrary to the standard bookmaking model. In addition, exchanges allow customers to place bets 'in-running' – once an event is underway. This is felt to have created a significantly more exciting betting experience. Typically, customers are charged a small commission for exchange betting services but the exchange does not otherwise impose an overround. Compared with bookmakers' odds exchange prices have tended to be highly competitive, at least for popular events.[11] The real hurdle for exchanges has been to achieve sufficient liquidity. Betfair was one of the first exchanges to market and is now by far the largest. It levies a standard commission of 5% on winning bets, falling to 2% for the heaviest users.[12] Betfair's early entry into the market and its decision to run with a model much closer to a standard financial exchange than some of its competitors (notably Flutter.com) are thought to have been pivotal its success.[13] Volumes on the exchange are estimated to have doubled from \$5.23bn to \$11.06bn between 2003 and 2004, and almost doubled again between 2004 and 2005.[14] These growth rates are well ahead of those for the gambling market generally. Figure 1 benchmarks Betfair to the world's largest financial exchanges in terms of trade frequency.[15] Betfair processes around seven million trades a day – greater than the number of daily trades on all the

[10] Merrill Lynch Research, 17 January 2006.

[11] The dominant exchange, Betfair, claims its prices are on average 20% more generous than bookmakers'. Ozgit (2005) and Croxson and Reade (2011) study the competitiveness of Betfair's pricing in basketball and football markets respectively. Ozgit finds that the exchange's basketball prices are more attractive than those of bookmakers, but that its markets sometimes fail to offer deep liquidity at inside (best) prices. Croxson and Reade find that Betfair offers the best prices for betting on football, even when bets are large.

[12] On 8 September 2008, Betfair announced the introduction from 22 September of an extra 'Premium Charge' to be paid by those customers whose winnings over the preceding 60 weeks have reached a certain threshold. The stipulated winnings threshold was set so high that the vast majority of Betfair users have so far been unaffected by the innovation to pricing.

[13] Flutter.com, founded in February 1999 by a group of management consultants, was the first person-to-person betting site. Laffey (2005) analyses some of the operational and marketing differences likely to have led to Betfair's dominance over (and eventual merger with) its main rival, despite Flutter having managed to attract a much more substantial amount of financial backing at its launch: 'Flutter believed that they could thrive by facilitating social bets between friends, for example about who would win a game of golf, and also limited the value and frequency of bets allowed'. 'Flutter's website was not based around the Betfair idea of matching pools of money from backers and layers, instead requiring a complete match between a single backer and a single layer. Multiple transactions on an event by a punter on Flutter were also treated separately which led to inefficiency whilst the Betfair model recognised mutually exclusive outcomes'.

[14] Merrill Lynch Research, 17 January 2006.

[15] This Figure is based on analysis undertaken by Stephen Roman, Analyst, FXCM, New York, commissioned and reported by prediction markets blog midas.org.

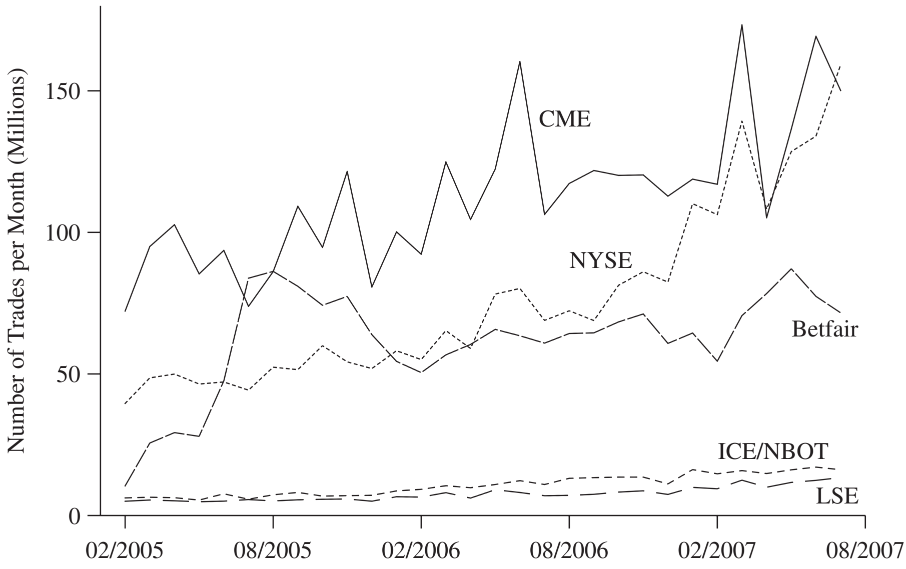

Fig. 1. *Betfair Versus Major Financial Exchanges: Daily Trading Intensity*
Source: Stephen Roman, analyst, FXCM, New York.

European Stock Exchanges combined.[16] And in the past few years the search term 'betfair' has overtaken 'FTSE' in popularity on Google (Figure 2).

The selection of markets Betfair offers is vast and covers most sporting events of popular interest, together with many non-sporting events (such as key political events and reality TV). Traditionally, horse racing has dominated exchange turnover, but soccer took over as the biggest source of Betfair gambling revenues in the financial year 2010–1. Within soccer betting, customers can place bets related to the 'Outright Winner' of a particular league or tournament, or the 'Top Scorer' of the competition, for instance. Meanwhile, 'Match Odds' markets allow betting on the outcome of individual games, by backing (betting on) or laying (betting against) the 'Home Win', 'Away Win' or 'Draw'. For those with less conventional betting preferences, there are markets such as 'Over 2.5 goals', 'Half-time Score' and exotic bets, such as Asian Handicaps and Multipliers.

Suppose a user wished to bet on the outcome of a recent Premiership encounter between Arsenal and Manchester United. Figure 3 shows the order book shortly before kick off.[17]

The order book indicates, among other things, that should he wish to back Manchester United, he might immediately stake up to $16,784 at odds of 3.3, and up to

[16] See http://corporate.betfair.com/media/press-releases/2012/29-06-2012.aspx?p=1 for more information.

[17] The Betfair order book shows the best three prices (and corresponding available volumes) on the back and the lay side. By clicking on the team name it is possible to view the full order book showing any prices and volumes available beyond the first three steps of the book, along with historical prices charts for each selection.

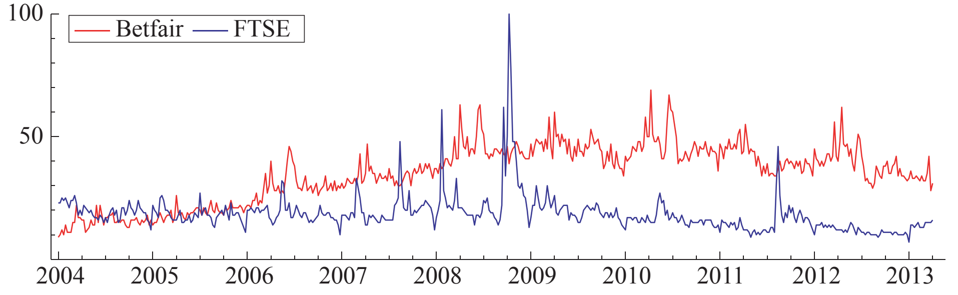

Fig. 2. *Frequency of Google Searches for 'Betfair' Versus 'FTSE'*

Notes. Scaling is relative to average searches for Betfair such that a value of one means that at that point the number of searches for either Betfair or FTSE was equal to the average number of searches over the entire sample period.

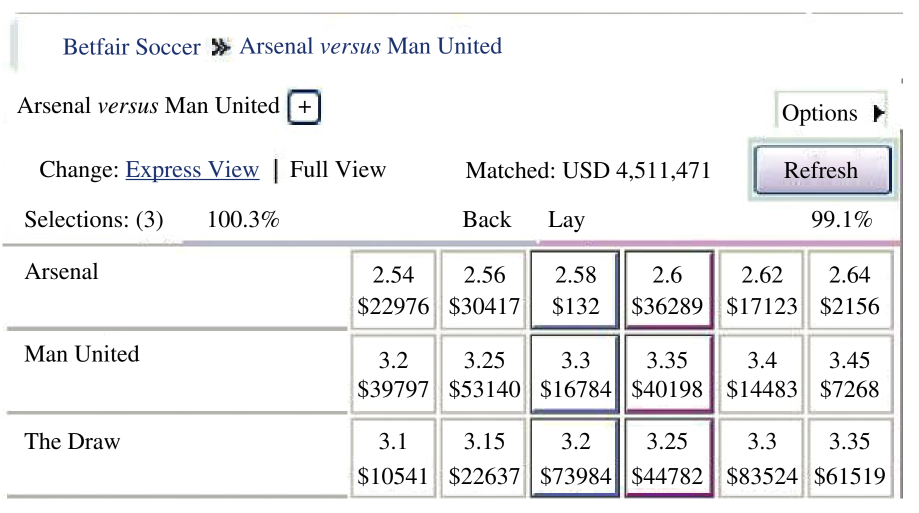

Fig. 3. *Betfair Order Book: Arsenal Versus Manchester United*

a further \$53,140 at slightly less attractive odds of 3.25. Betfair uses decimal odds which are inclusive of stake. So a \$10 bet to back Arsenal at odds of 2.58 would result in a gross return of \$25.80 (\$15.80 profit plus \$10 stake). All odds are displayed from the backer's point of view. Thus, 2.6 and \$16,289 on the 'Lay' side of that market implies that someone (or some combination of users) has submitted limit-orders hoping to back Arsenal asking for odds of 2.6 (i.e., slightly better than the prevailing market odds). If he were to accept \$10 of this 'volume', by placing a lay order at 2.6, the user would be betting against Arsenal and risking \$26 to win \$10.

3. Data

The data deployed in this article comprise second-by-second prices and volumes from Betfair's 'Match Odds' markets for 1,206 professional soccer games. We capture the evolution of each time series in-running (as the match is being played). Included in the sample are recent English Premiership matches (547), games played as part of the Euro 2008 Championships (101), games from the Champions League (165), the Scottish Premiership league (64), the UEFA Cup (249), the Intertoto Cup (14), the Asian Cup (24) and a number of international friendlies (42).[18] As discussed in the previous Section, 'Match Odds' soccer markets offer betting on the basic outcome of each match (Home Win, Away Win and Draw). Explicitly, the data set contains the following variables for each match:

(*i*) timestamp;
(*ii*) the game outcome to which the order book relates (e.g. Home Win);
(*iii*) the best three prices to 'back' this outcome and the volumes available to bet at each price;
(*iv*) the best three prices to 'lay' this outcome and the volumes available at each price;
(*v*) whether the market is 'in-play',
(*vi*) whether the market is 'suspended',
(*vii*) the total cumulative volume traded on the Match Odds market for this game.

The market for a particular match is 'in-play' when that match is in progress. As mentioned in the previous section, Match Odds markets for professional soccer matches tend to be heavily traded, particularly when the matches are in progress ('live betting'). Across the sample as a whole, the average match sees over \$6m staked on the three basic outcomes of the game. Typically, half of this is bet in-running, which equates to \$31,627 traded per minute and \$527 per second. Behind this headline average, the betting interest is quite variable across matches, with betting volume of \$50m in the most heavily traded match, compared with just over \$0.05m in the least traded. Summary statistics for the 1,206 matches in our sample are reported in Appendix A. Many English Premiership games are now televised and the sample features an interesting mix of televised and untelevised encounters. Television coverage tends to boost associated Betfair trading significantly.

Betfair briefly suspends its in-play soccer markets at kick-off and then briefly again upon the occurrence of what it defines to be a 'Material Event'. In the context of soccer, a Material Event is the scoring of a goal, the award of a penalty, or the sending off of a player (the awarding of a red card). As far as the Match Odds for a game are concerned, the scoring of a goal is the most important piece of news. Goals arrive fairly infrequently; across our sample there are on average 2.55 goals per match. During a goal-related trading suspension *Betfair* discards any unfilled orders, thereby clearing out the entire betting order book. When the order book reopens the odds have shifted, reflecting updating by the market about the relative chances of the Home Win, Away Win, and Draw. Figure 4 illustrates the suspension of trading and subsequent price updating in a recent English Premiership encounter between Bolton and Tottenham Hotspur.

[18] Due to technical and practical constraints encountered by the first author (who acquired the data set) it was not possible to collect data for all recent matches in these competitions. The sample selection is random, however. Appendix A contains summary information for matches sampled.

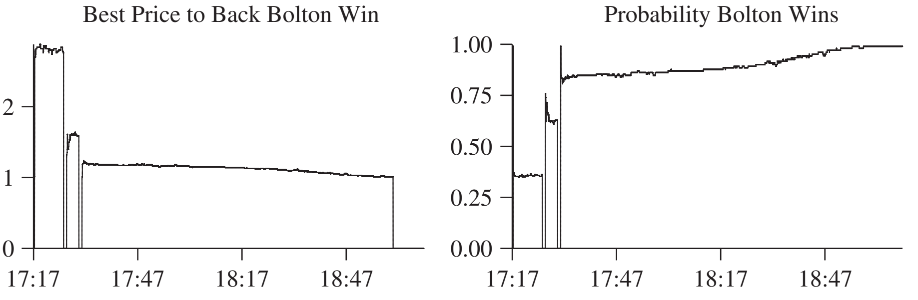

Fig. 4. *Price Evolution In-play: Bolton Wanderers Versus Tottenham Hotspur*

The left-hand panel plots the 'in-running' time series for the best price to back Bolton to win, and this price is converted into an implied probability in the right-hand panel.[19] Bolton scores two goals in quick succession, at 17:25 and 17:29, and the vertical lines clearly visible at both points in time represent the associated suspension of trading and removal of all unfilled orders. Once the market reopens following a goal, the book fills up quickly with new orders at new prices. This updating manifests in clear jumps in price and implied probability.

Data concerning the exact timing of goals and any other Material Events were obtained from SportingLife.com. Sometimes, matches kick off slightly later than officially planned (it is not atypical for a game to begin at 15:03 rather than 15:00, for example) and at the end of each half the referee adds on a small amount of extra playing time (usually called 'injury time'). This added time is to compensate for the loss of standard playing time due to injuries and other stoppages. Betfair records the precise duration of each half for the purposes of officially closing and settling the many markets it offers in relation to each soccer game. This allows us to infer exact match timings for the games in our sample, to the nearest second.

4. Testing for Efficiency: A Novel Identification Exploiting the Half-time Break in Soccer Matches

If Betfair markets are semi-strong form efficient, prices (and the probabilities these imply) should update to public news rapidly and fully. In this Section, we assess the immediacy and completeness of the Betfair price response to goals scored during the soccer games in our sample. Testing for immediacy is relatively straightforward but in testing for completeness we encounter an identification challenge and introduce a novel technique to overcome this, exploiting the half-time interval in play. We utilise our identification approach to carry out tests for both statistical efficiency and economic efficiency.

[19] Implied probabilities are computed as 1/(decimal odds). For instance, decimal odds of four would be a 25% probability. (As actual decimal odds often sum to more than one, a normalisation is applied to ensure that implied probabilities sum to unity.)

4.1. *Do Markets Respond Immediately to Goals?*

It is straightforward to confirm that prices respond immediately to the news of a goal. We have preliminary evidence of this already: from plots such as those in Figure 4 it is apparent that the price level has jumped between the market closing upon a goal being scored and it reopening shortly afterwards.[20] Table 1 looks more closely at the magnitude of this immediate market reaction to the 2,528 goals in our sample.[21]

The value in italics in the top left cell of this Table indicates that a goal on average induces an immediate 22 point increase in the scoring team's win probability. This statistic is in line with findings reported elsewhere regarding goal impact. For instance, in Gil and Levitt (2007) a World Cup 2002 goal induces a change of between 20 and 30 points in the implied probability that the scoring team wins. Intuitively, there is considerable variation behind this simple average, as the other cells in Table 1 suggest. Rows (2)–(8) consider subsets of goals grouped according to scorer type (whether the scoring side is the home team or the away team, the *a priori* favourite or the underdog), lateness in the game, and whether or not the match considered is an international fixture. Columns (2)–(7) classify goals according to the goal difference they create. Goals that change the status quo outcome (e.g. from a draw to a win) have the greatest impact, and among these, those that put the scoring side ahead (column 3) have a stronger impact on the odds than those that bring the scoring team level (column 2). Goals that merely extend a side's lead tend to have smaller effects. For example, a goal that increases a team's lead to two goals (column 5) increases its win probability by just 12 points on average. Goals scored in international matches in our sample tend to have a slightly smaller impact on the scoring side's win probability, raising this by 21 probability points on average (row 6, column 1).[22] Outcome-changing goals that

Table 1

Immediate Goal-induced Change in Scorer's Win Probability

			(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Goal difference immediately following goal					
		Total		0	1 (+)	1 (−)	2 (+)	2 (−)	# ≥ 3
(1)	All goals	2,528	*0.22*	0.16	0.30	0.06	0.12	0.03	0.01
(2)	Home goals	1,491	0.21	0.18	0.30	0.08	0.12	0.07	0.01
(3)	Away goals	1,037	0.23	0.15	0.33	0.04	0.14	0.01	N/A
(4)	Goals by favourites	1,126	0.21	0.20	0.30	0.09	0.11	0.04	0.01
(5)	Goals by outsiders	926	0.23	0.13	0.34	0.03	0.17	0.02	0.03
(7)	International	352	0.21	0.18	0.29	0.06	0.13	0.06	0.01
(8)	Domestic	2,176	0.22	0.16	0.30	0.06	0.12	0.02	0.01
(6)	Late goals (≥ 80 min)	357	0.30	0.12	0.64	0.02	0.05	0.06	N/A

[20] Recall from the previous discussion that Betfair suspends the market briefly in the event of a goal.

[21] In computing this shift, we look at the market price immediately before the goal is registered and compare this to the price shortly after the goal-induced trading suspension, once reasonable liquidity has returned to market. We exclude from the full sample any goals for which we have insufficient data around the time of the goal.

[22] McHale and Scarf (2006) document differences between domestic and international soccer games, notably that the gap in quality between competing teams tends to be smaller for domestic matches.

occur towards the end of the game tend to have the greatest impact, as would be expected. A goal scored late in the game – after the 80th minute – and which puts a team in the lead, adds on average 64 points to the probability that they go on to win the game (row 8, column 3).

4.2. *Is the Response also Complete?*

Whereas we can be comfortable on the strength of this evidence that there is an immediate reaction to goals in these markets, it is somewhat more complicated to ascertain whether the jumps observed reflect complete Bayesian updating or simply mark the beginning of an updating process that takes some time to complete. To pursue this question of completeness, we might think about comparing the new post-jump price level with the level several minutes later (assuming no further goals in that time) and construing any significant difference between these as evidence of informational inefficiency. However, to identify inefficiency in sports betting markets that are in-play one confronts an interesting and non-trivial complication: some amount of price drifting is perfectly consistent with and, indeed, evidence for, market efficiency since rational participants would be expected continually to update to minor news during the game, not least the passage of playing time without a goal. Consequently, if informational (in)efficiency is to be inferred from the post-goal evolution of prices, a strategy must be found to separate out 'efficient' drift (rational updating to the ticking down of the clock and other minor in-match news) from possible drift due to sluggish incorporation of major news (evidence for semi-strong form inefficiency).

To appreciate the nature and inevitability of time-related drift in in-play prices, consider that as match time elapses the likelihood of further goals fades and the probability thus grows that the current standing of the teams will come to reflect the final match outcome. In the absence of further goals, the probability associated with the contract that would win under the *status quo* scoreline should drift upwards over time, reaching one by the end of play. By contrast, the probabilities associated with the other possible outcomes of the game should drift downwards towards zero. Figure 5 illustrates time-related drift using the prices associated with two Premiership fixtures.

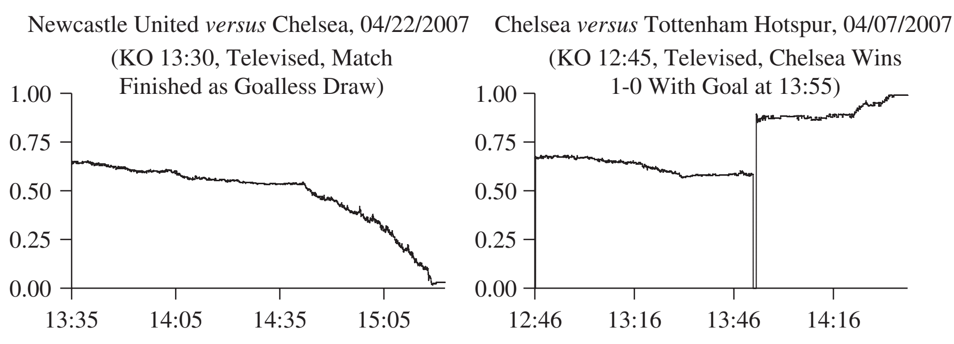

Fig. 5. *Illustrative Time-related Drift: Evolution of Chelsea-win Probability*

The left panel relates to an encounter between Newcastle and Chelsea. Depicted is the in-running probability (as implied by the best available 'back' price) that Chelsea – strong favorites at the start of the match – will win. The match ended in a goalless draw, and note that the win probability clearly drifts downwards as the clock ticks down and the chances recede of Chelsea breaking the deadlock. The right panel relates to another match involving Chelsea, in this case a game at home to Tottenham Hotspur a few weeks earlier. As the first half slips away without a goal, the probability of a Chelsea win begins again to drift downwards. At 13:55, just after the second half commences, Chelsea scores to move into the lead. As expected, the probability of a Chelsea win jumps up in response to the goal. It continues from there to drift upwards over the remainder of the game. This upward drift, at least partially, will reflect rational updating to the closing window of time and any other minor news. But it may also reflect some sluggishness in updating to the goal, and therein lies the identification challenge. In cases such as this, we might consider modelling rational price movement as a way to identify possible drift associated with inefficiency. Modelling even time-related drift is not trivial, however; it will depend on various factors, including the current scoreline (e.g., the magnitude of any lead) and the phase of play considered. In the next section, we introduce a simple and clean identification strategy that allows us to sidestep this complication; we exploit the (virtually) newsless window provided naturally by the half-time interval.

Concretely, we propose to focus on games where goals are registered on the cusp of half-time and examine the way that prices in these markets behave during the interval. The half-time break, where time-related drift cannot be present, implies a natural opportunity to test cleanly for news-related drift at the level of individual contracts.

Our data set contains 160 goals that arrive within 5 min of the end of the first half – henceforth 'cusp goals'.

Figure 6 takes a closer look at the distribution of such goals.[23] Home goals (H) account for 76 of the cusp goals; the other 84 therefore away goals (A). Favourites (Fav) score 103 and outsiders (Out) the remaining 57. Looking more closely at goal timings, a promising number of goals are scored extremely close to the end of first half; 53 occur in the final minute of play (within 60 seconds of the precise end of the first half of play); a further 27 arrive in the penultimate minute.[24] This relative abundance of goals on the very edge of the break will be helpful for the purposes of our empirical strategy; the closer the goal to half-time, the stronger the efficiency test.

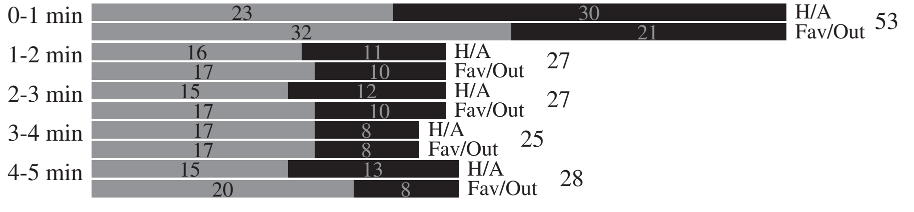

Fig. 6. *Cusp Goals:* 160 *Goals Scored Within* 5 *min of the Start of Half-time*

[23] A small number of matches feature two cusp goals and we include only the later goal in analysis (that is, the goal scored closest to the end of the first half).

[24] We obtain precise timings for the end of the first half from Betfair, which records these for the purpose of closing its 'half-time score' betting markets.

A visual look at the price series for a few of these matches is suggestive of efficient updating. Consider first Figure 7, which shows data associated with a match between Tottenham Hotspur (playing at home) and Manchester United. This match kicks off just after 16:00 and the plot in the left hand panel shows the probability of a Manchester win, as implied by the best Betfair back price. This probability is 56% at the beginning of the game (Manchester being favourites to win) but begins to drift downwards as the first half progresses without a goal. By the 44th minute it has fallen to under 50%. Then, right at the end of the first half, Manchester scores to take the lead and the market is suspended briefly. When it reopens, moments later, the probability has jumped up to 77%, and almost immediately the whistle blows for half time. Over the 15-minute interval that follows, the implied probability appears to remain remarkably constant at this 77% level, suggesting that updating to the goal was immediate and complete. A legitimate concern might be that such evidence for efficiency is an artefact of our half-time identification strategy: perhaps prices appear not to continue to update over half time only because trading interest drops off during the break. In the right hand panel we report trading activity. We verify that the market is actively traded throughout half time. In fact trading interest appears to step up somewhat during the interval in play.

For contrast, Figure 8 illustrates the case of an upset. Here, the *ex ante* favourite concedes a goal just before half-time. The post-goal probability (again, as implied by the best Betfair back price) seems somewhat more volatile in this game, yet still there

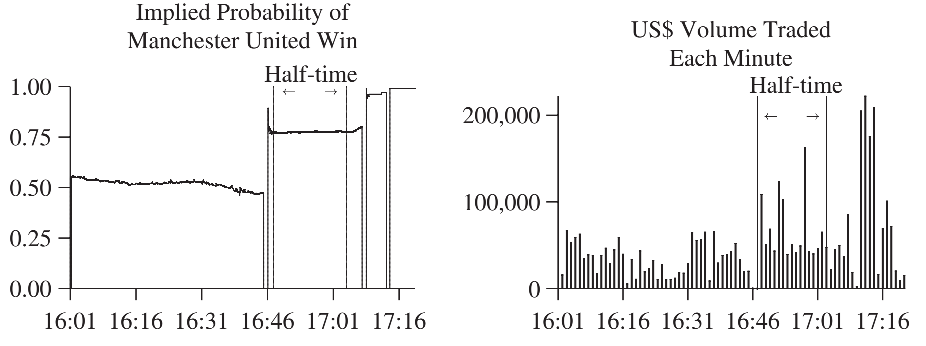

Fig. 7. *Visual Evidence for Efficient Updating: Tottenham Versus Manchester United*

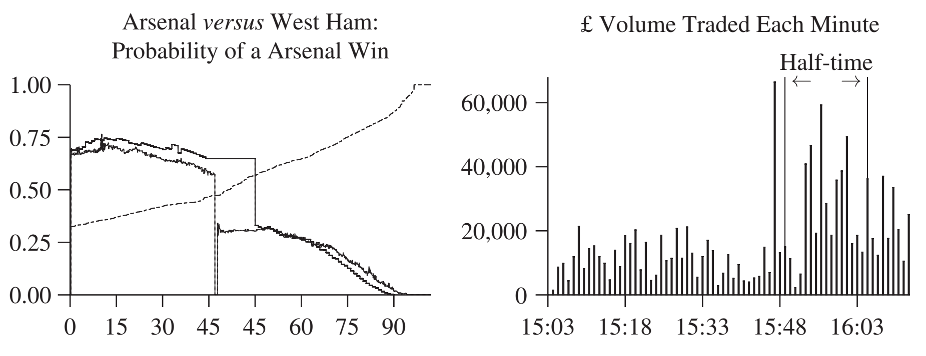

Fig. 8. *Further Visual Evidence for Efficient Updating: Arsenal Versus West Ham*

appears to be no obvious trending over the break and trading during the interval is again heavy. Looking across all matches in our sample an average of \$527 is traded per second of play and \$319 is traded per second of half time. In games featuring a goal just before half time, we see an elevated half-time trading volume of \$552 per second.

The apparent lack of half-time trending in such diagrams, despite heavy trading during the break, constitutes *prima facie* evidence that the market is semi-strong form efficient. The remainder of this Section implements two complementary tests to investigate formally whether efficiency holds. In both cases, our basic strategy is to test whether a goal occurring right at the end of the first half period creates any drift in prices observed over the half-time interval. The first test is a test for statistical efficiency; we use regression analysis to identify the presence or otherwise of drift in half-time prices. The second test is a test for economic efficiency; we explore whether customers could make positive returns over the half-time interval by exploiting any systematic drift in prices.

4.2.1. *A statistical test for efficiency*

An important first step in implementing our test for semi-strong market efficiency is to construct an appropriate model of prices over the half-time break. Suppose a security price at time t, P_t, can be written as the rational expectation of some fundamental value V^* conditional on information I_t available at t. Then we have $P_t = \mathrm{E}_t(V^*)$ and $P_{t+1}, = \mathrm{E}_{t+1}(V^*)$, which means, using the Law of Iterated Expectations, that $\mathrm{E}_t(P_{t+1} - P_t) = \mathrm{E}_t[\mathrm{E}_{t+1}(V^*) - \mathrm{E}_t(V^*)] = 0$. Thus, market efficiency means that realised changes in prices are unforecastable given information I_t. In other words, given currently known information, the expectation of an asset's price next period is simply its current price. Where this information set consists of historical prices then this is the Martingale hypothesis (Le Roy, 1989) and forms the basis of a test for weak-form efficiency. To implement this test would involve running regressions to ascertain whether or not current prices can be forecast on the basis of lagged prices. To test for semi-strong form efficiency (SSFE), which encompasses weak form efficiency but requires additionally that any public information is immediately incorporated in price, the information set comprises all relevant information that is publicly available at t. In our context, this means testing whether or not during the half-time interval current prices can be forecast on the basis of lagged prices and checking whether this forecastability is impacted by the arrival of a goal on the cusp of half-time.[25]

Pooling the half-time price data across our full sample of matches, we could estimate for each contract type $m \in \{h,a,d\}$ the following second-order autoregression:

$$pr_{c,m,t} = \theta_0 + \theta_1 pr_{c,m,t-1} + \theta_2 pr_{c,m,t-2} + \varepsilon_{c,m,t}. \tag{1}$$

where pr denotes the volume-weighted average price and the subscripts $m \in \{1,\ldots,M\}$, $c \in \{1,2,3\}$ and $t \in \{1,\ldots,T\}$ denote the particular match, contract traded (Home Win,

[25] By testing the Martingale hypothesis, we are effectively testing market efficiency under the assumption of risk neutrality. This simplifies our analysis, and is a tolerable assumption if bettors wager a small amount of their total wealth. We relax this assumption when we test for economic efficiency below.

Away Win, Draw) and second of time considered. For each contract type, we have a panel data set comprised of prices for the contract type in question over our $M = 1{,}206$ soccer matches. It makes sense to use panel estimation whenever there might be similarities or links between the processes generating the data in the different groups (here matches). In the presence of such links, combining the data can improve the efficiency of the estimation procedure. We do, however, run separate panel regressions for each contract type. Arbitrage opportunities make it very likely that the prices associated with the three match outcome contracts (for any given match) will be correlated; specifically, we can expect that, at any point during the match, the prices for the Home Win, Away Win and Draw contracts will imply probabilities that sum approximately to one. Running separate panel regressions for each contract type avoids potential complications due to this form of correlation in the data. Of course we can also expect the prices for an individual contract to be correlated over time but the inclusion of lagged dependent variables deals with this issue.

Under the null hypothesis of market efficiency, all coefficients in (1) would be zero except for the first lag of price, which would be significant and take a value of unity:

$$\mathrm{H}_0: \theta_0 = \theta_2 = 0, \quad \theta_1 = 1. \tag{2}$$

Note that the model in (1) constrains the regression coefficients to be the same for all units of the panel; each soccer match conforms to exactly the same data generating process. Although the efficient markets hypothesis does constrain the parameters of the model to be constant across matches, it seems somewhat restrictive to impose parameter homogeneity at the initial estimation stage; if the homogeneity assumption is wrong, the model will be misspecified and any testing adversely affected. In light of this concern, we elect to work with a more generalised version of the model:

$$pr_{c,m,t} = \theta_{0,c,m} + \theta_{1,c,m}pr_{c,m,t-1} + \theta_{2,c,m}pr_{c,m,t-2} + \varepsilon_{c,m,t}. \tag{3}$$

Here the parameters of the model, θ_i, $i = 1,2,3$, are allowed to vary across matches (we are already allowing the parameters to vary between contracts by modelling the Home Win, Away Win and Draw markets separately). The model in (3) allows matches with cusp goals to differ from other matches, because each individual match will have its own set of parameters (e.g. $\theta_{0,h,1}, \theta_{1,h,1}, \theta_{2,h,1}$ for the Home Win contract in match 1). If our testing accepts H_0 over the entire panel (implying that the restrictions $\theta_0 = \theta_2 = 0, \theta_1 = 1$ are valid across the panel), then we are able to conclude in favour of market efficiency: half-time prices reflect all relevant information, even when major news arrives on the cusp of half-time. If, on the other hand, market efficiency is rejected, then we can investigate relevant groupings of matches, such as matches with cusp goals, to determine whether particular types of matches drive any rejection of the null hypothesis.

The next step is to transform (3), as is standard for unit root testing, into:

$$\Delta pr_{c,m,t} = \theta_{0,c,m} + (\theta_{1,c,m} - 1 + \theta_{2,c,m})pr_{c,m,t-1} - \theta_{2,c,m}\Delta pr_{c,m,t-1} + \varepsilon_{c,m,t} \tag{4}$$

$$= \gamma_{0,c,m} + \gamma_{1,c,m}pr_{c,m,t-1} + \gamma_{2,c,m}\Delta p_{c,m,t-1} + \varepsilon_{c,m,t}. \tag{5}$$

where $\Delta pr_{c,m,t} = pr_{c,m,t} - pr_{c,m,t-1}$ and $\gamma_{0,c,m} = \theta_{0,c,m}$, $\gamma_{1,c,m} = \theta_{1,c,m} - 1 + \theta_{2,c,m}$ and $\gamma_{2,c,m} = -\theta_{2,c,m}$. With respect to this transformed model, the null hypothesis of market efficiency implies:

$$\mathrm{H}_0: \gamma_{0,c,m} = \gamma_{1,c,m} = \gamma_{2,c,m} = 0, \tag{6}$$

which is a standard *F*-test of joint significance of regression coefficients. We note that the null hypothesis for the standard Augmented Dickey–Fuller (ADF) unit root test would be simply $\gamma_{1,c,m} = 0$, and hence because the null hypothesis implies non-stationarity, we must compare the *F*-test of the semi-strong form efficiency hypothesis to a non-standard distribution. Patterson (2000) contains critical values for the joint test involving $\gamma_{0,c,m}$ and $\gamma_{1,c,m}$ for a particular contract and match, but not the joint test including the lagged difference term, nor a panel variant of the test. Our data is also high frequency and, as is often the case in such data series, our residuals are very leptokurtic compared to the standard normal distribution assumed for generating the *p*-values on which to calculate one of our two tests.[26] Therefore, we simulate critical values. We provide details of our simulation exercise in Appendix A. We simulate critical values for two common variants of panel unit root tests: the Maddala and Wu (1999) (M–W) and Im *et al.* (2003) (IPS) tests. The IPS test aggregates based on the ADF test statistics for each individual time series, whereas the M–W test is a Fisher test aggregating the p-values from the individual tests. The IPS test statistic is:

$$\mathrm{IPS}_c = \frac{1}{M}\sum_{m=1}^{M} Z_{m,c}, \tag{7}$$

where $Z_{m,c}$ is the ADF test statistic for match m and contract c. Critical values for this test are simulated by Im *et al.*, but not for the specific case we consider here, hence the need to simulate critical values. The Maddala–Wu test statistic is:

$$\mathrm{MW}_c = -2\sum_{m=1}^{M} \ln p_m \sim \chi^2_{2M}, \tag{8}$$

where p_i is the p-value for the ADF variant test, or SSFE test, in the ith time series of the panel. The test statistic is χ^2-distributed with $2M$ degrees of freedom for the standard unit root case when errors are assumed normally distributed. We simulate for the case where errors are t-distributed to reflect the leptokurtic nature of errors in high-frequency datasets, and compare the generated critical values with the standard critical values (provided in parentheses in Table 2).

Results for the test applied to the first five minutes of all half-time prices are shown in the top panel of Table 2 and results for the first ten minutes of all half-time prices appear in the bottom half of the Table.[27] In both cases we are able to compare (for the M–W test) the critical values under the standard assumption of normality (implying a χ^2_{2M} distribution for the test statistic) with the critical values from our simulations assuming that our errors are t-distributed with three degrees of freedom. Simulating our market efficiency test for individual time series reveals that critical values must be

[26] We conducted Doornik and Hansen (2008) normality tests on our prices for each match and found that in 97–100% of matches the test fails, suggesting that indeed the normality assumption is not an appropriate one. (See Table A.2. in subsection A.2 of Appendix A for tabulated results.)

[27] There is no need to report separate tables for cusp goals and non-cusp goals; instead we report information from all our matches and seek to understand if there are any significant differences between the two groups of matches using our panel estimation framework.

somewhat more generous in order to ensure appropriate test properties (as is the case with simple unit root tests), particularly at the 1% level (standard critical value is 2576.5, simulated critical values are all above 16,000), reflecting the leptokurtic nature of the *t*-distribution relative to the normal distribution.

Our test statistics appear in the final row of Table 2. Overall, we reject semi-strong form efficiency at the 1% level, but not at the 5% level. We conclude that the statistical efficiency of the markets at half-time cannot be rejected emphatically. If we had used the standard critical values, the rejection of the null hypothesis would have been clear-cut, both for the 5 and 10-minute regressions. However, as argued earlier, a leptokurtic distributional assumption is significantly more appropriate for high-frequency financial data series.

An attractive feature of the half-time strategy of this Section is its cleanness. A conceivable concern is that our results concerning efficiency could be specific to the break in play. Perhaps different types of trader are active during the half-time interval; perhaps major news interacts with more minor news during minutes of play, which might complicate updating. With these concerns in mind, we have also developed two robustness checks for testing the market's ability to update to the news of a goal whilst the match is in progress. Details of these additional robustness tests are reported in Appendix A.1, along with our results. The findings from these robustness checks support the view that drift observed in Betfair prices during minutes of play might is largely explained by efficient updating to the passage of playing time.

4.2.2. *A test for economic efficiency*

Most meaningful ultimately is not whether markets are efficient in a statistical sense, but whether customers could trade profitably on any inefficiency. In this subsection, we investigate economic efficiency, testing whether customers could make positive returns over the half-time interval by exploiting any systematic drift in prices (related to a cusp

Table 2

Results from Statistical Efficiency Test Applied to Prices from the First Five (Top Panel) and Ten (Bottom Panel) Minutes of Half-time

Time interval	Type of test Betfair market	Maddala and Wu (M–W) Home	Away	Draw	Im, Peseran, Shin (IPS) Home	Away	Draw
5 min	1% Simulated critical value	16,413.0	16,537.0	16,592.0	6.13	6.13	6.13
	(asymptotic critical value χ^2_{2M})	(2,576.5)	(2,576.5)	(2,576.5)			
	5% Simulated critical value	4,752.6	4,788.6	4,804.6	4.51	4.51	4.51
	(asymptotic critical value χ^2_{2M})	(2,527.4)	(2,527.4)	(2,527.4)			
	Test statistic	8,004.7	7,853.6	8,355.4	6.44	6.92	6.78
10 min	1% Simulated critical value	16,592.0	16,371.0	16,495.0	16.77	16.77	16.77
	(asymptotic critical value χ^2_{2M})	(2,576.5)	(2,576.5)	(2,576.5)			
	5% Simulated critical value	4,805.9	4,741.8	4,777.8	3.73	3.73	3.73
	(asymptotic critical value χ^2_{2M})	(2,527.4)	(2,527.4)	(2,527.4)			
	Test statistic	6,988.1	7,131.3	7,505.11	9.59	10.68	9.78

Notes. Standard χ^2_{2M} critical values for the M–W test are reported in parentheses beneath simulated critical values. The test statistics appear in the row marked 'Test Statistic'.

goal or otherwise). We evaluate two hypothetical trading strategies designed to exploit potential half-time price drift:

- Trading strategy *A*: backing (buying) a particular match outcome at the start of the half-time interval and laying this (selling it back to the market) 5 (or 10) minutes later. This would exploit any systematic downward drift in odds during the break, perhaps reflecting an initial underreaction to the arrival of a goal just before the half-time interval.
- Trading strategy *B*: laying (selling) a contract at the start of the half-time interval and backing this 5 (or 10) minutes later. This strategy would exploit any systematic upward movement in odds during the interval, perhaps reflecting an initial overreaction to a goal at the end of the first half.

The potential profitability of each strategy can be investigated using a difference in means test. Denote as $p_{m,b,i}$ the best back price for a particular outcome in minute m of the half-time interval in match i, the best lay price as $p_{m,l,i}$, and their respective means across all matches in the sample as $\bar{p}_{m,s}$, where $s \in (b, l)$ is the 'side' of the market (back or lay). Note that at any point in time, the best available price to back a particular outcome at that moment in time (e.g., decimal odds of 9) will be below the best available price to lay the same outcome (e.g., decimal odds of 9.2). This must be the case in any limit order book, otherwise the exchange could immediately match some of the orders in the book by crossing trades at prices between 9 and 9.2. Consequently, it will only be possible to profit from strategy *A* if then, to test the profitability of, for example, backing an outcome in the first minute of half-time and laying it in the fifth minute (Strategy *A*), a suitable difference in means test would calculate the t-statistic:

$$\mathrm{t} = \frac{\bar{p}_{1,b} - \bar{p}_{5,\ell}}{\sigma_{\bar{p}_{1,b}-\bar{p}_{l,\ell}}}. \tag{9}$$

The test is a paired t-test (comparing the prices at minute 1 with those at minute 5 for each match) and so $\sigma_{\bar{p}_{m,b}-\bar{p}_{m,\ell}}$ is simply the standard deviation of the difference between the relevant back and lay prices divided by the square root of the number of matches considered. If trading strategy *A* is profitable, we would expect $p_{1,b} - p_{5,\ell}$ (or $p_{1,b} - p_{10,\ell}$) to be significantly positive: the return from backing the outcome in question in the first minute of half-time must be greater than the exposure required to cover this position (sell it back into the market) in minute 5 (or 10) of the break. Since our only concern is whether $p_{1,b} - p_{5,\ell} > 0$ (or $p_{1,b} - p_{10,\ell} > 0$) the test is one tailed.

We report results from this test in Table 3. The first row gives results for all matches for which data was available (1,062 matches for the 5 minute test, 1,055 for 10 minutes). In the rows below this, we restrict our attention to gradually smaller subsections of the available matches, dictated by the volume available to trade at the start of half-time. Disaggregating by available volume will provide a finer picture of the viability of our hypothetical trading strategies for different sizes of bet. In the second row, we omit from consideration all matches where as half-time began less than \$5 was available to back; this leaves 653 matches. The third row reports results when we omit those matches where less than \$10 was available to bet at the best available back price; this leaves 553 matches. Finally, in the fourth and fifth rows we omit matches where less than \$20 and less than \$50 was available to bet at the best available back price; this leaves 478 and 372 games, respectively.

Although the t-statistics in Table 3 are quite large, they are negative, implying a clear rejection of the null hypothesis that the difference in means is non-positive. This result implies that Strategy *A* is not profitable: backing the event at the start of half-time and laying after 5 or 10 minutes does not yield a positive expected return.

Trading Strategy *B* involves laying an event at the start of half-time and subsequently backing the event (after 5 or 10 minutes). In this case, the trader makes a positive return only if $p_{5,b} - p_{1,\ell} > 0$ or $p_{10,b} - p_{1,\ell} > 0$. Hence again the test is one-tailed and the critical value is 1.96. The results are reported in Table 4.

As before, the first row of this table considers all matches for which data as available, whilst the rows below this consider progressively smaller subsets of matches according to the availability of volume at the best available lay price. In the second row, matches are omitted where as half-time began less than \$5 was available to lay (leaving 644 matches). In the third, fourth and fifth rows, matches are excluded where less than \$10, \$20, \$50 was available to lay (leaving 544, 471 and 367 matches, respectively).

The results in Table 4 confirm clearly that trading Strategy *B* is also unprofitable: the average decimal odds that must be offered for the lay trade is always strictly greater than those available for the back trade, implying that on average this strategy yields a negative return.

Overall then, our half-time identification yields conclusive evidence that Betfair markets are economically efficient: prices impound news so rapidly and completely that it is not possible to exploit any systematic drift over the half-time interval for profitable trading. This is so even where major news (a goal) arrives just seconds before the end of first half play.

5. Concluding Remarks

The recent emergence of online betting exchanges has made it possible to obtain high-frequency data relating to bets placed 'in-running' (during a live sports event). This implies a fertile new setting for empirical work and, in particular, it paves the way for a cleaner look at the topic of market efficiency. A market that is semi-strong form efficient updates swiftly and fully to publicly available information. A problem for those seeking to put this to the test in financial markets has been the possibility of news leakage not observed by the econometrician. In sports, however, major news (such as a goal in soccer) tends to break comparatively cleanly. We exploit this characteristic of sports events to offer a fresh study of efficiency. Prices for soccer-related markets are extracted from the live order book of the largest online betting exchange Betfair.com, and tested for efficiency in relation to the arrival of goals. A complication particular to this exercise relates to the difficulty in determining whether any price drift following a goal should be interpreted as sluggishness in updating (and hence evidence of inefficiency), or be considered simply an efficient response to the passage of playing time (goalless periods of play being themselves price-relevant news). To overcome this identification issue, we exploit the naturally newsless half-time interval – we study matches where goals arrive on the cusp of the half-time break. Our findings suggest that prices swiftly and fully impound news.

Table 3

Difference in Means Test for the Profitability of Trading Strategy A: Backing an Outcome at the Start of the Half-time Interval And Laying it (Selling) 5 or 10 Minutes Later

	Home Win					Away Win					Draw				
	Average price			Test		Average price			Test		Average price			Test	
	Back	Lay				Back	Lay				Back	Lay			
Interval minute	1	5	10	5	10	1	5	10	5	10	1	5	10	5	10
All	8.47	10.1	11.1	−3.40	−2.85	17.3	23.6	22.9	−4.40	−4.90	6.47	6.92	6.99	−5.99	−5.79
Vol>5	8.15	9.76	10.8	−3.22	−2.69	14.9	20.1	19.5	−3.63	−3.96	6.32	6.63	6.79	−6.86	−6.12
Vol>10	7.34	8.97	9.77	−2.91	−2.43	12.8	16.6	17.5	−3.37	−3.75	6.23	6.58	6.65	−6.60	−5.86
Vol>20	5.93	6.90	7.42	−2.92	−2.39	11.2	14.6	15.5	−2.93	−3.34	6.16	6.51	6.59	−6.01	−5.43
Vol>50	4.90	5.28	5.56	−4.79	−3.70	8.64	10.2	11.9	−2.69	−2.32	5.51	5.78	5.85	−4.27	−3.89

Table 4

Difference in Means Test for the Profitability of Trading Strategy B: Laying an Outcome at the Start of the Half-time Interval and Backing it 5 or 10 Minutes Later

	Home					Away Win					Draw				
	Average price			Test		Average price			Test		Average price			Test	
	Lay	Back				Lay	Back				Lay	Back			
Interval minute	1	5	10	5	10	1	5	10	5	10	1	5	10	5	10
All	11.1	8.55	8.77	−2.89	−2.93	23.0	18.1	18.4	−4.10	−3.79	7.14	6.44	6.51	−4.58	−4.08
Vol>5	13.2	9.89	10.1	−2.50	−2.63	21.7	19.0	19.1	−3.54	−3.17	8.45	7.62	7.60	−3.95	−3.69
Vol>10	13.5	9.84	10.0	−2.42	−2.59	20.5	18.0	18.2	−3.10	−2.61	8.38	7.67	7.67	−4.21	−4.54
Vol>20	12.6	9.22	9.41	−2.09	−2.30	20.0	17.3	17.4	−2.89	−2.56	7.57	6.99	7.01	−6.10	−5.65
Vol>50	11.9	8.15	8.38	−1.90	−2.12	18.4	15.8	15.9	−2.29	−1.92	5.98	5.68	5.53	−4.63	−4.29

A possible concern with our half-time identification might relate to the generalisability of our findings to news that arrives during minutes of play. For robustness, the article implements two further approaches to testing for efficiency in these markets, both of which provide a more direct perspective on the market's ability to incorporate information into prices whilst play is in progress. Our first additional test exploits our large sample to conduct a meaningful test for drift in average prices during minutes of play. This test is a close relative of the calibration tests of prediction markets now often reported in that literature. In a semi-strong form efficient market, average post-goal prices should not drift during minutes of play and we are unable to reject the null hypothesis of no such drift. Our second approach exploits statistical knowledge of the underlying Poisson goal arrival process. Concretely, we compare the drift observed in Betfair markets to that which would arise under hypothetically efficient updating to the passage of time, where our estimation of this 'efficient' drift is based on updating according to a Poisson model fitted well to historical match data. Our tentative conclusions are that these Betfair markets behave largely 'as if' they are updating efficiently to the ticking down of the clock. Overall, both our robustness checks provide support for the efficiency of prices in this large online betting exchange.

Appendix A.

A.1. *Additional Tests for Robustness*

An attractive feature of the half-time strategy presented in the main body of this article is its cleanness. A potential concern is that our results related to efficiency could be specific to the break in play. There are many conceivable reasons why this might be so. Perhaps different types of trader are active during the half-time interval; perhaps major news interacts with more minor news during minutes of play, which might complicate updating. In this Section, we develop two complementary strategies for testing the market's ability to update to the news of a goal whilst the match is in progress.

A.1.1. *Testing for post-goal drift at the aggregate level*

Although individual series will necessarily display drift, we should fail to find evidence of drift at the aggregate level if the market is efficient. The calibration tests now common to the prediction markets literature can be seen as special cases of a test for drift in average prices; a standard calibration test asks whether the current price is the best forecast of the final price. In common with standard calibration tests, and as explained in our Introduction, a test for drift in average in-play prices can only deliver meaningful results regarding efficiency when applied to a sufficiently large sample.

With 1,206 matches, we can hope to perform a meaningful test along these lines. For ease of benchmarking with previous work (Gil and Levitt, 2007), we do this deploying a regression of the form:

$$p_{m,c,w,t} = \beta_0 + \sum_{g=-14,g\neq 0}^{15} \beta_g Goal_{m,c,w,t+g} + \varepsilon_{m,c,w,t}, \quad \varepsilon_{m,c,w,t} \sim \mathrm{IID}(0,\sigma^2). \tag{A.1}$$

The model is estimated on a panel dataset consisting for each match and market of the weighted-average prices observed over the 30 min surrounding a goal (15 minutes either side of this news). p denotes the volume-weighted average price and the subscripts m, c, w and t denote the particular match, contract traded (we consider Home Win and Away Win contracts), goal 'window' and minute of time considered.[28] *Goal* is an indicator variable corresponding to a particular minute which is equal to unity when a goal is scored in favour of the contract and zero otherwise. The matches in our dataset yield a total of 3,078 goals and we are able to consider 2,528 of these in our panel dataset. (A large number occur either very near the beginning or towards the end of a match, leaving insufficient observations in the pre- or post-goal period to support estimation.) We estimate (10) using pooled ordinary least squares (OLS). The semi-strong form efficiency hypothesis takes the form:

$$H_0: \beta_1 = \beta_k, \quad k > 1. \tag{A.2}$$

We report our results in Figure A1 where we plot the coefficients on goals along with 95% confidence bands.

In common with Gil and Levitt (2007), we find an initial jump of around 0.2 in magnitude. However, in contrast to their study, we are unable to find evidence of post-news drift. Coefficients for post-goal minutes 2–15 do not fall outside the 95% confidence bands associated with the coefficient on the first post-goal minute. Hence, it seems that the coefficients are not drifting. Supporting this conclusion further, *F*-tests of the null hypothesis that $\beta_1 = \beta_k$, $k > 1$ are never rejected at the 5% level.

Thus our results from this Section would appear to support the view that these markets also update efficiently to major news during minutes of play. We are unable to find significant evidence of post-goal drift, in contrast to Gil and Levitt (2007), and despite deploying tests comparable to the test in their article. As Gil and Levitt have a relatively small sample (50 matches) drawn from considerably thinner betting markets, we suggest that there are two possible explanations for their apparent finding of some inefficiency (post-goal drift). One possibility certainly is that the markets they study are inefficient, perhaps because of cognitive biases on the part of traders or simply because these markets are very thin (low volumes, infrequent trades). An alternative explanation might be that the implemented test for efficiency, being a test for 'average' in-play drift in binary assets, cannot yield meaningful results when applied to small samples.

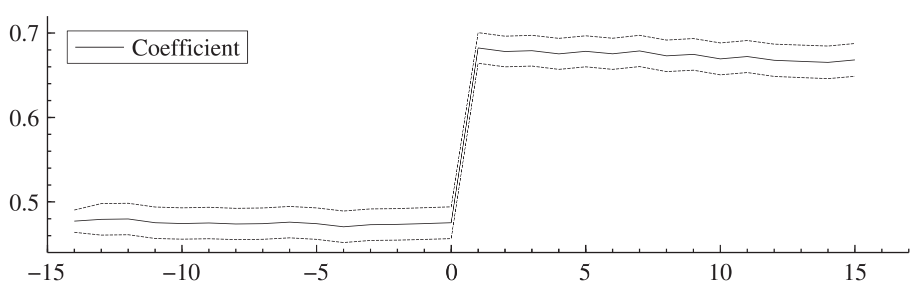

Fig. A1. *Testing for Semi-strong Form Efficiency During Minutes of Play, by Looking for Inefficient Post-goal Drift in Average In-play Prices*

Notes. This Figure presents the β coefficients from model 10, where the time of a goal is normalised to $t = 0$.

[28] Gil and Levitt (2007) also demean their price data; since this is a linear transformation its effect is simply captured here in the constant coefficient, β_0. Gil and Levitt omit this term.

A.1.2. *Modelling 'efficient' in-play drift in individual matches*

In this subsection, we develop a simple model for generating minute-by-minute probabilities of final match outcomes. We use this model to construct an 'efficient' purely time-related drift for the 547 English Premiership matches in our sample. Then, for each match, we compare our synthetic drift to the drift actually observed in Betfair implied probabilities in order to draw inferences regarding the extent to which observed Betfair price drift in individual games reflects the market's efficient adjustment to the ticking down of playing time.

In order to construct efficient time-related drift, we begin by looking for a well-fitting model of goal arrival and using this to back out minute-by-minute match outcome probabilities. Our approach is to combine two statistical models in an intuitive way. First, we utilise the Bivariate Poisson model developed by Karlis and Ntzoufras (2003). We must break the match-level analysis of Karlis and Ntzoufras (2003) into smaller intervals in order to uncover the in-match variation and, in particular, drift, that we are interested in. It is well documented that at the match level, goal arrival is Poisson distributed and examination of our Premiership match outcome database reveals that the Poisson assumption is also valid for minute-by-minute action: across all English Premiership matches from the 2006–7 and 2007–8 seasons, goal arrival in a given minute follows a Poisson process with a mean of 0.016 goals per team per minute and a variance also equal to 0.016. Thus, extending the Karlis–Ntzoufras framework for modelling minute-long intervals for each match is valid statistically.[29] This provides estimates of the probability of a Home Win, Away Win and Draw for a given minute interval. However, we require probabilities of eventual match outcomes, as opposed to the outcomes for each minute. As such, we take these estimated probabilities and treat these as the $p = 3$ events repeated n times in a multinomially distributed event. The n events are the remaining minute intervals before the end of the match, and thus our approach provides, for every minute in the match, a final match-outcome probability for each market. As a number of plots will reveal, the resulting model delivers a rather accurate prediction of the match outcome probabilities implied by Betfair prices.

Figure A2 shows the calibration of our model's predictions to observed match outcomes. The model provides a good fit overall. Meanwhile, Figure A3 illustrates the fit between the in-running probabilities implied by Betfair prices and those predicted by our model for five matches selected at random from our sample. Some discrepancies between the two series are visible but overall the drift observed in these illustrative matches appears well approximated by our generated series; Figure A4 plots the difference between the two series in these four matches and shows that any remaining drift in the Betfair series is negligible.

As a case study of our basic attempts to compare 'efficient' drift with Betfair price drift, we take a closer look at a match between Manchester United and Blackburn Rovers, which took place during the 2006–7 season. In Figure A5, we plot the probability of a Manchester United win, as implied by the observed Betfair price series, along with the predicted probability series from our model. As with a number of other matches, in the first half of the game, our predicted time series for the probability is somewhat above actual Betfair probabilities. Yet, as the right panel shows, during all phases in play our series is capturing the slope of the drift in Betfair prices almost perfectly. The first goal is scored by Blackburn at 1,700 seconds into playing time. In response to this goal, both series jump down (reflecting a drop in the probability of a Manchester win). Our estimated probability series drops less than the Betfair series, and the predicted downward drift remains marginally above the drift in Betfair probabilities as further goalless minutes pass but again shares a similar slope. During the newsless half-time interval, unsurprisingly, we observe a relatively flat series both in observed and predicted probabilities. Following the break, at around 5,000 seconds into the match, Manchester United levels the score and, following this, our predicted series and the actual Betfair series converge rapidly. By the time Manchester United

[29] For modelling purposes, we assume that the market uses sample averages in forming its estimates of the 'injury time' likely to be added on by the referee at the end of each half of play.

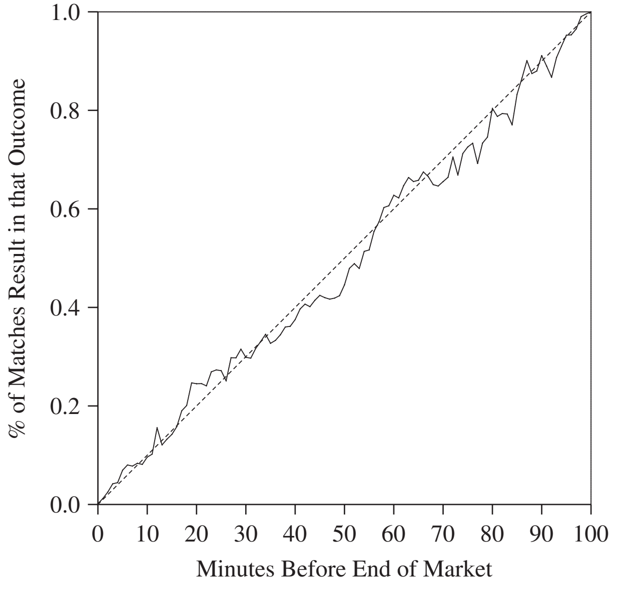

Fig. A2. *Calibration of the Poisson Model to Historical Match Data*

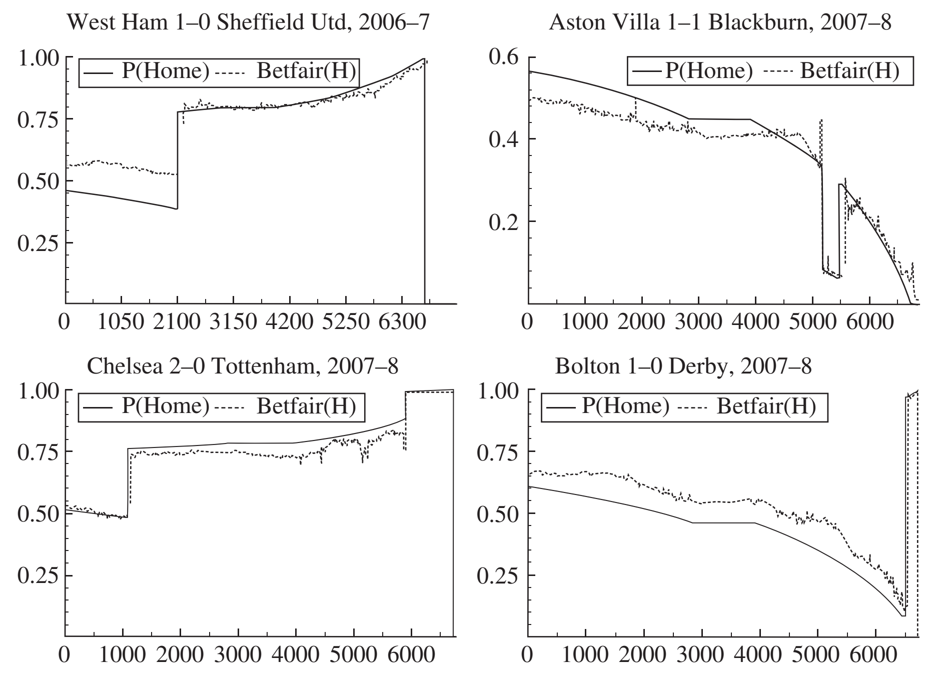

Fig. A3. *Plots of the Poisson–Multinomial Minute-by-minute Probability Series and the Betfair Implied Probability Series for Illustrative English Premiership Matches*

Notes. The smoother, thicker plot is the Poisson series.

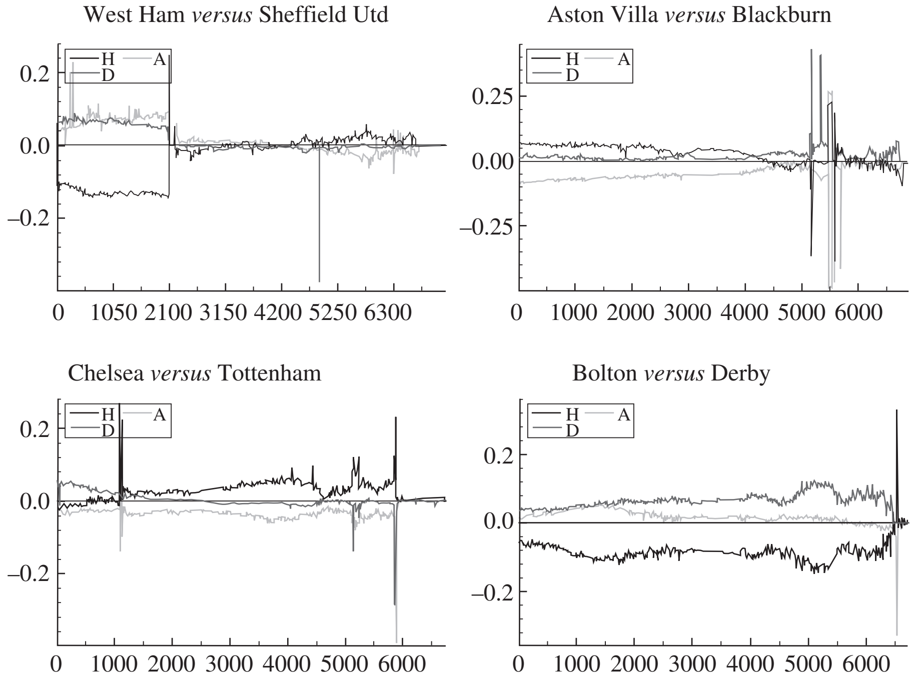

Fig. A4. *Illustrative Plots of the Difference Between the Poisson–Multinomial Minute-by-minute Probability Series and the Betfair Implied Probability Series, i.e.* $\hat{P}_{Betfair,t} - \hat{P}_{Poisson,t}$

scores again to take the lead (at around 5,700 s into the game) our model's predicted 'efficient' trend and the observed trend in Betfair probabilities coincide.

A basic metric for closeness of fit between our Poisson model's predicted in-running time series and the observed Betfair series is a sum of squared deviations measure. We compute second-by-second deviations of Betfair probabilities from our model's predicted probabilities and aggregate to obtain a total per game sum of squared deviations (SSD):[30]

$$\mathrm{SSD} = \sum_{t=1}^{6540} (\hat{P}_{Betfair,t} - \hat{P}_{Poisson,t})^2. \tag{12}$$

We report the summary statistics for this measure for our full sample of 547 English Premiership games in Table A1. Since this is a relative measure and perhaps difficult to interpret in the abstract, we present in Table A2 the individual SSD values for the representative matches depicted in our plots in Figures A3 and A5.[31]

[30] The number 6,450 reflects the average number of seconds in a match (computed by adding to the 90 min of normal playing time, an extra minute for first half injury time, a further 3 minutes for second half injury time, and finally, 15 minutes for half-time). Hence, dividing each SSD by 109 would give an average (cumulated) squared deviation per minute.

[31] Some of these SSD values may appear rather high when one computes the per second average deviation but follow-up investigation suggests that once outliers are removed (due to slight mistracking of goal times and some spurious events towards the end of games where market liquidity often dries up leaving unrepresentative prices in the market) the average difference between the series is very modest, as the plots, which we have selected for their representativeness, indicate.

Manchester United 4–1 Blackburn Rovers, 2006–7

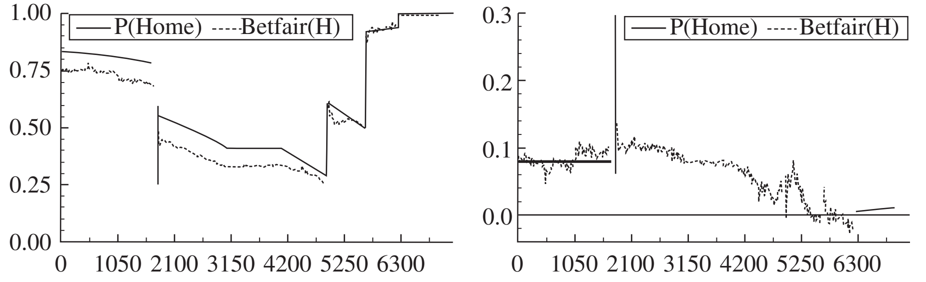

Fig. A5. *The Fit Between the Betfair Implied Probability Series and Our Poisson–Multinomial Minute-by-minute Probability Series for Manchester United Versus Blackburn Rovers* (2006–7)
Notes: The left panel depicts the two series again, the smoother series is the poisson series, and the right panel tracks the difference between the two.

Table A1
Sum of the Squared Deviations Between the In-running Probabilities Predicted by Our Poisson Model and Those Implied by Observed Betfair Prices for all 547 English Premiership Matches

Market	Mean	Maximum	SD
Home	1,410.2	6,047.1	1,233.6
Away	1,087.8	5,655.7	1,193.7
Draw	383.6	1,601.1	310.7

Table A2
Sum of the Squared Deviations Between the In-running Probabilities Predicted by Our Poisson Model and Those Implied by Observed Betfair Prices for the Matches Depicted in Figures A3 and A5

Match	Home	Away	Draw
West Ham *versus* Sheff Utd	1,311.9	770.3	101.0
Aston Villa *versus* Blackburn	1,734.3	1,160.5	133.4
Chelsea *versus* Tottenham	183.1	22.8	93.9
Bolton *versus* Derby	394.3	253.9	427.7
Man Utd *versus* Blackburn	961.3	419.0	241.1

In summary, the simple modelling exercise carried out in this section gives preliminary support to the view that the majority of drift observed in Betfair markets during minutes of play might reasonably be explained by efficient updating to the passage of playing time.

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Additional Supporting Information may be found in the online version of this article:

Appendix B: Supplementary Table B.1 and Table B.2.

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