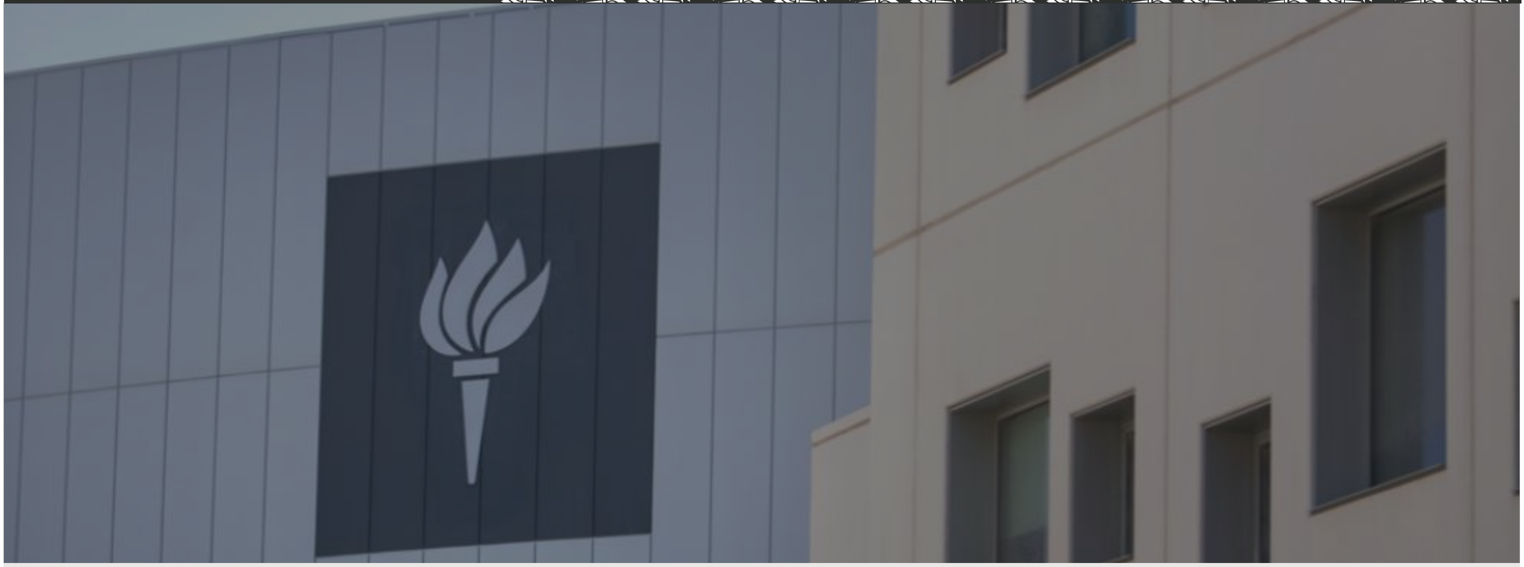

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How Market Prices React to Information: Evidence from Binary Options Markets

Romain Gauriot[*] Lionel Page[†][‡]

October 27, 2021

Abstract

Using a natural experiment setting on binary options markets, we compare the evolution of market prices in situations where the occurrence or not of information shocks depends on knife-edge situations and where shocks can be considered as good as random. We find that most of the time, prices react surprisingly efficiently to information shocks with no evidence of abnormal average returns. We nonetheless find evidence of under-reaction in specific situations where information shocks are large.

Keywords: Market efficiency, Information shock, Prediction markets, Under-reaction.

JEL codes: D84, G14.

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[*] New York University, Abu Dhabi. Email: romain.gauriot@nyu.edu.

[†] University of Technology Sydney.

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1 Introduction

The efficient market hypothesis (EMH) states that financial market prices quickly incorporate new information in an unbiased way. It is one of the most influential concepts in economics and finance. This possible ability of financial markets to aggregate information in prices has motivated the use of market prices as tools to forecast future events and to help inform decision-makers. A large interest has grown, in particular, for *prediction markets* (Wolfers and Zitzewitz 2004, Arrow et al. 2008). These markets feature binary options, Arrow-Debreu state-contingent securities, which pay a positive return if a specific future event is realised. The price of a binary option can be seen as forecasting the probability of the event (Snowberg et al. 2013). Prediction markets have been used to forecast the future results of corporations (Berg et al. 2009, Cowgill and Zitzewitz 2015, Dianat and Siemroth 2021), political events (Oliven and Rietz 2004, Chen et al. 2008), and the replicability of scientific studies (Dreber et al. 2015).

In the present study, we investigate the ability of binary options' prices to react efficiently to the arrival of new public information. We cleanly identify market prices' reaction to information shocks using a natural experiment: situations where the occurrence or not of an information shock depends on *knife edge situations* and where the occurrence of these shocks is credibly *as good as random.* We isolate such situations in a large betting exchange on Association Football matches results: when a shot lands on a goal post. Following Gauriot and Page (2019)'s identification strategy, we leverage these situations to compare the evolution of binary options prices after an information shock (a shot hits the post and goes in the goal) to their evolution in the counterfactual situations with no information shock (a shot hits the post and bounces off the goal).[1] We find that, contrary to what is often found in financial markets (Jiang and Zhu 2017, Kapadia and Zekhnini 2019), the binary

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[1] Our empirical approach consists not in using a big data approach relying on the large number of outcomes which can be observed in a match, but on the careful selection of very specific events which generate a natural experiment. By zooming in on these events, out of all the possible events we could be looking at, we ensure that we use observations where a clean causal inference can be made.

options prices react *surprisingly quickly and efficiently* to the arrival of information: there is no evidence of average abnormal returns. Thanks to our large number of observations, this null result is quite precise. Nonetheless, we find that, when the information shocks are large, towards the end of the markets' life, some significant under-reaction occurs, possibly due to traders' budget constraints (Ottaviani and Sørensen 2015).

Our study contributes to the literature on the usefulness of market prices as forecasting and decision tools. In the widely used case of binary options markets, interpreting prices as probability has been shown to be justified under reasonable assumptions (Manski 2006, Wolfers and Zitzewitz 2006, Iyer et al. 2014, Ottaviani and Sørensen 2015). Empirical research has confirmed that binary options prices tend to be well-calibrated: the expected frequency of success of an option is close to the price at which this option is bought (Page and Clemen 2013, Deck and Porter 2013, Atanasov et al. 2017). At the same time, recent experimental evidence suggests that prices may only incorporate a fraction of the available information (Page and Siemroth 2017, Page and Siemroth 2020, Anderson et al. 2020).

Identifying over- or under-reaction in archival market prices faces well-known difficulties (Fama 1991). We can list at least three identification challenges. First, we never observe the counterfactual evolution of market prices in the absence of information shock. The estimation of prices' over/under reaction, therefore, relies on the definition of normal returns (which requires assumptions about market equilibrium). A statistical test rejecting efficiency may either reflect real inefficiencies in the market or, instead, incorrect assumptions underlying the definition of normal return ("joint hypothesis problem").

Second, the timing of information shocks is not random. In the case of information relevant to forecast the future results of a corporation it is often not released randomly, but at strategic times (Michaely et al. 2016). Similarly, the timing of informational shocks during electoral competitions, such as "bombshell news", is often influenced by the strategical decisions of those holding the information (Gratton et al. 2018). The non-random nature of news arrival means that market reactions to this news can be in part affected by uncontrolled aspects such as the unobserved variables which are determining the release of news.

Third, the exact timing of information shocks can be ambiguous. Information about firms' profitability or government/central bank policies can potentially leak to some traders, before being publicly released (Jiang and Zhu 2017). Similarly, opinion polls and bombshell news are often known by a number of people before becoming public. When this information is made public, some of its implications may already be priced by markets.

One solution to these issues is to use experimental markets in the laboratory where all the information structure can be controlled (Plott and Sunder 1988, Bossaerts 2009, Jiang and Zhu 2017, Kocher et al. 2019, Page and Siemroth 2020). Laboratory experiments provide a useful complement to field studies. However, they also raise questions about their external validity given their small size and the relative lack of experience of standard experiment participants.

Betting exchanges offer an interesting alternative (Croxson and Reade 2014). They are characterised by high liquidity, substantial trading volumes, and traders with extensive experience. A few papers have looked at the evolution of prices on betting exchanges with mixed results. For instance, Gil and Levitt (2012) and Choi and Hui (2014) pointed to possible mispricing in the form or under-reaction in some cases and over-reaction in others after the arrival of goals in football matches by looking at price drifts occurring after a goal. A difficulty of this approach is that prices should drift in non-trivial ways as time passes (as the uncertainty about the outcome of the match is progressively resolved). To avoid this issue, Croxson and Reade (2014) looked at an interesting small sample of matches where a goal arrives just before half-time. They found that prices do not drift after a goal before the half-time break, when no new information arrives on the market.

Our methodological approach empirical strategy addresses the three challenges we have described. First, we can match situations where an information shock occurs with counterfactual situations where no shock occurred. Second, our matching removes the concerns about the non-random timing of information shocks.[2] Third, the arrival of shocks is unambiguous and very precisely measured. In addition, the use of a large dataset allows us to carry more powerful statistical test than in laboratory experiments where the number of observations tends to be relatively limited. For these reasons, our approach provides an ideal setting to investigate how binary options prices' react to informational shocks, in markets with high liquidity and a large number of traders.

Beyond binary options markets, our study contributes to the understanding of the efficiency of financial market prices after the arrival of new information. We follow a long tradition in finance using the clean setting of binary options markets on a betting exchange to study market efficiency (Thaler and Ziemba 1988, Camerer 1998, Rhode and Strumpf 2004, Gandhi and Serrano-Padial 2015, Borochin and Golec 2016, Andrikogiannopoulou and Papakonstantinou 2020).

Our finding that prices react quickly and most often efficiently to the arrival of information brings new insights to the large literature on financial markets efficiency. A large body of evidence points to anomalies in how financial market prices incorporate new information. Market efficiency implies that no systematically profitable trading strategy should exist. In contradiction to this requirement, a pattern of short-run momentum (under-reaction) and long-term reversal (over-reaction) has been found (Cooper et al. 2004). In the short-run, under-reaction has been found in a wide range of situations: after announcements of unexpected earnings (Bernard and Thomas 1989), after stock splits (Ikenberry and Ramnath 2002), after unexpected events (Brooks et al. 2003), after public news (Chan 2003), after unexpected increase in a firm R&D (Eberhart et al. 2004), after asset growth (Cooper et al. 2008), after news about firms in related industries (Ali and Hirshleifer 2019).

One of the main explanations proposed for under-reaction is that investors are subject to

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[2] There is no significant difference between the timing of information shocks and counterfactual situations in our data. This aspect of our strategy is important. Previous research on such binary options markets has shown that different biases in prices are likely to happen at different moments in time, either because traders have time preferences (Page and Clemen 2013), or because the proportion of naive traders on the market vary (Brown et al. 2019).

limited attention and therefore do not process relevant information in a timely fashion (Peng and Xiong 2006, Hirshleifer et al. 2009). This explanation implies that under-reaction should depend on the salience and complexity of the information (Ali and Hirshleifer 2019): one would expect it to be more prevalent in situations where information is harder to observe and more complex to interpret. In reverse, one may expect under-reaction to be smaller when information is easy to notice and interpret. In that regard, our results add to recent evidence that under-reaction of market prices may be lower when information shocks are easily perceptible (Ben-Rephael et al. 2017, Huang et al. 2018). The information shocks on our markets have, in particular, two characteristics. They are *salient*: the information shocks we are looking at (goals) are noticeable and unambiguously important to determine the value of the asset. They are also *transparent*: the qualitative effect of the shocks on the value of the asset is clear (goals increases the winning chances of the scoring team and reduces those of the conceding team). Our results suggest that market prices may react efficiently to new information when these two conditions are present.

2 Data description

2.1 Betting exchange

Betting exchanges are financial platforms which replace the role of bookmakers. They allow bettors to bet against each other on current events. The bets are binary options which take a positive value if a specific event occurs and are worth nothing otherwise. Betfair is the largest betting exchange in the world with highly liquid markets. As of 2016 it had a total revenue of 620 million dollars, and more than 1.7 millions active customers. Betfair organises markets on a wide range of domains, including politics and current affairs. Sporting events constitute the bulk of Betfair's markets. In our dataset, the average amount traded over per match is around $2.2m (£1.8m); in total, we observe trades totalling $17 billion (£14 billion). We obtained data on millisecond by millisecond trading for Betfair markets for matches of the five largest European leagues over the period from August 2006 to November 2014: England (N=1,811), France (N=1,401), Germany (N=1,251), Italy (N=1,554), Spain (N=1,686).[3] Table 1 presents the breakdown of our observation per national leagues.[4]

Competition	Matches	Post-out	Post-in	Avg. Vol. per match (in £)
Bundesliga	1,251	738	155	926,852
Ligue 1	1,401	649	150	426,233
Premier League	1,811	1,096	226	3,723,391
Serie A	1,554	818	222	1,188,707
Liga	1,686	905	217	2,082,364
Total	7,703	4,206	970	1,799,016

Table 1: Dataset description. Excluding post on own goal.

On Betfair's markets, the payout ("odds") of the binary option ("bets") are determined by the supply and demand to buy ("back") or sell ("lay") them. The transactions are done by continuous double auction. Backing a bet with a stake of \$1 is buying a binary option which gives the bet's *odds* in dollars in case of success. Let's consider, for example, a market where the odds were at some point 1.66 to back the outcome "*Team A wins the match*".[5] If a trader buys the bet ("backs" the outcome) with \$1, he will earn \$1.66 if Team A wins and \$0 otherwise. Therefore, he will make a profit of \$1.66-\$1=\$0.66 if Team A wins and make a loss of \$1 if it doesn't win. The normalised price of a bet, to win \$1 in case of success, is $p = \frac{1}{odds}$. This price is also the *market-implied probability* that the event underlying the bet will occur (Snowberg and Wolfers 2010) since the fundamental value of a binary option is its expected value.[6] We use this implied probability p throughout our analyses as the price of the binary option.[7]

As an illustrative example, consider the match between Nuremberg and Cologne on the

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[3] We obtained the data from Fracsoft, a third party authorised by Betfair to sell its trading data.

[4] Figure A.1, in Appendix, presents the location of the shots (landing on the post) in our dataset.

[5] See Figure B.1 in Appendix for a screenshot of the interface traders faced on the Betfair website.

[6] When ignoring time discounting, which we do here, since we look at prices observed only a few hours before the option's payoff is determined.

[7] It is the price of the Arrow-Debreu security which pays \$1 if the event underlying the bet is successful. Each bet exchanged can be considered as being composed of these securities.

18th February 2012 in the Bundesliga. Nuremberg hit the post four times in this match. At the 28' and 85' minutes the ball went inside the goal, and at the 70' and 90' minutes the ball bounced away from the goal. Cologne also scored at the 66' minutes (the ball did not hit the post then). Figure 2.1 illustrates how the market price reacts to a post-in (information shock) and to a post-out (counterfactual). It reacts strongly to the arrival of a goal, but it does not react to the situations where the ball bounced off the post.

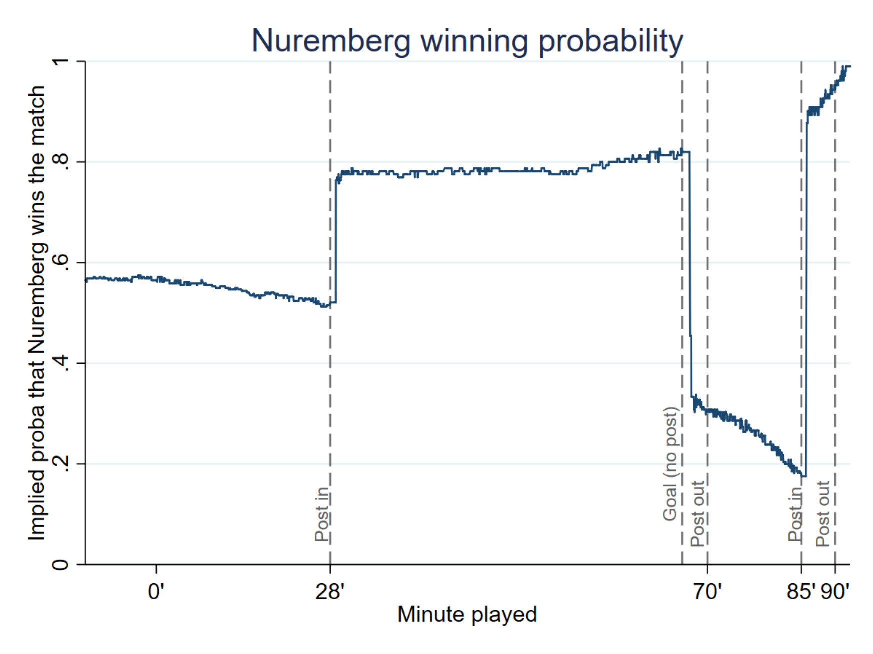

Figure 2.1: Market's implied probability that Nuremberg (home team) wins against Cologne (Bundesliga, 18th February 2012).

2.2 Match data

We obtained from Opta, a company collecting sports in-play data, all the shots hitting the post over that period. Once merged with the Betfair data, we observe 5,176 shots hitting a post. Among these events, 4,206 shots bounced off the post, away from the goal line, 970 shots bounced in, leading to a goal. For geometrical reasons, more angles lead a shot to bounce out than in, hence the largest number of shots bouncing away from the goal.[8]

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[8] See Appendix A for further description of the dataset.

Gauriot and Page (2019) have shown that, controlling for the shots' locations, there is no significant difference in the characteristics of players and teams (attacking and defending) for shots getting in or out after hitting the post.[9]

3 Effect of a goal on market efficiency

3.1 Assessing the presence of abnormal returns prior to the information shock

We first assess whether prices are unbiased before the information shock. We can leverage here the fact that binary options have a definite value determined at the end of their (finite) life duration. The fundamental value of a binary option is its expected value. So, for a given price p, the frequency of positive outcomes should tend to be equal to p.

We define *outcome*, a dummy variable equal to 1 if the bet is successful (the event underlying the option happens). The return of a binary option is $r = outcome - p$. Well-calibrated prices require $\mathbb{E}(r|p) = \mathbb{E}(outcome|p) - p = 0$, that is, for a price p, the corresponding probability of success is indeed p. Following Page and Clemen (2013), we use both non-parametric and parametric (structural) approaches to estimate $\mathbb{E}(r|p)$ using the empirical frequencies of *outcome* for each p.

The calibration of market prices is related to weak-form efficiency. When binary options' prices are well-calibrated, it is impossible to design profitable strategies purely on the basis of present prices. Calibration does not imply stronger forms of efficiency. It can, for instance, co-exist with an imperfect integration of all the available information.[10]

We start by assessing the overall calibration of market prices, using all the observed prices in our dataset (not restricted to situations where a shot hits a post). Figure 3.1 shows the non-parametric estimation of $\mathbb{E}(r|p)$, the returns conditional on prices, for the options *"Home*

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[9] See Appendix C for balance tests on covariates across post-in and post-out situations.

[10] Page and Siemroth (2017) provide an extended discussion of the relationship between calibration and aggregation of information on binary options markets.

team wins the match". We find that market prices are very well calibrated with returns being very close from zero.[11] A careful look suggests the existence of a small deviation in the form of a "longshot bias": the returns tend to be negative for prices below 50% and positive for prices above 50%.[12]

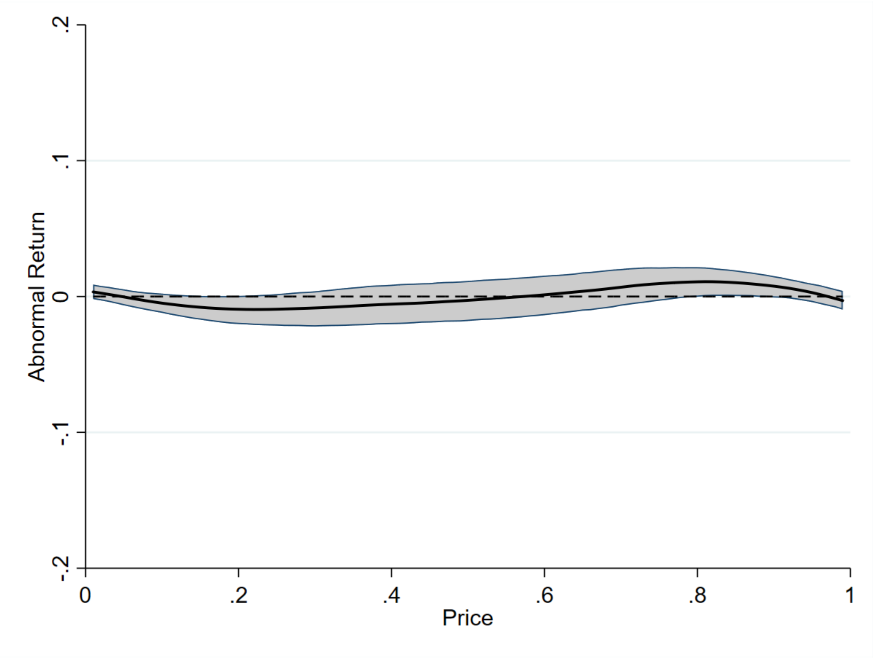

Figure 3.1: Expected returns for all the prices we observe for the options *"Home team wins the match"*. Prices are divided in 100 bins ([0,0.01],[0.01,0.02],...,[0.99,1]). In each bin 10 observations are selected randomly to give equal weight to matches with different volume. The non-parametric estimation is a local linear regression with an Epanechnikov kernel and a bandwitdh of 0.1. Confidence intervals obtained by percentile bootstrap, using 1,000 replications.

We complement this non-parametric estimation with a structural estimation of possible mispricings. Let's consider the possibility for the price of the option to differ from the probability of the underlying event. We can write $p = f(\pi)$, with f not being necessarily the identity function. The return of a contract is then:

$$r = outcome - f(\pi)$$

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[11] We find virtually the same result on the options *"Away team wins the match"*.

[12] These results are similar to those of Andrikogiannopoulou and Papakonstantinou (2020) for an online boomaker's odds on football matches.

To study possible mispricing patterns we use the flexible parametric function proposed by Lattimore et al. (1992):

$$p = f(\pi) = \frac{\delta \pi^{\gamma}}{\delta \pi^{\gamma} + (1-\pi)^{\gamma}} \tag{3.1}$$

Prices are well calibrated for $\delta = \gamma = 1$ (f is then the identity function). This parametrization can accommodate a wide range of mispricings: overall positive abnormal returns ($\delta < 1$: the price p is lower than the probability π); overall negative abnormal returns ($\delta > 1$: the price p is higher than the probability π); longshot bias ($\gamma < 1$).

By inverting f we get the events' probability as a function of market prices: $\pi = f^{-1}(p)$. The likelihood of observing the final outcomes of a set S of options is therefore:

$$L = \Pi_{i \in S} \left\{ f^{-1}(p_i) \right\}^{outcome_i} \left\{ 1 - f^{-1}(p_i) \right\}^{1-outcome_i} \tag{3.2}$$

Table 2 presents the result of the maximum likelihood estimation. We find an estimated δ of precisely 1. The parameter γ is estimated to be 0.964 and is statistically different from 1 ($p = 0.018$). There is, therefore, a small and significant longshot bias.

Parameter	Estimate	Confidence Interval
δ	1	[0.946,1.059]
	(0.938)	
γ	0.964*	[0.933,0.994]
	(0.018)	
N matches	7,703	
N prices	1,888,282	

Table 2: Maximum likelihood estimation of the function from LTW. All trade made on the home team. The standard errors are computed with 1,000 bootstraps samples and are clustered by match. In bracket p-value testing whether the estimate equal 1. 95% Confidence Interval in square bracket.

The longshot bias has been observed in a wide range of markets. In the case of binary options markets, it has been explained by traders' risk attitudes (Ali 1977), budget constraints (Manski 2006), misperception of probabilities (Snowberg and Wolfers 2010), time discounting (Page and Clemen 2013), budget constraints and heterogenous priors (Ottaviani and Sørensen 2015).[13] While we find evidence of a small deviation towards a longshot bias, the markets are remarkably well-calibrated. The highest possible abnormal return which can be achieved with this longshot bias is 1.09% (when buying at a price of 0.81). In comparison, using the same approach on binary options markets from a different betting exchange (Tradesport), Page and Clemen (2013) found a parameter γ substantially lower, 0.8, and the highest abnormal return was substantially larger, 4%.

3.2 Assessing the emergence of abnormal returns after an information shock

Having established the good overall calibration of the prices, we now look at the reaction of these prices to the arrival of new information. First, we check whether the calibration of market prices after a post differs between scoring situations (post-in) and non-scoring situations (post-out). We call "Team A", the team hitting the post when trying to score. We select the market "*Team A wins*" from the markets "*Home team wins*" and "*Away team wins*". We therefore look at how prices react on the markets for the team either scoring or nearly scoring.

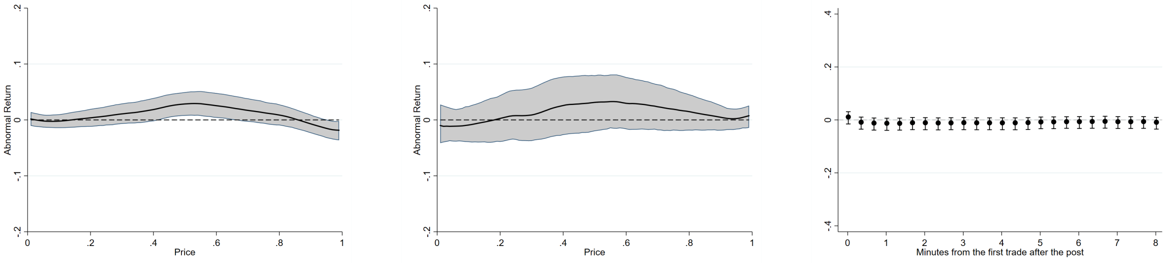
(a) Post-out (b) Post-in (c) Returns after a goal: r

Figure 3.2: Market price reactions after a post following a shot by Team A. Returns for the market *"Team A wins"'* (a) after a post-out and (b) after a post-in; (c) Abnormal returns, $\widehat{\tau}_M$ estimated by kernel matching, when buying the asset "Team A wins" at different times after following a positive information shock.

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[13] See Ottaviani and Sørensen (2008) for an extended discussion of the main explanations of the longshot bias.

Figure 3.2 displays the non-parametric estimates of the returns per price for the first transaction after a post-in (panel a) and after a post-out (panel b).[14] Overall the market prices are well-calibrated after a post.[15] This non-parametric approach pools all the observations in two groups (information shock vs no information shock) to compare them. This comparison could still be influenced by the fact that the whole sample of situations with a post-in may differ in some way from all the situations with a post-out. For instance, information shocks may tend to happen at times where the price calibration is slightly different from situations where no information shock occurs.

We use our precise data on shots' locations to address this possible concern. We match shots taken from a very close position on the pitch, which ended having different outcomes (post-in or post-out). We then compare the returns of market prices after the post between these two situations. To do so, we implement a matching approach, using spatial (i.e. Euclidean) distances computed from the (x,y) coordinates of the shots' location on the pitch. This approach ensures that our study of the market reaction to information shocks relies on the comparison of very similar situations.

For each binary option i observed after a shot on a post, we define the dummy $post_i$ which takes value 1 if the shot ended inside the goal and 0 otherwise. Our variable of interest is the return r_i from buying it after a post. We define: $r_i(t) = outcome_i - p_i(t)$, where t is the period after the post was hit. If the option is successful it provides a positive return of $1-p_i(t)$. If it is unsuccessful, it provides a negative return of $-p_i(t)$. We use kernel matching to build a synthetic counterfactual as a local weighted average of r_i for nearby shots with a different outcome. Our matching is quite precise, the weighted average distance between each observation and their counterfactuals is 54cm. We compute the p-values and confidence intervals by parametric bootstraps.[16] Calling $\widehat{r_i}(0)$ and $\widehat{r_i}(1)$ the potential outcome values of r obtained from the observations and their synthetic counterfactuals, the matching estimator

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[14] See Appendix D for a description of how we identify the first trade after a post.

[15] Maximum likelihood estimations of equation 3.2 also find that parameters δ and γ do not significantly deviate from 1 (detail in Appendix E).

[16] See Appendix F for details.

$\widehat{\tau}_M$ quantifying the causal effect of interest, is defined as:

$$\widehat{\tau}_M = \frac{1}{N}\sum_{i=1}^{N}\left(\widehat{r}_i(1) - \widehat{r}_i(0)\right) \tag{3.3}$$

$$\widehat{r}_i(1) = \begin{cases} r_i & \text{if a goal is scored} \\ \widehat{r}_i^{KR} & \text{if no goal is scored} \end{cases}$$

$$\widehat{r}_i(0) = \begin{cases} \widehat{r}_i^{KR} & \text{if a goal is scored} \\ r_i & \text{if no goal is scored} \end{cases}$$

Where

$$\widehat{r}_i^{KR} = \frac{\sum_{j\in\mathcal{M}_i} K_h(x_i - x_j)K_h(y_i - y_j)r_j}{\sum_{j\in\mathcal{M}_i} K_h(x_i - x_j)K_h(y_i - y_j)}$$

With $\mathcal{M}_i$ being the set of counterfactual observations matched to observation i and K_h an Epanechnikov kernel function with bandwidth $h = 0.64\text{cm}$.[17]

We test the null hypothesis that the arrival of a goal does not induce abnormal returns for trades taking place just after the shot, $H_0 : \widehat{\tau}_M = 0$. This hypothesis means that the information shock does not lead to a relative under-reaction ($\widehat{\tau}_M > 0$), nor does it lead to a relative over-reaction ($\widehat{\tau}_M < 0$).

Figure 3.2 (panel c) shows the evolution over time of the estimated effect. We find that market prices observed just after the shock re-adjust right away with the first trades following a post, without significant over/under-reaction. The estimate of $\widehat{\tau}_M$ using the first price observed after the information shock is 1.12% (p = 0.409, N=5,176). Therefore, we cannot reject the null hypothesis that the changes in market prices following a goal accurately track the changes in the associated winning chances. This result is quite precise. The 95% confidence interval of $\widehat{\tau}_M$ is $[-1.52\%, 3.11\%]$. Our analysis therefore gives fairly small bounds

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[17] This bandwidth is determined using the data-driven approach proposed by Huber et al. (2015) and implemented by Jann (2019): it is 1.5 the 90th quantile of the distribution between the matched treated and controls.

for market over/under-reaction.[18] After this initial adjustment, the estimate of $\widehat{\tau}_M$ closely approximates 0 over the following minutes.

4 Reaction to information across different market situations

We now leverage our large dataset to investigate whether this result can be generalised to many different market conditions.

4.1 Different timings

We first look at how prices react after a post-in or -out, depending on the timing of the event in the match. Timing is important: an early goal leaves plenty of time for the outcome of the match to change; A late goal is more likely to determine the final outcome of the match. As a consequence, late goals induce in general larger information shocks.

Figure 4.1 reproduces figures 3.1 and 3.2 for different timings. The first and second rows show the expected returns during the first half (1-45 minutes), and the second half (46-90 minutes), respectively. Prices appear very well calibrated in the first half. A small but visible longshot bias appears in the second half. Given this pattern, we also split our estimation into shorter periods. The third row presents the result for the last 15 minutes (76-90 minutes) of the match.[19] At the end of the match, the winning chances of the then favourite team tends to be underestimated. So buying at prices higher than 0.50 yields positive returns on average.

In each row, the second column shows the expected returns after a *post without goal*,

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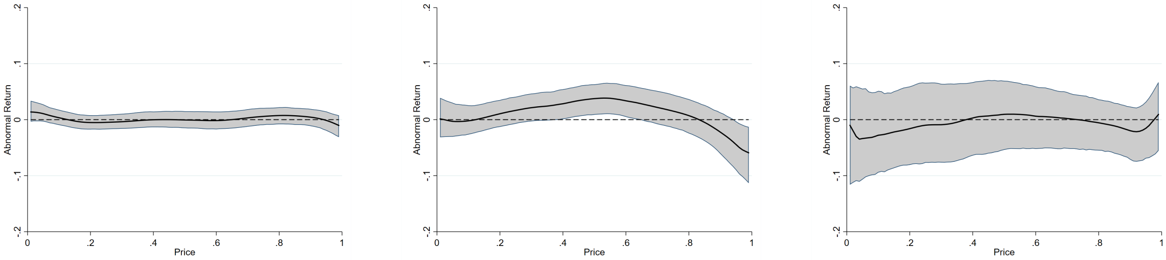
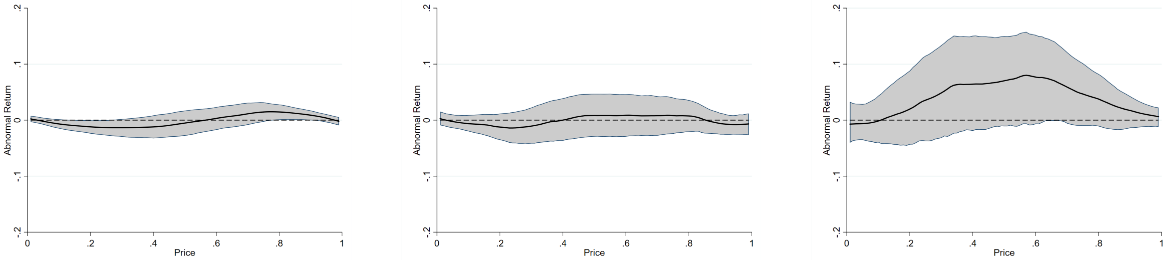
[18] A calculation of the minimum detectable effect shows that we would be able to detect any effect greater than 3.7% with 80% power. Beside the MDE, the CI determines the maximum possible value of the parameter to consider *conditional on the estimates found* (Mair et al. 2020). In our case, it is 3.11%.

[19] We include additional injury time in all analyses using the first half, second half and the last fifteen minutes of the match. See Figure G.1 in Appendix for the expected returns for all the 15 minutes periods of the match.

(a) All bets, first half (b) Post-out, first half (c) Post-in, first half



(d) All bets, 2^{nd} half (e) Post-out, second half (f) Post-in, second half



(g) All bets, last 15 min (h) Post-out, last 15 min (i) Post-in, last 15 min

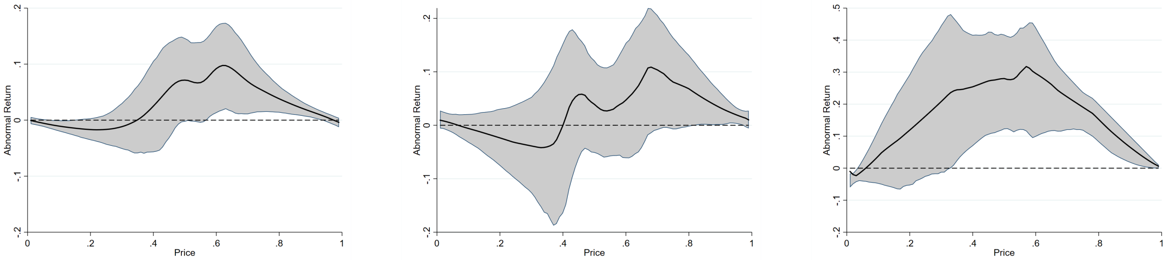


Figure 4.1: Expected returns for all the prices observed (first column), for the first price observed after a post-in (second column), and for a post-out (third column) for the asset *"Team A wins the match"* where Team A is the team hitting the post.

and the third column shows the expected returns after a *post with a goal*. The confidence intervals are larger due to the smaller samples, but the pattern is the same in both cases than over all the observations. We observe a very good calibration in the first half. But, in the second half, the calibration seems a bit worse after a goal and the pattern is particularly pronounced in the last 15 minutes. At the very end of the match, large positive returns suggest an under-reaction of prices after an information shock.

These abnormal returns after a post-in are confirmed by our parametric estimates of equation 3.2. Table 3 presents these estimates. The prices after a post are mostly well-calibrated during the match. But they are poorly calibrated after a goal in the last 15 minutes of the match, with the coefficient $\delta = 0.521$ (significant at 0.1%), indicating under-reaction with prices being too low.

	First 45 min		Last 45 min		Last 15 min	
	post-out	post-in	post-out	post-in	post-out	post-in
δ	0.897*	1.02	1.04	0.819	0.846	0.521**
	(0.031)	(0.881)	(0.528)	(0.123)	(0.165)	(0.002)
	[0.365]		[0.092]†		[0.079]†	
γ	1.01	0.994	1	0.947	0.910	0.732†
	(0.820)	(0.956)	(0.999)	(0.577)	(0.177)	(0.075)
	[0.926]		[0.629]		[0.286]	
N	1,899	426	2,307	544	890	210

Table 3: Maximum likelihood estimation of the function (3.1). First price after a post for the market *"Team A wins"'*. In bracket p-value testing whether the estimate equal 1. In square bracket p-value testing whether the estimate for the post in and out are equal. Std errors clustered by markets. † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level

4.2 Different timings and scorelines

Besides the timing of the goal, the scoreline at the time of the goal also matters. A goal occurring in a match with a close scoreline is more likely to change the outcome of the match (and therefore the value of the binary option) than a goal taking place when the scoring team is already winning. We therefore cross timings and scorelines to look at different situations of interest. In the following, we call "Team A" the team hitting the post when attempting to score. We define four categories of scorelines. First, when Team A trails by more than one goal, it would still be losing after a goal. Second, when Team A trails by one goal, a goal would lead to a draw. Third, when the two teams are tied, a goal would lead Team A to get into a winning position. Finally, when Team A is already ahead, a goal would then just add to its existing winning advantage.

Figure 4.2 gives an overview of how prices react in each of these situations, by periods of 15 minutes. For completeness, we present the three types of markets: Team A (hitting the post) wins, Team B (defending) wins, draw. For clarity of exposition, we define abnormal returns such that positive estimates always indicate an under-reaction, and negative estimates always indicate an over-reaction. Specifically, we look at abnormal returns estimated by τ_M when buying after a positive information shock (panels a, d, g, j, c, f) or selling after a negative information shock (panels b, e, h, k, i, l). The significance of abnormal returns is indicated with stars in the panel. As we look at subsamples (135 overall in this section) we follow Anderson (2008) and control for the False Discovery Rate by computing the sharpened q-value (Benjamini et al. 2006).[20]

The pattern emerging from 4.2 is that, overall, market prices seem to be adjusting quickly and accurately to the arrival of new information, most of the time. This result needs to be tempered by the fact that, as we look at smaller subsamples, the prediction of our estimates decrease. We therefore cannot systematically exclude the presence of some under/over-reaction in all the subsamples where results are insignificant.[21] However, there is a significant degree of under-reaction when the information shock is large: when a late goal is set to change the outcome of the match. The largest deviation is found when a goal moves the scoreline from a draw to a win in the last 15 minutes of the match. We then observe an under-reaction of 17% ($p = 0.001$, $q = 0.039$, N=296). It is a substantial effect, and it is robust to controlling the False Discovery Rate. Further analysis shows that most of the effect reduces quickly, but an under-reaction still remains 5 minutes after the post.[22]

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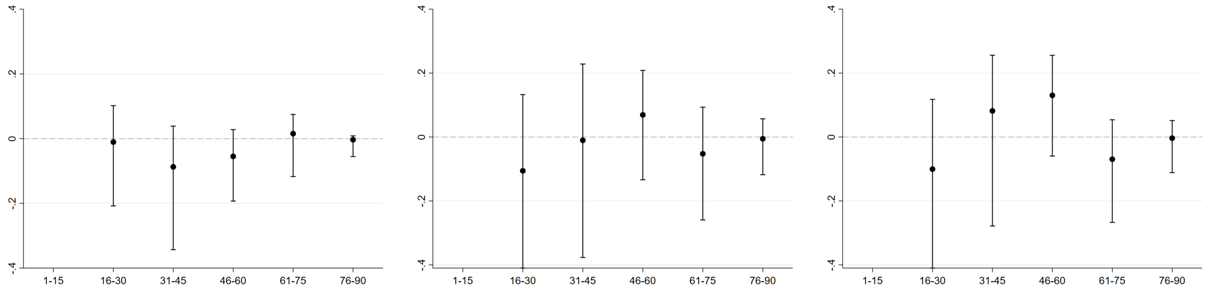
[20] For three of the 135 sub-samples, we only observe two posts, and we, therefore, cannot perform our estimation. We, thus, control the False Discovery Rate for 132 statistical tests. This sub-samples correspond to the three markets in the first 15 minutes of the match when Team A is trailing by at least two goals. See Appendix H for detailed results of the matching estimations depicted in Figure 4.2.

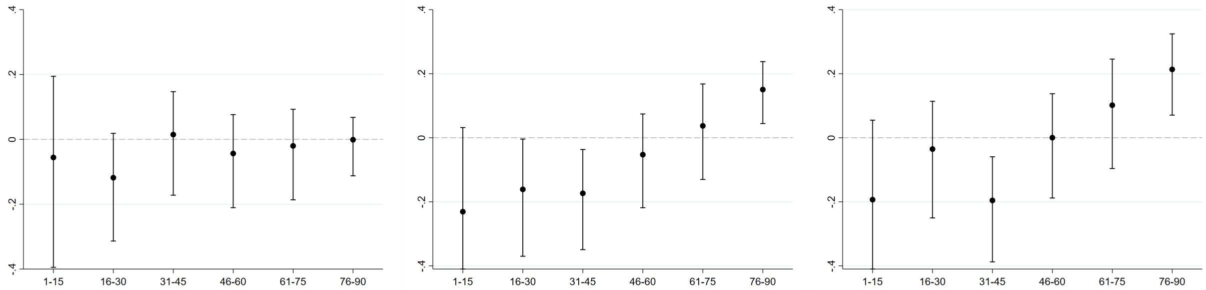
[21] Table M.1 in Appendix shows the minimum detectable effect size in all subsamples. Some subsamples are underpowered, which is reflected in large confidence intervals in Figure 4.2.

[22] Figure I.3 in Appendix shows the evolution of this effect over time.

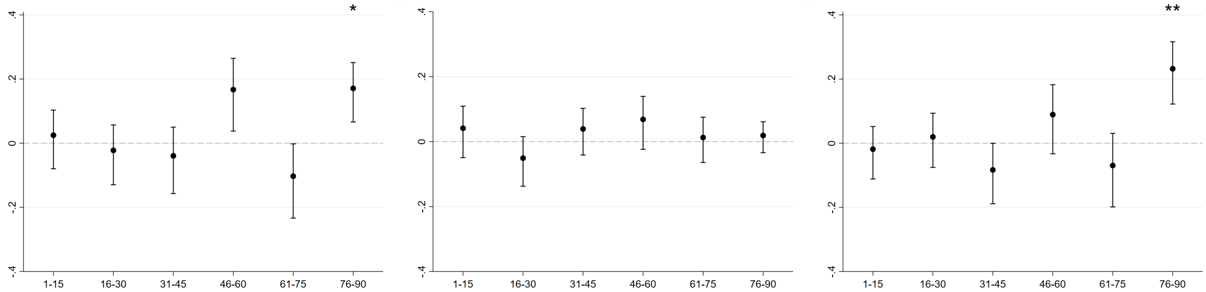
Team A hitting the post trailing by at least two goals


(a) Asset "*Team A wins*" (b) Asset "*Team B wins*" (c) Asset "*Draw*"

Team A hitting the post trailing by one goal


(d) Asset "*Team A wins*" (e) Asset "*Team B wins*" (f) Asset "*Draw*"

Scoreline is tied


(g) Asset "*Team A wins*" (h) Asset "*Team B wins*" (i) Asset "*Draw*"

Team A hitting the post leading by at least one goal

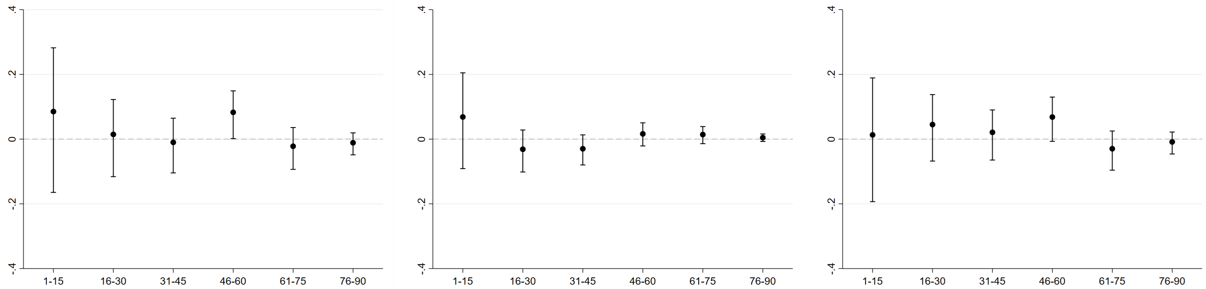

(j) Asset "*Team A wins*" (k) Asset "*Team B wins*" (l) Asset "*Draw*"

Figure 4.2: Estimate of abnormal returns after buying following positive news ($r = outcome - p$, panels a, d, g, j, c, f) or selling following negative news ($r = p - outcome$, panels b, e, h, k, i, l). Positive values indicate under-reaction. With conterfactuals, kernel matching estimator, matching on *x*-*y* with Euclidean distance, standard error computed with 50,000 bootstraps. Significant at * 5% level, ** 1% level for the sharpened q-values.

5 Discussion

5.1 Using counterfactuals

Our use of a natural experiment to study the effect of information shocks on the efficiency of market prices allows us to eliminate possible confounds due to mispricings which may exist prior to the information shock. Such mispricings indeed exist in our setting: a small longshot bias is observed overall, with a more pronounced one being present towards the end of the match. This longshot bias lowers returns when prices are low (longshots are overpriced) and increases returns when prices are high (favourites are underpriced). If we were not using counterfactual situations to study abnormal returns, these biases could lead us to wrongly conclude that prices tend to over-react when prices are low (returns are biased downward) and to under-react when prices are high (returns are biased upward). It is what we find when estimating the effects presented in Figure 5.1 without counterfactuals. Most estimates move in the direction of the longshot bias, suggesting significant under-reaction in several situations (panels e, f, g, h, i, j, k, l).[23] Most of these significant abnormal returns disappear when using our counterfactual approach. Part of the reason is that our matching estimates have slightly larger standard errors, but our matching approach also eliminates possible mispricings prior to the arrival of information.

The quality of our counterfactuals is key to eliminate such pre-existing biases. Our counterfactuals are situations where an information shock (goal) could have happened but did not. We find that there is no significant difference in terms of players and teams strength between goal-scoring situations and the counterfactuals. Given that the longshot bias is specific to the price levels, it is important that these counterfactuals are observed for the same price levels as the goal-scoring situations. We find that the distribution of prices is very similar for goal-scoring situations and their counterfactuals. We also check the robustness of our matching estimates by matching on different variables in addition to the spatial distances

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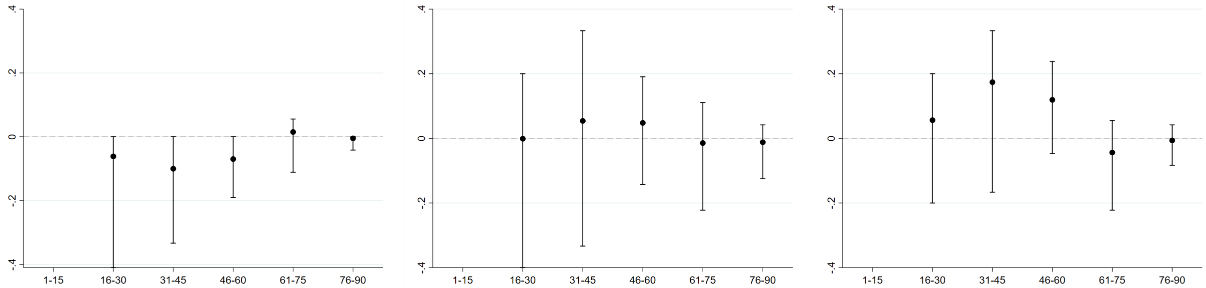
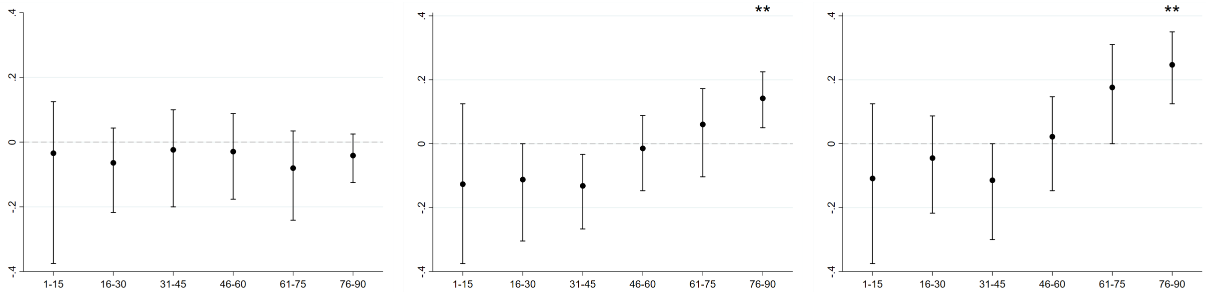
[23] See Appendix J for detailed results of the estimations depicted in Figure 5.1.

Team A hitting the post trailing by at least two goals



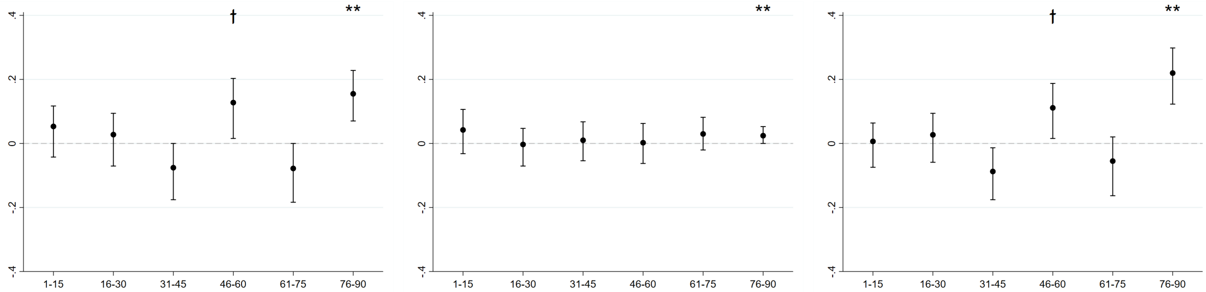
(a) Asset "*Team A wins*" (b) Asset "*Team B wins*" (c) Asset "*Draw*"

Team A hitting the post trailing by one goal



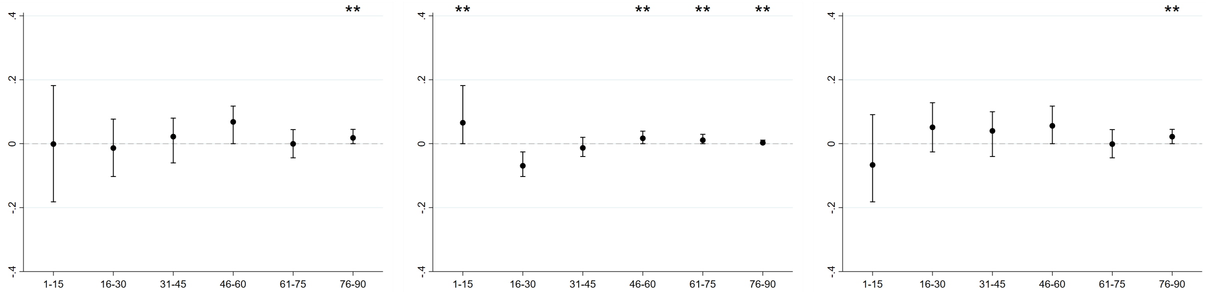
(d) Asset "*Team A wins*" (e) Asset "*Team B wins*" (f) Asset "*Draw*"

Scoreline is tied



(g) Asset "*Team A wins*" (h) Asset "*Team B wins*" (i) Asset "*Draw*"

Team A hitting the post leading by at least one goal



(j) Asset "*Team A wins*" (k) Asset "*Team B wins*" (l) Asset "*Draw*"

Figure 5.1: Estimate of abnormal returns after buying following positive news ($r = outcome - p$, panels a, d, g, j, c, f) or selling following negative news ($r = p - outcome$, panels b, e, h, k, i, l). Positive values indicate under-reaction. Without controlling for counterfactuals, kernel matching estimator, matching on x-y with Euclidean distance, standard error computed with 50,000 bootstraps. Significant at * 5% level, ** 1% level for the sharpened q-values.

between shots: the price of the binary option *at the time* of the shots, or the timing of the shots, or the price of the binary option *after* the shots. The results using these alternate matching approaches are nearly identical to our main results.[24]

5.2 Possible mechanisms behind the under-reaction

While market prices seem to react quickly and efficiently most of the time, we find evidence of mispricing towards the end of the match when scoring a goal makes a big difference on the likely final outcome. Several theoretical models have been proposed to explain under-reaction as the result of investors' psychological biases, in particular their limited attention (Hirshleifer et al. 2009). In the specific case of binary options markets, Ottaviani and Sørensen (2015) show that an under-reaction can also emerge naturally when rational traders do not share the same priors and when they have budget constraints.[25] The fact that we do not observe under-reaction for most of the markets' lifespan suggests that these factors do not play a role substantial enough to distort prices. However, goals in the last minutes of matches may have larger effects on prices and on volumes. And these movements could be more likely to bind the traders' budget constraints.

In terms of price, when a late goal happens in a match where the score is tied, the information shock is very large. It typically changes the value of the binary option "Team A wins" from a price close to \$0 to a new price close to \$1. Large information shocks require traders to be able to move the price in the direction of the shock with their trades.[26] But, for any given budget a trader has, the number of bets this budget can buy decreases as the price of the bet increases.

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[24] Balancing tests and tests of price distribution prior to the information shocks are included in Appendix C. Robustness checks with different matching choices are included in Appendix K.

[25] The assumption of a budget constraint is reasonable for two reasons. First, betting exchanges feature a large proportion of traders with limited budgets. Second, even wealthy traders should optimally follow some rules such as the Kelly-criterion and limit their exposure on a given market to only a small share of their overall wealth.

[26] Formally, Ottaviani and Sørensen's model is a one-period model with only one information shock and one trading period. This discussion of how their theoretical predictions relate to what happens at the end of matches should therefore be seen as suggestive.

Figure 5.2 plots the estimated under-reaction τ_M vs the effect of goals on volume and on prices. It shows that situations where goals are followed by the highest abnormal returns (under-reaction) tend also to be characterised by the largest increases in prices and volume (top right corners).

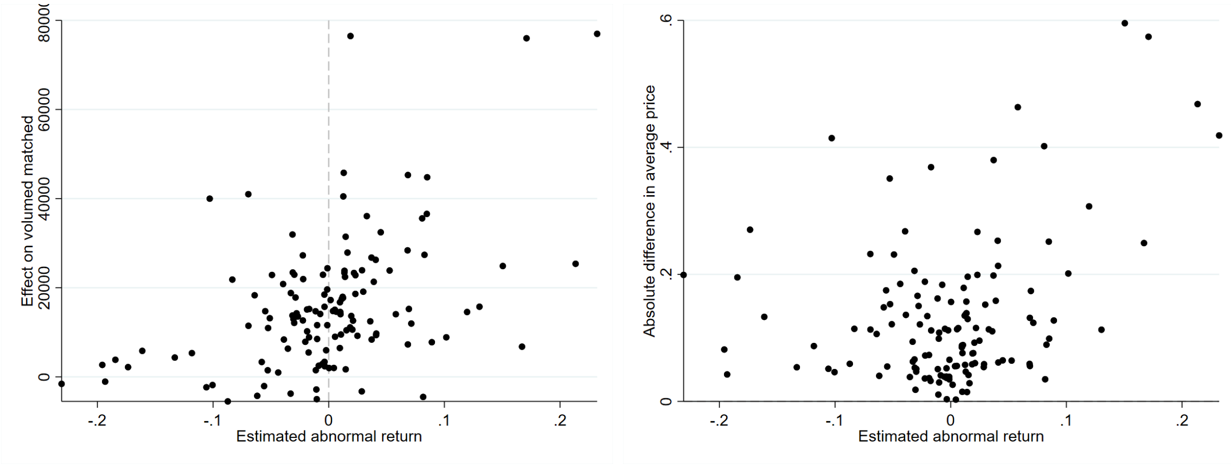

Figure 5.2: Estimated abnormal returns (τ_M) compared to the effect of the goal on volume (left) and prices (right).

A further look at the data shows that the largest movements in volume are for the goals happening in the last minutes of matches.[27] The average effect of a goal in the match on volume is to increase it by £17,419 ($21,100). But when a goal allows Team A to move from a draw to a winning position in the last 15 min, it increases the volume of transaction five times more: by on average £86,242 ($104,700).

These larger volumes after late goals mean that traders are buying a larger number of binary options.[28] Furthermore, towards the end of the match, traders may already have used a large part of their budget. They may therefore be more likely to reach their budget constraint when trading after a large shock. The pattern of under-reaction observed at the end of matches is therefore compatible with Ottaviani and Sørensen (2015)'s model whereby traders reach their budget constraints when information shocks are large.[29]

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[27] See Appendix L for detailed analyses of the effect of information shocks on volumes as a function of their timing.

[28] Note that "selling" an option is akin to buying the reverse option which also takes from the traders' budget when they did not have the option to start with.

[29] We can also conceive other types of explanations using behavioural assumptions. For instance, traders

6 Conclusion

Binary options markets, through their use as prediction markets, have attracted a lot of interest for their possible ability to aggregate available information and provide, through their prices, forecasts for the probability of future events. We investigate here how binary options markets prices react to the arrival of new public information. We compare knife-edge situations where information shocks occur with their counterfactuals where no such information shock occur. This comparison gives a high degree of confidence in the identification of possible mispricings.

We find evidence of under-reaction in specific contexts: towards the end of the markets' lives, in situations where the information shocks and the volume traded are large. This under-reaction may be due to the specific market structure of binary options markets, as predicted by Ottaviani and Sørensen (2015), not to traders' psychological biases. Our main result is however that, most of the time, prices react surprisingly quickly and efficiently to information shocks: they move immediately to new levels which are not associated with abnormal returns.

This study contributes to evaluate the usefulness of prediction markets as forecasting tools. Our result suggests that, following an information shock, the evolution of prediction markets prices can be a good reflection of the inference we should draw from the newly arrived information in regard to the probability of the future event of interest. The markets we studied are highly liquid, feature a large number of traders, and attract expert traders who invest in quantitative techniques to take advantage of potential mispricings. They may therefore be considered as a favourable setting for prices to efficiently react to information. The robustness of this finding to settings where markets are smaller and less liquid would be worth investigating.

Our result also contributes to our understanding of the efficiency of financial markets in

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could tend to overweight small probabilities more towards the end of the match. We see the budget constraint channel as the simplest one able to explain the patterns in the data, using standard assumptions.

general. The existing evidence points to the presence of under-reaction to information on financial markets. The cause of this under-reaction is often thought to be the limited attention of traders (Hirshleifer et al. 2009). In that regard, the information shocks on the markets we are studying have two relevant characteristics. First, they are *salient*. Traders are unlikely to miss out on the arrival of this information as they typically follow the events on which the markets are based. Recent studies have stressed the possible effect salience can have on asset prices by focusing the attention of traders on some aspects of assets or on relevant news (Bordalo et al. 2013, Andrei and Hasler 2015, Frydman and Wang 2020). Second, the information shocks are also quite *transparent*. The interpretation of how a new informational shock should impact price is typically fairly clear, at least in terms of direction. Research on information updating has found that when provided with feedback, traders can learn to be Bayesian and use new information appropriately to update their beliefs (Payzan-LeNestour and Bossaerts 2015). This is the case even in situations where informational shocks were unlikely and therefore mostly unexpected (Payzan-LeNestour 2018). It is reasonable to assume that these two characteristics may help market prices to react faster and better to the arrival of news. Relative to betting exchanges, traditional financial markets are populated by more sophisticated traders tracking mispricing opportunities. Our results suggest that, even when markets are characterised by high-frequency trading, prices may react efficiently to information shocks when information is salient and transparent enough.

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Online Appendix

A Data Description

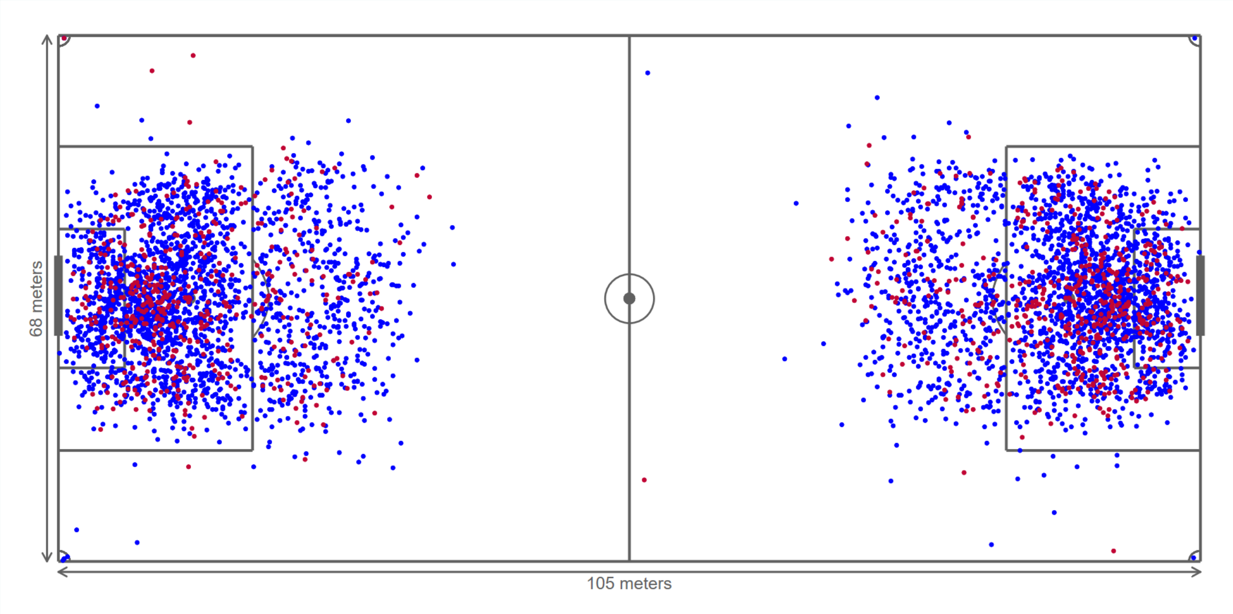
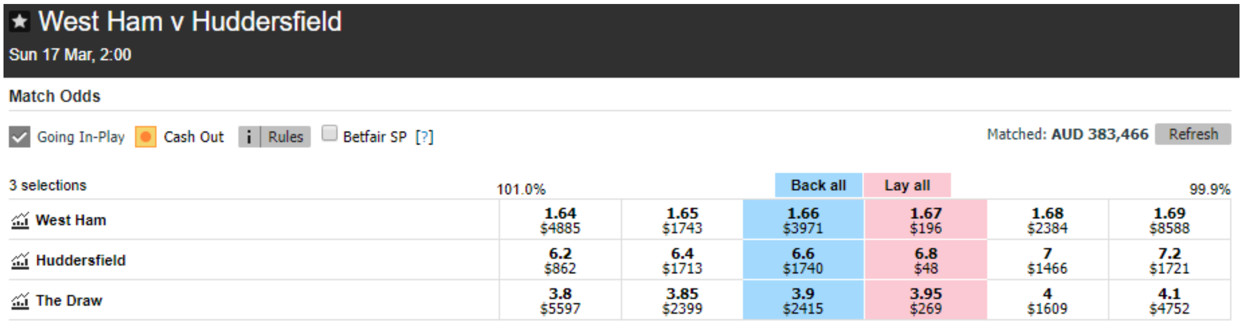


Figure A.1: Graphical representation of the starting point of shots ending on the posts. In red the posts in and in blue the posts out.

B Betfair's Interface



West Ham v Huddersfield

Sun 17 Mar, 2:00

Match Odds

Matched: **AUD 383,466**

3 selections	101.0%		Back all	Lay all		99.9%
West Ham	**1.64** $4885	**1.65** $1743	**1.66** $3971	**1.67** $196	**1.68** $2384	**1.69** $8588
Huddersfield	**6.2** $862	**6.4** $1713	**6.6** $1740	**6.8** $48	**7** $1466	**7.2** $1721
The Draw	**3.8** $5597	**3.85** $2399	**3.9** $2415	**3.95** $269	**4** $1609	**4.1** $4752

Figure B.1: Screenshot of the interface faced by traders face on the Betfair website.

Figure B.1 shows a screenshot of the interface traders faced on the Betfair website for the match West Ham vs Huddersfield. In this example, the best price available to back the outcome *West Ham wins the match* is \$1.66. It means that if one backs this outcome (i.e. buys the bet) with \$1 he/she will earn \$1.66 if West Ham wins and \$0 otherwise. Therefore, he/she will make a profit of \$1.66-\$1=\$0.66 if West Ham wins and make a loss of \$1 if West Ham doesn't win. At the price of \$1.66 there is \$3,971 which are available to be matched. This means that on the other side of the market, traders have proposed \$3,971 to lay this outcome at \$1.66.

C Balance tests

Table C.1 shows differences in covariates between the posts in and out. We used the same kernel matching estimator as in our main result, matching on the (x,y) coordinates of where the shot was taken.[30] There is no significant difference in any of the covariates.

Table C.1 shows that just before the post there is no difference in the average probability implied by the markets (first three rows). To assess whether there is a difference in the distribution of prices just before posts in and posts out we perform a Kolmogorov-Smirnov test on those two group of prices. Figure C.1 reports the results. In the three different markets, we cannot reject the null hypothesis that there is no difference in the distributions of prices before the posts.

We perform the same test with the timing of the goal. Figure C.2 shows a Kolmogorov-Smirnov test testing whether there is a difference in the distribution of minutes in the match at which the post occurs between the posts in and out. We do not find difference in the timing of the goal.

---

[30] The standard error are computed by standard bootstrap (i.e. resampling with replacement).

	Diff	p-value	N
Ex-ante probability from betting odds			
Prob team hitting post wins	0.006	0.625	5,176
Prob team conceding post wins	−0.005	0.666	5,176
Prob of a draw	−0.002	0.798	5,176
Player's basic characteristics			
Player starting the match	−0.001	0.932	5,176
Forwards	−0.016	0.377	5,176
Midfielder	0.016	0.381	5,176
Defender	$1.6 * 10^{-4}$	0.990	5,176
Home team	$-3.21 * 10^{-6}$	1.000	5,176
Player's performance since the start of the season			
Number of goal scored	0.011	0.945	5,023
Average rating	−0.001	0.151	1,949
Number of post inside	−0.023	0.616	5,023
Frequency of post inside	−0.003	0.875	2,071
Market values			
Player's market value	$144, 014$	0.799	5,158
Team's average market value	58969.36	0.843	5,176
Opponent team's average mv	$-156, 749$	0.412	5,176
Period in the match			
Minute in the match	0.382	0.692	5,176

Table C.1: Tests of balance of covariates between matched observations. Kernel matching on (x,y) coordinates. Standard errors computed with 1,000 bootstraps.

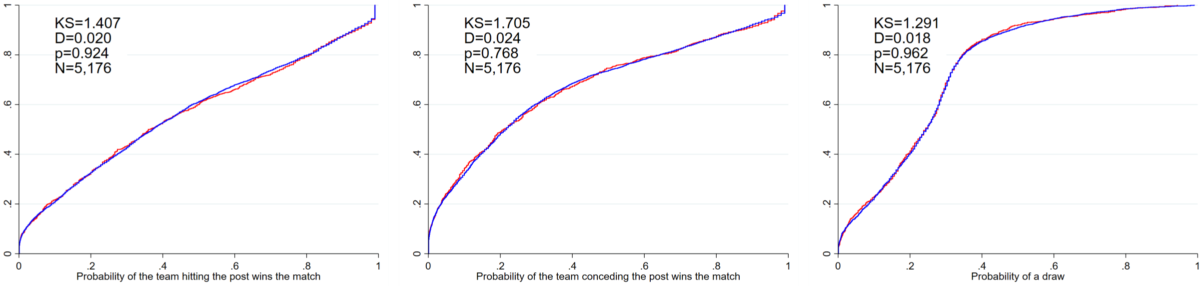


Figure C.1: Kolmogorov-Smirnov test testing whether there is a difference in the distribution of prices just before the post between the post-in and out. In red the post-in and in blue the post-out. On the left the market "Team which hits the post wins the match", in the middle "Team which concedes the post wins the match", on the left "Match ends as a draw"

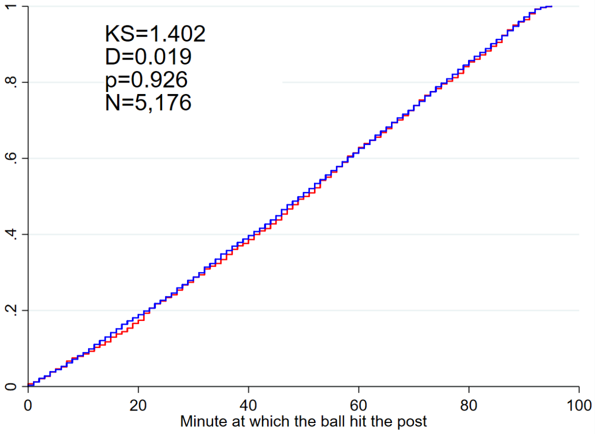


Figure C.2: Kolmogorov-Smirnov test testing whether there is a difference in the distribution of minutes in the match at which the post occurs between the posts in and out. In red the post-in and in blue the post-out.

D Defining the first price after a post-in and a post-out

A key aspect of our analysis is to identify the price of the first transaction after a post occurs. In the Betfair data, we have information about the market at regular intervals. We sometimes have information multiple times per second, and sometimes there is a few second (e.g. 10 sec) between the updates. The timestamp of the update is to the nearest millisecond. In the Opta data, we have a timestamp of when the post occurs to the nearest second.

We merge the time at which the post occurs (from Opta) to the prices (in the Betfair data) using the timestamp to the second. The two timestamps from Opta and Betfair are synchronized.

On Betfair, when a goal occurs, trading is suspended for a certain period (on average during 62 seconds). During this period the entire betting books are cleared so any trading happening when the market re-opens cannot be for orders placed before the goal. In the Fracsoft data, we do not know when the market is suspended or open. We have much fewer market updates when the market is suspended.

For each update, we know the "*Last price which has been matched*", as well as the "*total volume, matched on this market up to that timestamp*", (in British pounds). We, therefore, know how much is traded between the different updates. However, we do not know at what time between two updates trade happens.

The Opta timestamp is recorded by a human and the start of the period at which Betfair is stopping trade is also recorded by a human. It is, therefore, possible that there is a few second of discrepancy between these two timestamps. By contrast, the timestamps of the market updates are recorded by a computer and are, therefore, exact.

We identify the first trade after the post-in and out as explained below.

D.1 First price after a post-in

Let's define $t_{post,Opta}$ the timestamp of the post recorded by Opta (to the nearest second), $t_{update,Betfair}$ the timestamp of the updated prices in Betfair (to the nearest millisecond). We want to identify $t_{0,Betfair}$ which is the first Betfair market update, after a post-in occurred, in which a trade occurred.

- We define a period without trade or update a period in which there is either no market update or the *'total volume matched on this market up to that timestamp'* does not increase. This definition is not necessary a period without trade. Indeed, it could just be that we do not have an update on the market during this period.
- We identify the longest period without trade or update which include at least one seconds $t_{post,Opta} \in [-3, 9]$. We denote this period *blockodds*.
- We look at the first trade at the end of *blockodds*. That is the first time the "*total volume matched on this market up to that timestamp*" increases since the beginning of this period.
- If the "*Last price which has been matched*" is different at the end of this period than at the beginning. We define this first trade as being the one just after the market opens.
- If the "*Last price which has been matched*" is **not** different at the end of this period than at the beginning. Then we look at the next trade, and we define the next trade as being when the market opens. Indeed if the "*total volume matched on this market up to that timestamp*" increases at time t it could be for any trade between the update at time t and the previous update. So the first time the "*total volume matched on this market up to that timestamp*" increases, it could be for trade which happened before the market was suspended.

D.2 First price after a post-out

As we have seen above, after a goal, Betfair suspends the market. Therefore, for a post-in we look at the first trade after the market re-opens.

After a post-out, the market is not suspended. We define the first price after a post as being the first trade occurring 10 seconds after $t_{post,Opta}$. Importantly, our results are not sensitive to how we define the first price after a post-out. Specifically we find the same results if we define first price after a post as being the first trade occurring t second after $t_{post,opta}$ for $t \in \{-5, 1, .., 15\}$.

D.3 Price when no trade occurs after the post

When there is not much uncertainty about the outcome of the match (e.g. p close to 0 or 1), there is sometimes no trade occurring after the post.

For instance, when the probability implied by the market is close to 1. If a team hits the post and the ball goes in, the team hitting the post is even more likely to win the match. In that case, there may not be any trader willing to lay the leading team. Therefore we may not observe any trade after the post and the market may not update. Similarly, when the probability implied by the market is close to 0, and the post does not change the likelihood that the team hitting the post wins the match then there may not be anyone willing to back the losing team, and the market may not update.

In our analysis, we included the posts for which no trade occurred after the post and used as the implied market price the last price matched before the post. All of our results are robust to excluding those posts

E Detailed results of maximum likelihood estimations

Table 2 presents the estimates of parameters δ and γ using maximum likelihood. Table E.1 shows that the parameters are not significantly different from 1 in either situation after a post. Table 3 shows that the parameters becomes significantly different from 1 after a post-in, in the last minutes of a match.

	Post-out	Post-in
δ	0.95	0.93
	(0.245)	(0.405)
	[0.814]	
γ	1	0.97
	(0.886)	(0.655)
	[0.620]	
N	4,206	970

Table E.1: Maximum likelihood estimation of the function (3.1). First price after a post for the market *"Team A wins"'*. In bracket p-value testing whether the estimate equal 1. In square bracket p-value testing whether the estimate for the post in and out are equal. Std errors clustered by markets and computed by 1,000 bootstraps.

F Parametric Bootstrap

In this Section, we describe the parametric bootstrap used to compute the p-values and confidence intervals of the matching estimates.

1. For each observation i:
   (a) Generate $outcome_i^* \sim Bernoulli(p_i)$.
   (b) Compute $r_i^* = outcome_i^* - p_i$.
2. Compute the matching estimate τ^* on the bootstraped sample $(r_1^*, ..., r_N^*)$ with equation (3.3).
3. Repeat Step (1-2) B times. Denote τ_j^* matching estimate for the j^{th} bootstrapped sample.
4. Compute the matching estimate $\widehat{\tau}$ on the original sample $(r_1, ..., r_N)$ with equation (3.3).

5. Compute the two-sides equal tail p-value as:

$$pval = 2 * min(\frac{1}{B}\sum_{i=1}^{B} \mathbb{1}_{\tau_j^* \leq \widehat{\tau}}, \frac{1}{B}\sum_{i=1}^{B} \mathbb{1}_{\tau_j^* > \widehat{\tau}})$$

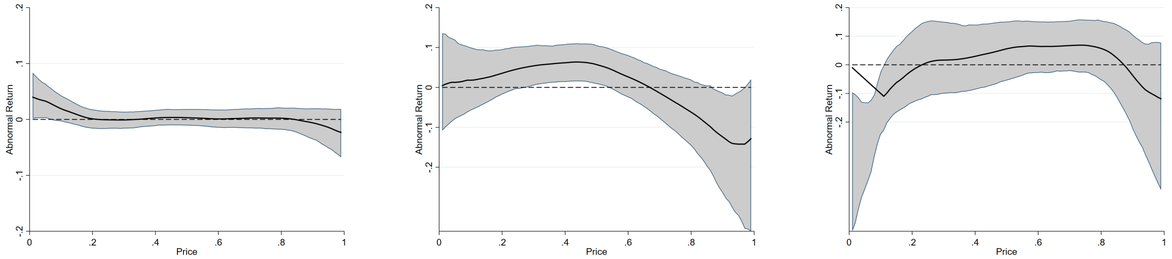
   (Equation (4) of MacKinnon (2009))

6. Compute the 95% Confidence Interval as the 0.025 and 0.975 centile of the centered bootstrapped sample $(\tau_1^* - \widehat{\tau}, ..., \tau_B^* - \widehat{\tau})$.

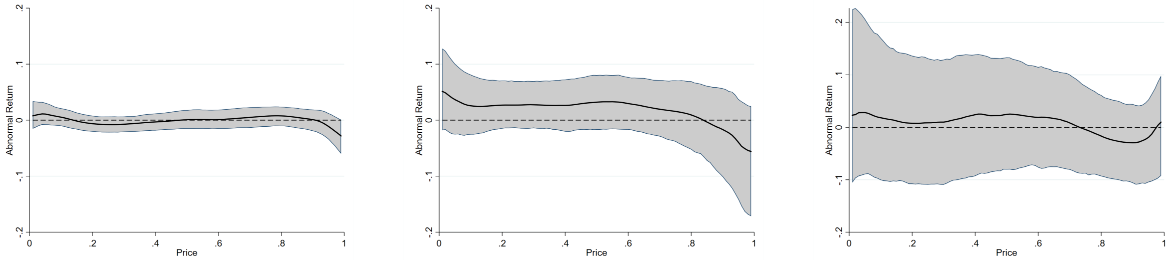
7. Compute the the 0.025, 0.2, 0.80 and 0.975 centile of the bootstrapped sample $(\tau_1^*, ..., \tau_B^*)$ and denote them as $c_{0.025}$,$c_{0.2}$,$c_{0.8}$,$c_{0.975}$. The Minimum Detectable Effect for a positive effect is defined as $c_{0.975}+c_{0.8}$ and the Minimum Detectable Effect for a negative effect is defined as $c_{0.025}+c_{0.2}$.

We use a large number of bootstrap samples, 50,000, to have a distribution of p-values as continuous as possible in order to compute the q-values to control for the False Discovery Rate.

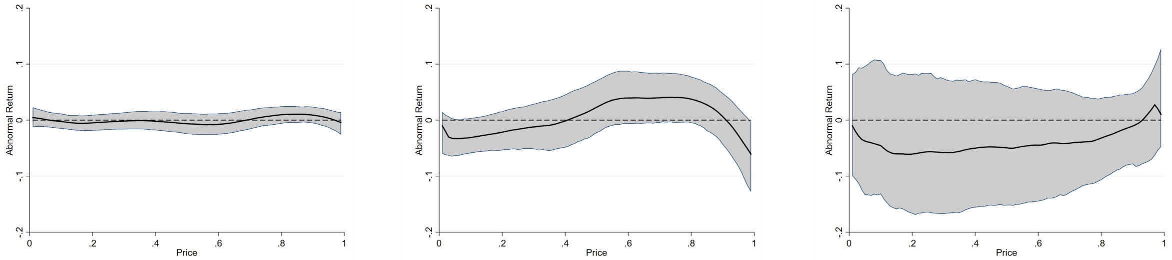
G Market calibration for different timings



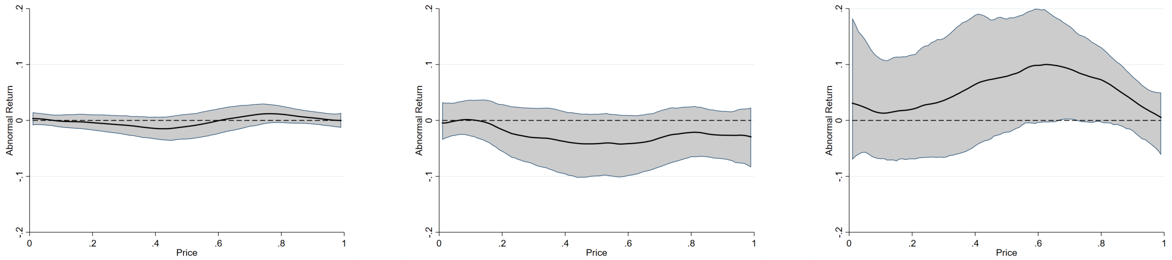
(a) All bets, minute 1 to 15 (b) Post-out, minute 1 to 15 (c) Post-in, minute 1 to 15



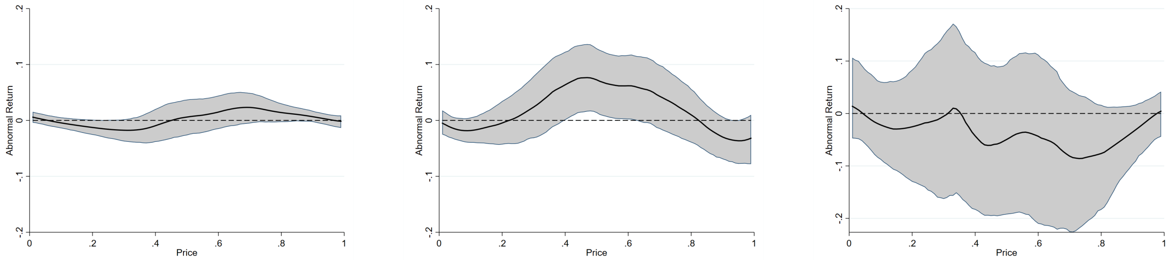
(d) All bets, minute 16 to 30 (e) Post-out, minute 16 to 30 (f) Post-in, minute 16 to 30



(g) All bets, minute 31 to 45 (h) Post-out, minute 31 to 45 (i) Post-in, minute 31 to 45



(j) All bets, minute 46 to 60 (k) Post-out, minute 46 to 60 (l) Post-in, minute 46 to 60



(m) All bets, minute 61 to 75 (n) Post-out, minute 61 to 75 (o) Post-in, minute 61 to 75

Figure G.1: Expected returns for all the prices observed (first column), for the first price observed after a post-in (second column), and for a post-out (third column) for the asset *"Team A wins the match"* where Team A is the team hitting the post.

H Kernel Matching on x-y with Euclidean Distance

Asset *Team A wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.011	−0.011	0.023	0.020	−0.029	−0.031	0.071	−0.049	0.041
(0.409)	(0.626)	(0.137)	(0.672)	(0.448)	(0.393)	(0.034)*	(0.111)	(0.033)*
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.400]	[1.000]	[0.400]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.017	−0.062	−0.010	.	−0.011	−0.087	−0.055	0.015	−0.003
(0.513)	(0.553)	(0.763)	(.)	(0.529)	(0.692)	(0.483)	(0.558)	(0.230)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
−0.039	−0.058	−0.027	−0.056	−0.118	0.015	−0.044	−0.020	−0.001
(0.261)	(0.347)	(0.505)	(0.762)	(0.217)	(0.860)	(0.615)	(0.836)	(0.944)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.023	−0.007	0.081	0.025	−0.022	−0.039	0.167	−0.103	0.171
(0.351)	(0.826)	(0.030)*	(0.645)	(0.688)	(0.511)	(0.011)*	(0.143)	(0.001)**
[1.000]	[1.000]	[0.400]	[1.000]	[1.000]	[1.000]	[0.247]	[1.000]	[0.039]*
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.010	−0.005	0.010	0.085	0.015	−0.010	0.083	−0.022	−0.011
(0.603)	(0.880)	(0.588)	(0.536)	(0.884)	(0.817)	(0.046)*	(0.549)	(0.555)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.510]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table H.1: Estimate of abnormal returns after buying asset "Team A wins" following positive news ($r = outcome - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on *x-y* with Euclidean distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Team B wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.012	−0.017	0.030	0.018	−0.064	−0.028	0.036	0.014	0.037
(0.293)	(0.386)	(0.019)*	(0.663)	(0.052)†	(0.328)	(0.189)	(0.567)	(0.009)**
[1.000]	[1.000]	[0.329]	[1.000]	[0.562]	[1.000]	[1.000]	[1.000]	[0.233]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.002	−0.033	0.005	.	−0.106	−0.010	0.069	−0.052	−0.005
(0.983)	(0.842)	(0.878)	(.)	(0.627)	(0.954)	(0.475)	(0.639)	(0.985)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
−0.017	−0.184	0.058	−0.231	−0.161	−0.173	−0.053	0.037	0.151
(0.643)	(0.005)**	(0.198)	(0.205)	(0.141)	(0.069)†	(0.538)	(0.692)	(0.005)**
[1.000]	[0.158]	[1.000]	[1.000]	[1.000]	[0.783]	[1.000]	[1.000]	[0.158]
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.022	0.007	0.033	0.041	−0.051	0.039	0.068	0.013	0.019
(0.233)	(0.813)	(0.163)	(0.384)	(0.266)	(0.369)	(0.154)	(0.787)	(0.527)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.002	−0.031	0.010	0.068	−0.031	−0.030	0.016	0.014	0.004
(0.885)	(0.171)	(0.227)	(0.471)	(0.401)	(0.293)	(0.468)	(0.375)	(0.509)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table H.2: Estimate of abnormal returns after buying asset "Team B wins" following positive news ($r = outcome - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y with Euclidean distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Draw*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
−0.004	−0.004	−0.001	−0.001	−0.033	0.004	−0.030	0.053	−0.022
(0.794)	(0.882)	(0.944)	(0.992)	(0.371)	(0.907)	(0.377)	(0.104)	(0.328)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
0.010	0.029	0.011	.	−0.100	0.082	0.130	−0.069	−0.004
(0.790)	(0.755)	(0.779)	(.)	(0.646)	(0.565)	(0.167)	(0.473)	(0.976)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
0.041	−0.133	0.120	−0.193	−0.035	−0.196	0.000	0.102	0.213
(0.313)	(0.035)*	(0.020)*	(0.282)	(0.747)	(0.034)*	(0.991)	(0.318)	(0.002)**
[1.000]	[0.400]	[0.329]	[1.000]	[1.000]	[0.400]	[1.000]	[1.000]	[0.119]
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.014	−0.019	0.085	−0.019	0.020	−0.083	0.089	−0.070	0.232
(0.560)	(0.519)	(0.019)*	(0.688)	(0.708)	(0.148)	(0.153)	(0.313)	(< 0.001)***
[1.000]	[1.000]	[0.329]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.001]**
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.012	0.029	0.005	0.013	0.045	0.021	0.068	−0.030	−0.009
(0.454)	(0.430)	(0.774)	(0.972)	(0.482)	(0.666)	(0.079)†	(0.407)	(0.633)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.915]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table H.3: Estimate of abnormal returnsafter buying asset “Draw” following positive news ($r = outcome - p$, first three lines) or selling following negative news ($r = outcome - p$, last two lines). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y with Euclidean distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15min. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

I Evolution of abnormal returns after a post-in

We present here the estimation of abnormal returns after a post-in. The CIs do not control for multiple testing. We indicate with a star the estimates which are significant when controlling for multiple testing. Figure I.1 shows our estimate $\widehat{\tau}_M$ of the abnormal returns for different goal timings by periods of 15 minutes in the match. Figure I.2 shows our estimate of the abnormal returns over time the other fifteen-minute period of the match. Figure I.3 shows our estimate of the abnormal returns over time in the last fifteen minutes of the match when Team A scores and the scoreline is tied.

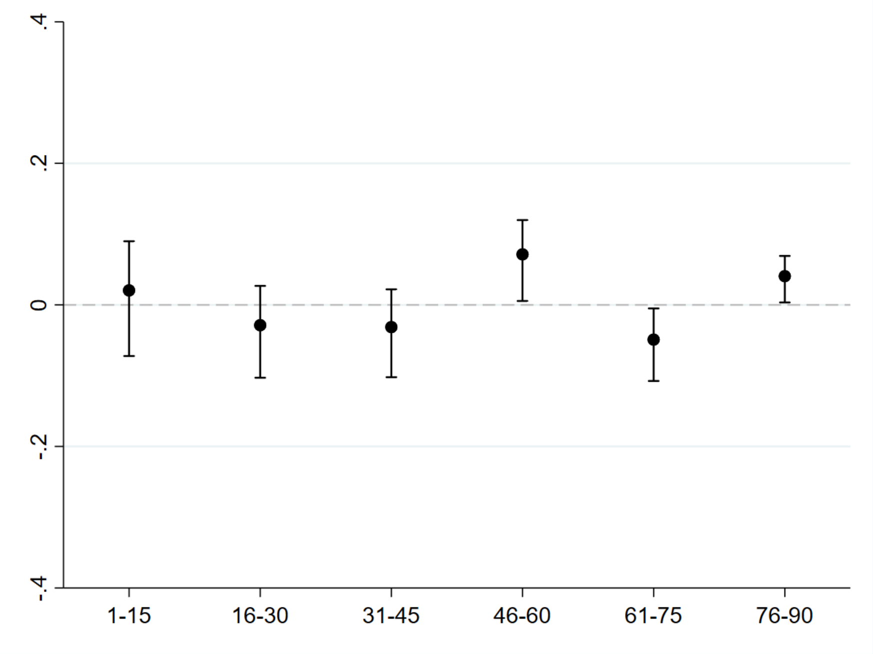
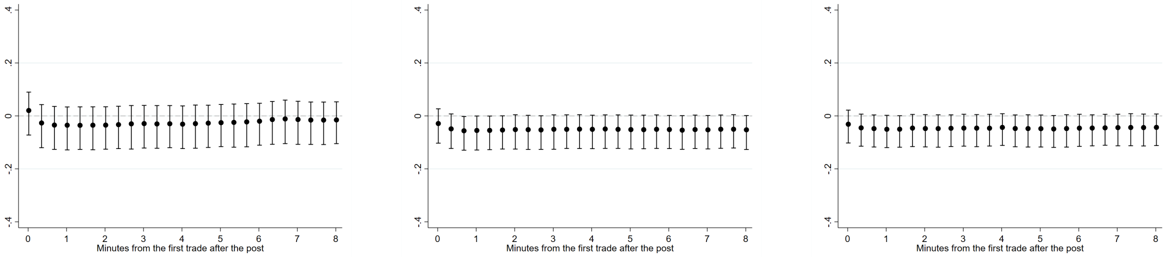


Figure I.1: Estimate of abnormal returns after buying following positive news ($r = outcome - p$). Positive values indicate under-reaction. With conterfactuals, kernel matching estimator, matching on x-y with Euclidean distance, standard error computed with 50,000 bootstraps.

(a) $\widehat{\tau}_M$, [1-15] (b) $\widehat{\tau}_M$, [16-30] (c) $\widehat{\tau}_M$, [31-45]



(d) $\widehat{\tau}_M$, [46-60] (e) $\widehat{\tau}_M$, [61-75] (f) $\widehat{\tau}_M$, [75-90]

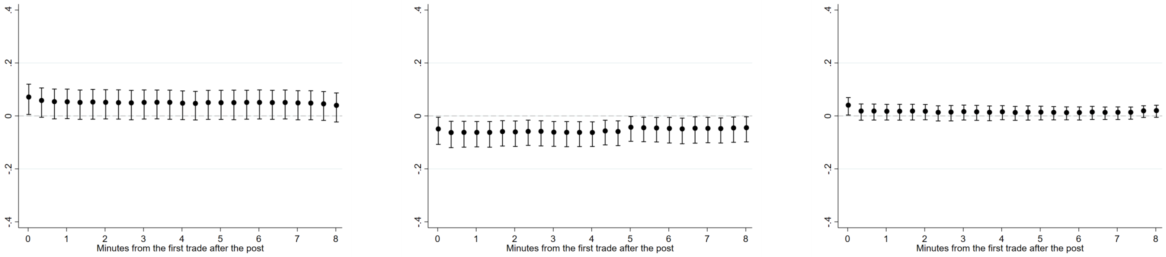


Figure I.2: Estimated returns after an information shock (“post-in”): τ_M for the asset *team A wins*.

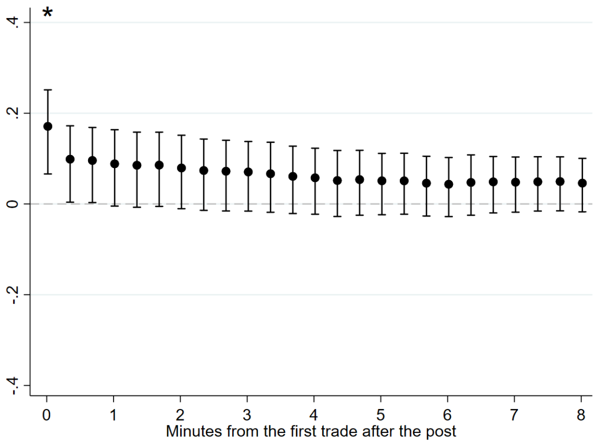


Figure I.3: Estimated returns after an information shock (“post-in”): τ_M for the asset *team A wins* in the last fifteen minutes of the match when the scoreline is tied.

J Estimate of abnormal returns *without controlling for counterfactuals*

Asset *Team A wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.011	−0.003	0.022	0.041	0.000	−0.036	0.054	−0.036	0.041
(0.323)	(0.886)	(0.089)†	(0.288)	(0.940)	(0.302)	(0.051)†	(0.190)	(0.008)**
[0.806]	[1.000]	[0.383]	[0.748]	[1.000]	[0.773]	[0.261]	[0.640]	[0.066]†
970	426	544	114	152	160	170	164	210
Team A hitting the post trailing by at least two goal								
−0.031	−0.083	−0.021	.	−0.062	−0.100	−0.070	0.015	−0.005
(0.276)	(0.673)	(0.623)	(.)	(0.557)	(0.983)	(0.416)	(0.319)	(0.226)
[0.725]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[0.942]	[0.806]	[0.660]
75	12	63	.	5	6	21	18	24
Team A hitting the post trailing by one goal								
−0.045	−0.040	−0.048	−0.034	−0.064	−0.024	−0.029	−0.080	−0.042
(0.164)	(0.519)	(0.225)	(0.889)	(0.557)	(0.681)	(0.854)	(0.396)	(0.518)
[0.578]	[1.000]	[0.660]	[1.000]	[1.000]	[1.000]	[1.000]	[0.942]	[1.000]
164	61	103	8	23	30	34	29	40
Scoreline is tied								
0.035	0.007	0.078	0.053	0.028	−0.076	0.128	−0.078	0.155
(0.082)†	(0.776)	(0.010)*	(0.210)	(0.544)	(0.183)	(0.014)*	(0.264)	($<$ 0.001)***
[0.378]	[1.000]	[0.076]†	[0.653]	[1.000]	[0.640]	[0.096]†	[0.722]	[0.001]**
423	253	170	94	85	74	64	49	57
Team A hitting the post leading by at least one goal								
0.018	0.006	0.024	−0.001	−0.014	0.022	0.068	−0.000	0.018
(0.154)	(0.764)	(0.040)*	(0.722)	(0.950)	(0.487)	(0.016)*	(0.844)	($<$ 0.001)***
[0.563]	[1.000]	[0.209]	[1.000]	[1.000]	[0.992]	[0.103]	[1.000]	[0.001]**
308	100	208	11	39	50	51	68	89

Table J.1: Estimate of abnormal returns after buying asset "Team A wins" following positive news ($r = outcome - p$) *without controlling for counterfactuals.* We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Team B wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.007	-0.013	0.023	0.030	-0.037	-0.022	0.009	0.023	0.034
(0.458)	(0.440)	(0.027)*	(0.341)	(0.160)	(0.419)	(0.750)	(0.202)	(0.002)**
[0.942]	[0.942]	[0.164]	[0.826]	[0.577]	[0.942]	[1.000]	[0.653]	[0.013]*
970	426	544	114	152	160	170	164	210
Team A hitting the post trailing by at least two goal								
0.006	0.002	0.007	.	-0.001	0.054	0.048	-0.014	-0.012
(0.725)	(0.688)	(0.704)	(.)	(0.518)	(0.389)	(0.408)	(0.838)	(0.750)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[0.942]	[0.942]	[1.000]	[1.000]
75	12	63	.	5	6	21	18	24
Team A hitting the post trailing by one goal								
-0.004	-0.124	0.067	-0.127	-0.112	-0.132	-0.015	0.060	0.142
(0.941)	(0.038)*	(0.055)†	(0.679)	(0.271)	(0.150)	(0.870)	(0.338)	($<$ 0.001)***
[1.000]	[0.206]	[0.265]	[1.000]	[0.722]	[0.563]	[1.000]	[0.826]	[0.002]**
164	61	103	8	23	30	34	29	40
Scoreline is tied								
0.018	0.018	0.018	0.042	-0.003	0.010	0.002	0.030	0.024
(0.248)	(0.381)	(0.363)	(0.270)	(0.838)	(0.666)	(0.957)	(0.227)	($<$ 0.001)***
[0.677]	[0.942]	[0.902]	[0.722]	[1.000]	[1.000]	[1.000]	[0.660]	[0.001]**
423	253	170	94	85	74	64	49	57
Team A hitting the post leading by at least one goal								
-0.002	-0.026	0.009	0.066	-0.069	-0.013	0.017	0.011	0.003
(0.783)	(0.232)	($<$ 0.001)***	($<$ 0.001)***	(0.072)†	(0.417)	($<$ 0.001)***	($<$ 0.001)***	($<$ 0.001)***
[1.000]	[0.660]	[0.001]**	[0.001]**	[0.339]	[0.942]	[0.001]**	[0.001]**	[0.001]**
308	100	208	11	39	50	51	68	89

Table J.2: Estimate of abnormal returns after buying asset "Team B wins" following positive news ($r = outcome - p$) *without controlling for counterfactuals.* We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Draw*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
-0.009	-0.009	-0.008	-0.008	-0.033	0.013	-0.040	0.043	-0.023
(0.443)	(0.619)	(0.571)	(0.888)	(0.329)	(0.715)	(0.192)	(0.097)†	(0.306)
[0.942]	[1.000]	[1.000]	[1.000]	[0.813]	[1.000]	[0.640]	[0.401]	[0.773]
970	426	544	114	152	160	170	164	210
Team A hitting the post trailing by at least two goal								
0.036	0.094	0.025	.	0.056	0.174	0.119	-0.044	-0.006
(0.247)	(0.228)	(0.449)	(.)	(0.709)	(0.105)	(0.125)	(0.826)	(0.825)
[0.677]	[0.660]	[0.942]	[.]	[1.000]	[0.432]	[0.505]	[1.000]	[1.000]
75	12	63	.	5	6	21	18	24
Team A hitting the post trailing by one goal								
0.063	-0.087	0.153	-0.109	-0.045	-0.114	0.022	0.176	0.247
(0.062)†	(0.154)	(0.001)**	(0.805)	(0.717)	(0.245)	(0.798)	(0.029)*	(< 0.001)***
[0.298]	[0.563]	[0.005]**	[1.000]	[1.000]	[0.677]	[1.000]	[0.164]	[0.001]**
164	61	103	8	23	30	34	29	40
Scoreline is tied								
0.032	-0.014	0.100	0.006	0.027	-0.088	0.111	-0.055	0.220
(0.090)†	(0.618)	(0.001)**	(0.879)	(0.453)	(0.090)†	(0.015)*	(0.439)	(< 0.001)***
[0.383]	[1.000]	[0.006]**	[1.000]	[0.942]	[0.383]	[0.099]†	[0.942]	[0.001]**
423	253	170	94	85	74	64	49	57
Team A hitting the post leading by at least one goal								
0.026	0.033	0.023	-0.066	0.051	0.040	0.056	-0.001	0.022
(0.029)*	(0.195)	(0.052)†	(0.636)	(0.147)	(0.207)	(0.118)	(1.000)	(< 0.001)***
[0.164]	[0.640]	[0.261]	[1.000]	[0.563]	[0.653]	[0.485]	[1.000]	[0.001]**
308	100	208	11	39	50	51	68	89

Table J.3: Estimate of abnormal returns after buying asset “Draw” following positive news ($r = outcome - p$, first three lines) or selling following negative news ($r = outcome - p$, last two lines) *without controlling for counterfactuals*. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

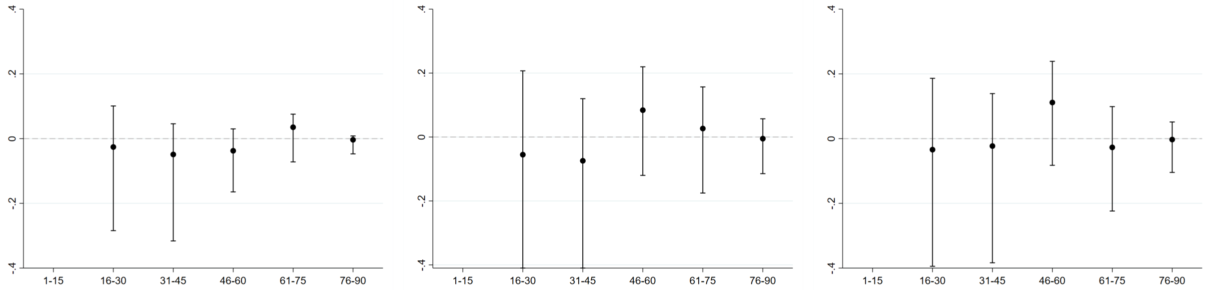
K Robustness checks on matching variables

K.1 Matching on price before post

Figure K.1, Table K.1, K.2 and K.3 reproduce the main results matching on the (x,y) coordinates and the price just before the post and using the Mahanabolis distance.

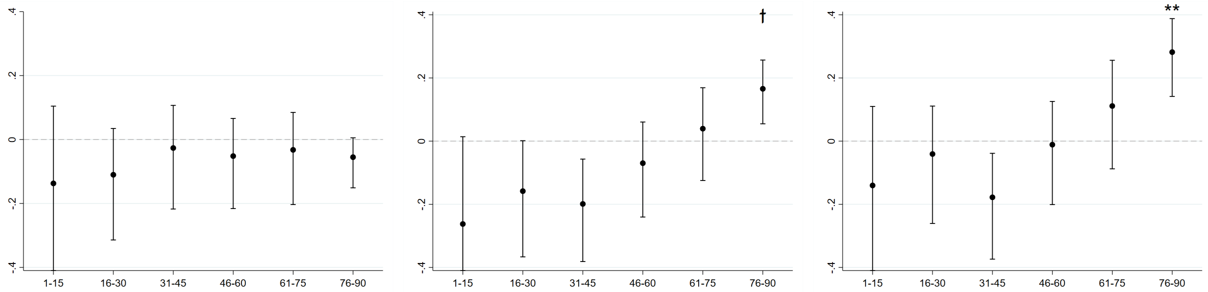
Team A hitting the post trailing by at least two goals

(a) Asset "*Team A wins*" (b) Asset "*Team B wins*" (c) Asset "*Draw*"



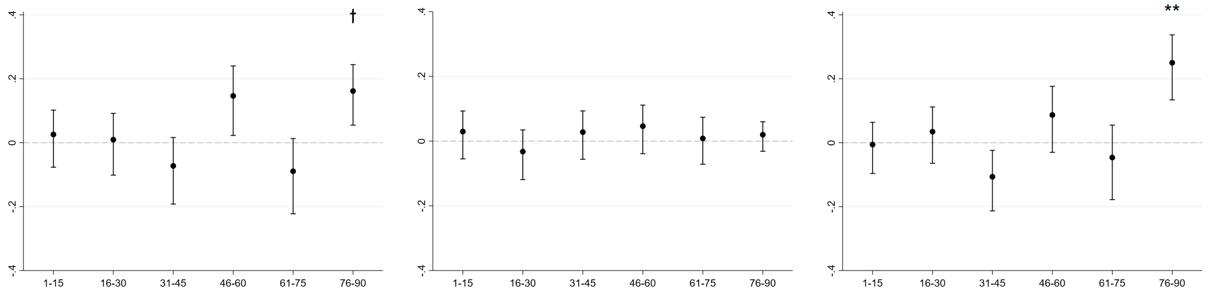
Team A hitting the post trailing by one goal

(d) Asset "*Team B wins*" (e) Asset "*Team B wins*" (f) Asset "*Draw*"



Scoreline is tied

(g) Asset "*Team A wins*" (h) Asset "*Team B wins*" (i) Asset "*Draw*"



Team A hitting the post leading by at least one goal

(j) Asset "*Team A wins*" (k) Asset "*Team B wins*" (l) Asset "*Draw*"

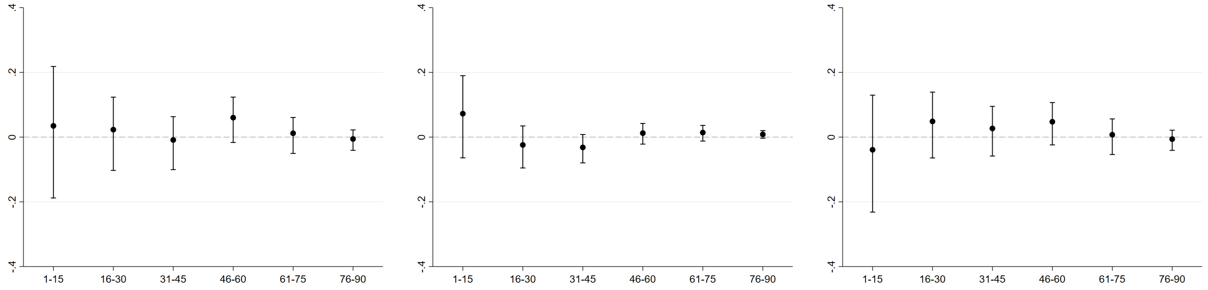


Figure K.1: Estimate of abnormal returns after buying following positive news ($r = outcome - p$, panels a, d, g, j, c, f) or selling following negative news ($r = outcome - p$, panels b, e, h, k, i, l). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance, standard error computed with 50,000 bootstraps. Significant at * 5% level, ** 1% level for the sharpened q-values.

Asset *Team A wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.013	−0.010	0.029	0.016	−0.004	−0.044	0.070	−0.027	0.044
(0.343)	(0.671)	(0.065)†	(0.743)	(0.916)	(0.238)	(0.028)*	(0.408)	(0.027)*
[1.000]	[1.000]	[0.763]	[1.000]	[1.000]	[1.000]	[0.373]	[1.000]	[0.373]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.007	−0.056	−0.002	.	−0.026	−0.049	−0.038	0.035	−0.004
(0.788)	(0.628)	(0.989)	(.)	(0.548)	(0.755)	(0.633)	(0.356)	(0.230)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
−0.035	−0.075	−0.032	−0.137	−0.110	−0.027	−0.052	−0.032	−0.055
(0.311)	(0.235)	(0.416)	(0.436)	(0.277)	(0.797)	(0.543)	(0.728)	(0.197)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.030	−0.005	0.084	0.026	0.010	−0.073	0.146	−0.089	0.162
(0.234)	(0.892)	(0.022)*	(0.627)	(0.866)	(0.236)	(0.019)*	(0.205)	(0.002)**
[1.000]	[1.000]	[0.357]	[1.000]	[1.000]	[1.000]	[0.357]	[1.000]	[0.074]†
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.013	0.011	0.019	0.035	0.023	−0.009	0.060	0.012	−0.006
(0.458)	(0.789)	(0.266)	(0.807)	(0.765)	(0.828)	(0.138)	(0.750)	(0.734)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table K.1: Estimate of abnormal returns after buying asset "Team A wins" following positive news ($r = outcome - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Team B wins*

All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.007	−0.024	0.029	0.021	−0.048	−0.028	0.023	0.020	0.040
(0.544)	(0.206)	(0.023)*	(0.611)	(0.164)	(0.340)	(0.362)	(0.453)	(0.007)**
[1.000]	[1.000]	[0.357]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.155]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.006	−0.038	0.005	.	−0.055	−0.074	0.084	0.027	−0.005
(0.915)	(0.811)	(0.876)	(.)	(0.857)	(0.705)	(0.386)	(0.739)	(0.963)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
−0.035	−0.199	0.048	−0.262	−0.158	−0.199	−0.070	0.039	0.166
(0.352)	(0.004)**	(0.278)	(0.172)	(0.154)	(0.044)*	(0.432)	(0.668)	(0.002)**
[1.000]	[0.122]	[1.000]	[1.000]	[1.000]	[0.602]	[1.000]	[1.000]	[0.074]†
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.026	0.007	0.031	0.029	−0.032	0.028	0.046	0.008	0.020
(0.156)	(0.787)	(0.184)	(0.512)	(0.477)	(0.550)	(0.304)	(0.884)	(0.476)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
−0.001	−0.020	0.011	0.072	−0.024	−0.032	0.012	0.014	0.008
(0.910)	(0.371)	(0.110)	(0.347)	(0.510)	(0.236)	(0.538)	(0.314)	(0.154)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table K.2: Estimate of abnormal returns after buying asset "Team B wins" following positive news ($r = outcome - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

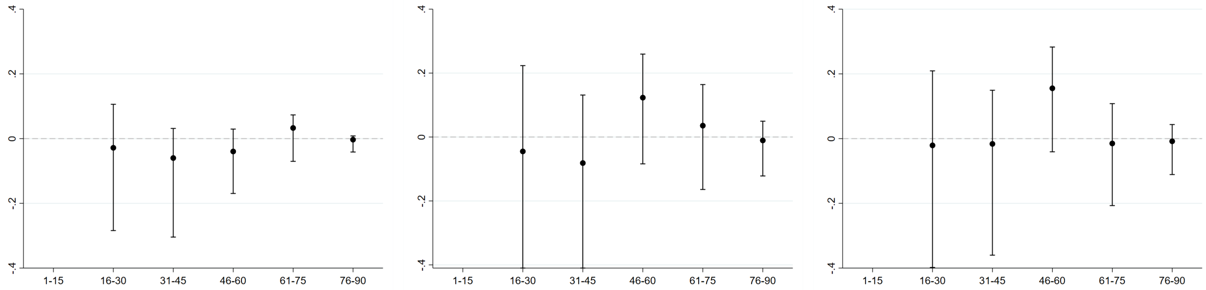
Asset *Draw*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
−0.010	−0.013	−0.009	0.007	−0.039	0.017	−0.041	0.035	−0.015
(0.485)	(0.578)	(0.616)	(0.863)	(0.303)	(0.633)	(0.205)	(0.313)	(0.511)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.006	0.019	−0.000	.	−0.034	−0.023	0.112	−0.027	−0.003
(0.898)	(0.811)	(0.974)	(.)	(0.965)	(0.941)	(0.239)	(0.824)	(0.959)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
0.019	−0.130	0.116	−0.140	−0.041	−0.178	−0.011	0.111	0.282
(0.629)	(0.048)*	(0.022)*	(0.456)	(0.716)	(0.061)†	(0.914)	(0.277)	($<$ 0.001)***
[1.000]	[0.606]	[0.357]	[1.000]	[1.000]	[0.763]	[1.000]	[1.000]	[0.001]**
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.015	−0.018	0.096	−0.006	0.034	−0.106	0.087	−0.046	0.250
(0.532)	(0.550)	(0.007)**	(0.886)	(0.515)	(0.067)†	(0.151)	(0.500)	($<$ 0.001)***
[1.000]	[1.000]	[0.155]	[1.000]	[1.000]	[0.763]	[1.000]	[1.000]	[0.001]**
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.019	0.034	0.013	−0.039	0.049	0.027	0.047	0.007	−0.006
(0.224)	(0.333)	(0.444)	(0.676)	(0.436)	(0.572)	(0.222)	(0.853)	(0.707)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table K.3: Estimate of abnormal returns after buying asset "Draw" following positive news ($r = outcome - p$, first three lines) or selling following negative news ($r = outcome - p$, last two lines). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

K.2 Matching on price before post and minute of the post

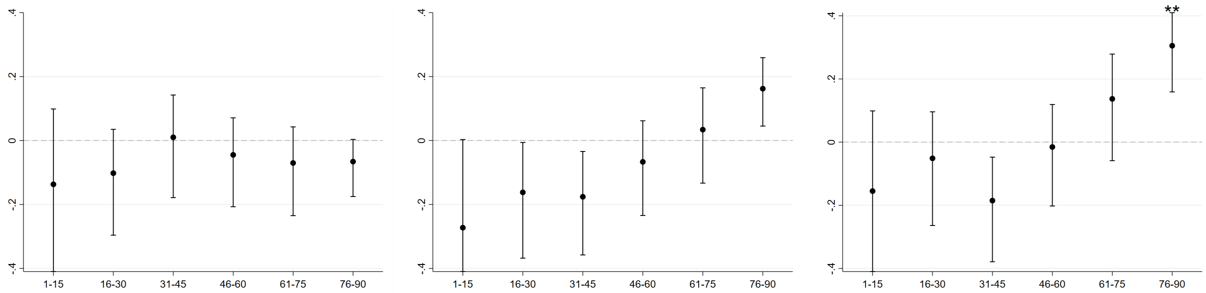
Figure K.2, Table K.4, K.5 and K.6 reproduce the main results matching on the (x,y) coordinates, price just before the post and minute in the match at which the post occurred using the Mahanabolis distance.

Team A hitting the post trailing by at least two goals



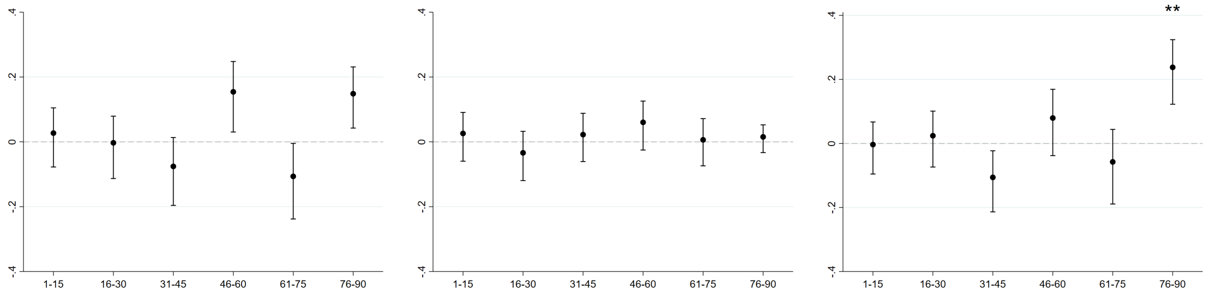
(a) Asset "*Team A wins*" (b) Asset "*Team B wins*" (c) Asset "*Draw*"

Team A hitting the post trailing by one goal



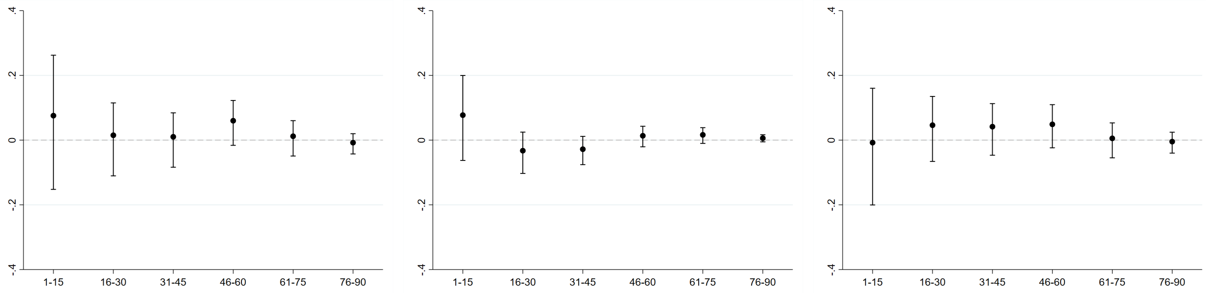
(d) Asset "*Team B wins*" (e) Asset "*Team B wins*" (f) Asset "*Draw*"

Scoreline is tied



(g) Asset "*Team A wins*" (h) Asset "*Team B wins*" (i) Asset "*Draw*"

Team A hitting the post leading by at least one goal



(j) Asset "*Team A wins*" (k) Asset "*Team B wins*" (l) Asset "*Draw*"

Figure K.2: Estimate of abnormal returns after buying following positive news ($r = outcome - p$, panels a, d, g, j, c, f) or selling following negative news ($r = outcome - p$, panels b, e, h, k, i, l). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance, standard error computed with 50,000 bootstraps. Significant at * 5% level, ** 1% level for the sharpened q-values.

Asset *Team A wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.011	−0.015	0.031	0.019	−0.010	−0.044	0.069	−0.028	0.038
(0.421)	(0.521)	(0.047)*	(0.685)	(0.792)	(0.246)	(0.032)*	(0.370)	(0.065)†
[1.000]	[1.000]	[0.690]	[1.000]	[1.000]	[1.000]	[0.562]	[1.000]	[0.912]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.006	−0.045	0.001	.	−0.028	−0.060	−0.040	0.033	−0.003
(0.868)	(0.641)	(0.852)	(.)	(0.548)	(0.421)	(0.608)	(0.390)	(0.230)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
−0.045	−0.056	−0.036	−0.137	−0.102	0.010	−0.045	−0.070	−0.066
(0.179)	(0.374)	(0.370)	(0.429)	(0.286)	(0.893)	(0.594)	(0.391)	(0.176)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.024	−0.011	0.073	0.027	−0.003	−0.076	0.154	−0.107	0.148
(0.329)	(0.741)	(0.040)*	(0.614)	(0.961)	(0.220)	(0.013)*	(0.133)	(0.005)**
[1.000]	[1.000]	[0.688]	[1.000]	[1.000]	[1.000]	[0.225]	[1.000]	[0.145]
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.013	0.012	0.015	0.076	0.015	0.010	0.060	0.012	−0.008
(0.463)	(0.781)	(0.386)	(0.564)	(0.858)	(0.873)	(0.136)	(0.747)	(0.643)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table K.4: Estimate of abnormal returns after buying asset "Team A wins" following positive news ($r = outcome - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Team B wins*

All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.004	−0.028	0.030	0.021	−0.052	−0.029	0.027	0.015	0.046
(0.741)	(0.152)	(0.020)*	(0.618)	(0.126)	(0.329)	(0.285)	(0.580)	(0.002)**
[1.000]	[1.000]	[0.320]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[0.106]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
0.004	−0.054	0.025	.	−0.045	−0.081	0.123	0.036	−0.011
(0.902)	(0.694)	(0.559)	(.)	(0.876)	(0.693)	(0.223)	(0.666)	(0.927)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
−0.027	−0.181	0.054	−0.273	−0.162	−0.176	−0.067	0.034	0.162
(0.474)	(0.008)**	(0.231)	(0.155)	(0.135)	(0.073)†	(0.443)	(0.717)	(0.004)**
[1.000]	[0.212]	[1.000]	[1.000]	[1.000]	[0.912]	[1.000]	[1.000]	[0.142]
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.016	0.004	0.029	0.026	−0.034	0.022	0.060	0.006	0.015
(0.365)	(0.879)	(0.195)	(0.573)	(0.452)	(0.637)	(0.174)	(0.925)	(0.554)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
−0.001	−0.026	0.011	0.077	−0.033	−0.028	0.013	0.016	0.006
(0.850)	(0.234)	(0.142)	(0.324)	(0.382)	(0.293)	(0.489)	(0.235)	(0.314)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table K.5: Estimate of abnormal returns after buying asset "Team B wins" following positive news ($r = \mathit{outcome} - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Draw*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
−0.010	−0.010	−0.007	0.005	−0.037	0.017	−0.037	0.030	−0.002
(0.471)	(0.670)	(0.700)	(0.900)	(0.325)	(0.623)	(0.264)	(0.382)	(0.940)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
0.001	−0.008	0.016	.	−0.021	−0.016	0.156	−0.015	−0.008
(0.948)	(0.986)	(0.673)	(.)	(0.947)	(0.933)	(0.115)	(0.927)	(0.926)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
0.042	−0.127	0.130	−0.155	−0.051	−0.185	−0.015	0.137	0.305
(0.293)	(0.051)†	(0.011)*	(0.412)	(0.628)	(0.047)*	(0.877)	(0.172)	(< 0.001)***
[1.000]	[0.699]	[0.224]	[1.000]	[1.000]	[0.690]	[1.000]	[1.000]	[0.001]**
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.020	−0.021	0.090	−0.003	0.024	−0.106	0.079	−0.058	0.238
(0.381)	(0.481)	(0.012)*	(0.922)	(0.648)	(0.070)†	(0.188)	(0.404)	(< 0.001)***
[1.000]	[1.000]	[0.224]	[1.000]	[1.000]	[0.912]	[1.000]	[1.000]	[0.003]**
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.019	0.040	0.011	−0.008	0.046	0.042	0.049	0.005	−0.005
(0.213)	(0.247)	(0.541)	(0.880)	(0.456)	(0.384)	(0.218)	(0.897)	(0.760)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

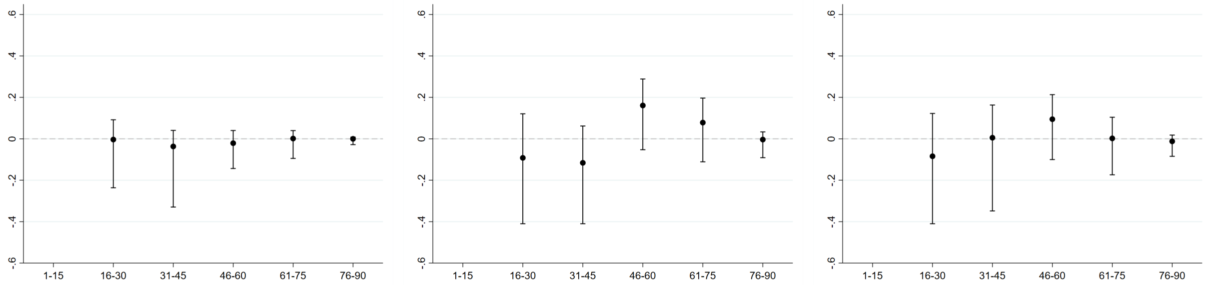
Table K.6: Estimate of abnormal returns after buying asset "Draw" following positive news ($r = \mathit{outcome} - p$, first three lines) or selling following negative news ($r = \mathit{outcome} - p$, last two lines). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price before the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

K.3 Matching on price after post and (x,y) coordinates

This robustness check is unusual since we match on a variable (price) observed after the effect of the shock. This robustness check helps to show that the main effects are not driven by different mispricings happening for different level of prices after the shock. Figure K.3, Table K.7, K.8 and K.9 reproduce the main results matching on the (x,y) coordinates, first price observed after the post using the Mahanabolis distance.

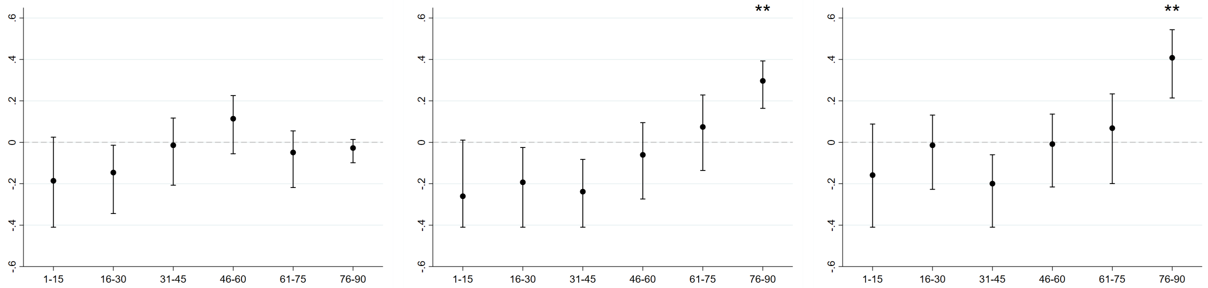
Team A hitting the post trailing by at least two goals

(a) Asset "*Team A wins*" (b) Asset "*Team B wins*" (c) Asset "*Draw*"



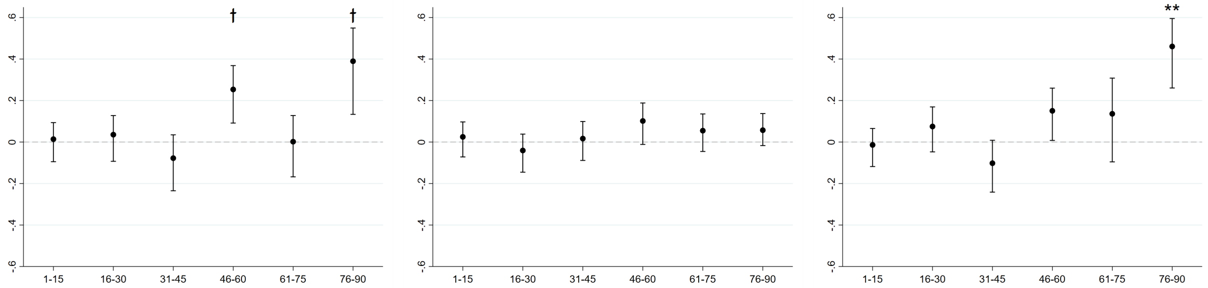
Team A hitting the post trailing by one goal

(d) Asset "*Team B wins*" (e) Asset "*Team B wins*" (f) Asset "*Draw*"



Scoreline is tied

(g) Asset "*Team A wins*" (h) Asset "*Team B wins*" (i) Asset "*Draw*"



Team A hitting the post leading by at least one goal

(j) Asset "*Team A wins*" (k) Asset "*Team B wins*" (l) Asset "*Draw*"

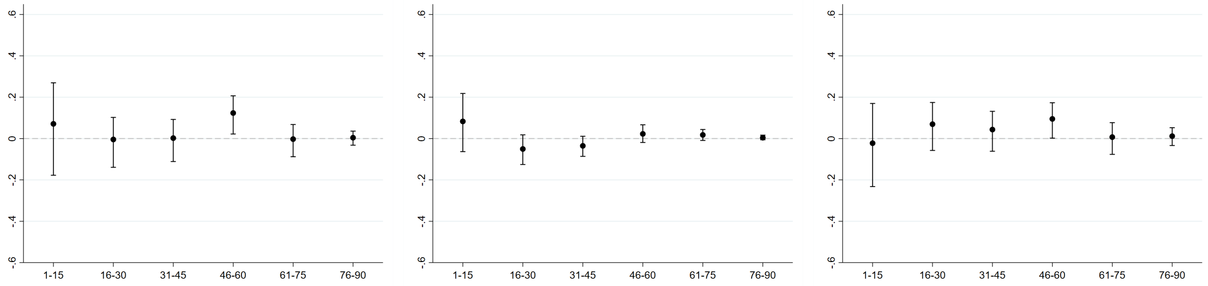


Figure K.3: Estimate of abnormal returns after buying following positive news ($r = outcome - p$, panels a, d, g, j, c, f) or selling following negative news ($r = outcome - p$, panels b, e, h, k, i, l). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price after the post with Mahalanobis distance, standard error computed with 50,000 bootstraps. Significant at * 5% level, ** 1% level for the sharpened q-values.

Asset *Team A wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.009	−0.021	0.025	0.016	−0.013	−0.052	0.075	−0.013	0.012
(0.547)	(0.416)	(0.128)	(0.748)	(0.773)	(0.224)	(0.032)*	(0.723)	(0.517)
[1.000]	[1.000]	[0.833]	[1.000]	[1.000]	[1.000]	[0.356]	[1.000]	[1.000]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.002	−0.025	0.003	.	−0.004	−0.037	−0.021	0.001	−0.000
(0.983)	(0.754)	(0.663)	(.)	(0.524)	(0.733)	(0.843)	(0.568)	(0.178)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[0.920]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
0.001	−0.080	0.020	−0.186	−0.146	−0.014	0.114	−0.049	−0.028
(0.938)	(0.178)	(0.497)	(0.232)	(0.108)	(0.912)	(0.170)	(0.573)	(0.384)
[1.000]	[0.920]	[1.000]	[1.000]	[0.730]	[1.000]	[0.920]	[1.000]	[1.000]
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.079	−0.001	0.288	0.014	0.036	−0.078	0.254	0.002	0.389
(0.024)*	(0.988)	(<0.001)***	(0.798)	(0.573)	(0.327)	(0.003)**	(0.981)	(0.003)**
[0.333]	[1.000]	[0.002]**	[1.000]	[1.000]	[1.000]	[0.052]†	[1.000]	[0.052]†
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.029	0.022	0.043	0.071	−0.004	0.002	0.123	−0.003	0.004
(0.212)	(0.650)	(0.098)†	(0.612)	(0.921)	(1.000)	(0.013)*	(0.913)	(0.902)
[1.000]	[1.000]	[0.675]	[1.000]	[1.000]	[1.000]	[0.214]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table K.7: Estimate of abnormal returns after buying asset “Team A wins” following positive news ($r = outcome - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price after the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Team B wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
0.005	−0.035	0.033	0.013	−0.058	−0.051	0.037	0.014	0.045
(0.718)	(0.135)	(0.034)*	(0.780)	(0.136)	(0.142)	(0.226)	(0.605)	(0.034)*
[1.000]	[0.833]	[0.356]	[1.000]	[0.833]	[0.840]	[1.000]	[1.000]	[0.356]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
−0.002	−0.119	0.025	.	−0.092	−0.116	0.161	0.078	−0.004
(0.999)	(0.318)	(0.425)	(.)	(0.756)	(0.430)	(0.125)	(0.367)	(0.956)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[0.833]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
−0.048	−0.214	0.128	−0.260	−0.193	−0.238	−0.061	0.074	0.296
(0.397)	(0.004)**	(0.088)†	(0.170)	(0.094)†	(0.025)*	(0.589)	(0.493)	(< 0.001)***
[1.000]	[0.064]†	[0.637]	[0.920]	[0.671]	[0.333]	[1.000]	[1.000]	[0.004]**
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.026	−0.005	0.063	0.025	−0.041	0.017	0.102	0.055	0.057
(0.313)	(0.869)	(0.058)†	(0.625)	(0.454)	(0.787)	(0.083)†	(0.316)	(0.202)
[1.000]	[1.000]	[0.486]	[1.000]	[1.000]	[1.000]	[0.624]	[1.000]	[1.000]
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.002	−0.020	0.015	0.083	−0.050	−0.035	0.023	0.018	0.004
(0.939)	(0.491)	(0.079)†	(0.343)	(0.267)	(0.257)	(0.433)	(0.246)	(0.479)
[1.000]	[1.000]	[0.619]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

Table K.8: Estimate of abnormal returns after buying asset "Team B wins" following positive news ($r = outcome - p$). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price after the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Draw*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
-0.007	-0.017	-0.002	-0.001	-0.050	-0.001	-0.026	0.038	-0.016
(0.656)	(0.500)	(0.916)	(0.997)	(0.252)	(0.993)	(0.473)	(0.292)	(0.509)
[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
5,176	2,325	2,851	662	778	885	852	899	1,100
Team A hitting the post trailing by at least two goal								
-0.027	-0.071	-0.017	.	-0.084	0.005	0.095	0.002	-0.012
(0.349)	(0.569)	(0.580)	(.)	(0.723)	(0.769)	(0.297)	(0.897)	(0.605)
[1.000]	[1.000]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
-0.014	-0.113	0.130	-0.158	-0.014	-0.200	-0.009	0.068	0.408
(0.785)	(0.078)†	(0.061)†	(0.383)	(0.904)	(0.030)*	(0.954)	(0.568)	($<$ 0.001)***
[1.000]	[0.619]	[0.486]	[1.000]	[1.000]	[0.356]	[1.000]	[1.000]	[0.001]**
880	312	568	31	121	160	162	173	233
Scoreline is tied								
0.067	-0.001	0.231	-0.014	0.075	-0.102	0.150	0.136	0.461
(0.019)*	(0.964)	($<$ 0.001)***	(0.790)	(0.237)	(0.182)	(0.039)*	(0.261)	($<$ 0.001)***
[0.297]	[1.000]	[0.001]**	[1.000]	[1.000]	[0.920]	[0.377]	[1.000]	[0.001]**
2,364	1,463	901	576	475	412	307	298	296
Team A hitting the post leading by at least one goal								
0.045	0.062	0.039	-0.022	0.070	0.043	0.095	0.007	0.012
(0.043)*	(0.163)	(0.110)	(0.798)	(0.321)	(0.466)	(0.044)*	(0.921)	(0.720)
[0.386]	[0.920]	[0.730]	[1.000]	[1.000]	[1.000]	[0.386]	[1.000]	[1.000]
1,549	492	1,057	53	165	274	302	333	422

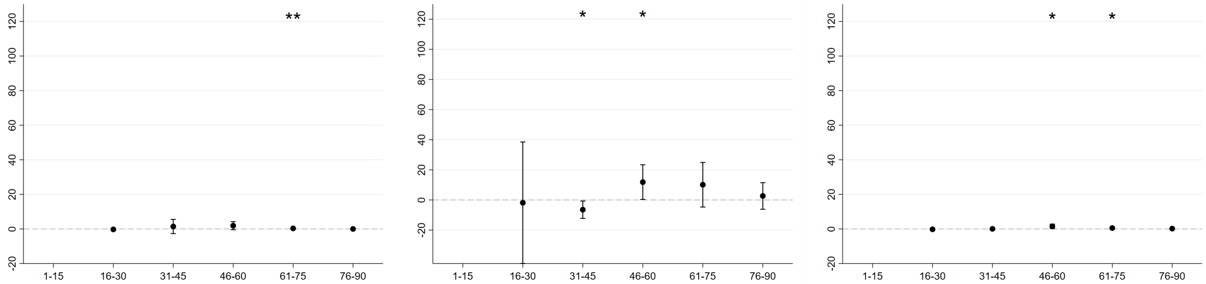
Table K.9: Estimate of abnormal returns after buying asset “Draw” following positive news ($r = outcome - p$, first three lines) or selling following negative news ($r = outcome - p$, last two lines). Positive values indicate under-reaction. Kernel matching estimator, matching on x-y and price after the post with Mahalanobis distance. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case. pvalues computed by 50,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

L Effect of scoring on the volume matched in the 60 seconds following a post (in £)

The following tables and figures shows the effect of a post in on the volume matched (in £) in the 60 seconds following a post. Similarly, to Section C the standard error are computed by standard bootstrap (i.e. resampling with replacement).

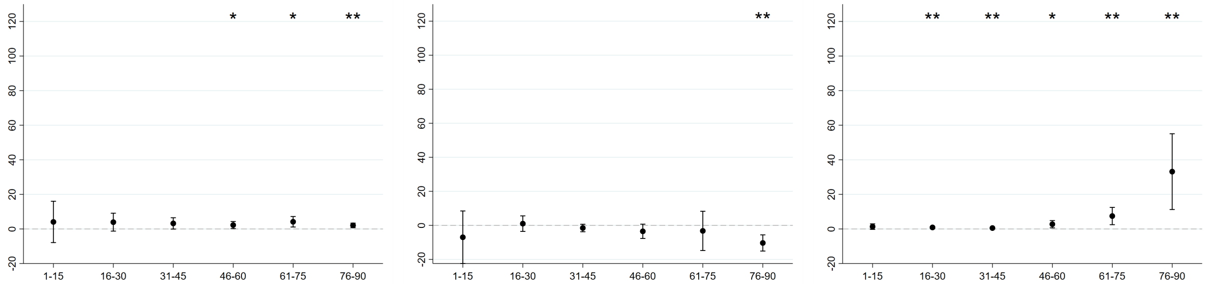
Team A hitting the post trailing by at least two goals

(a) Asset "*Team A wins*" (b) Asset "*Team B wins*" (c) Asset "*Draw*"



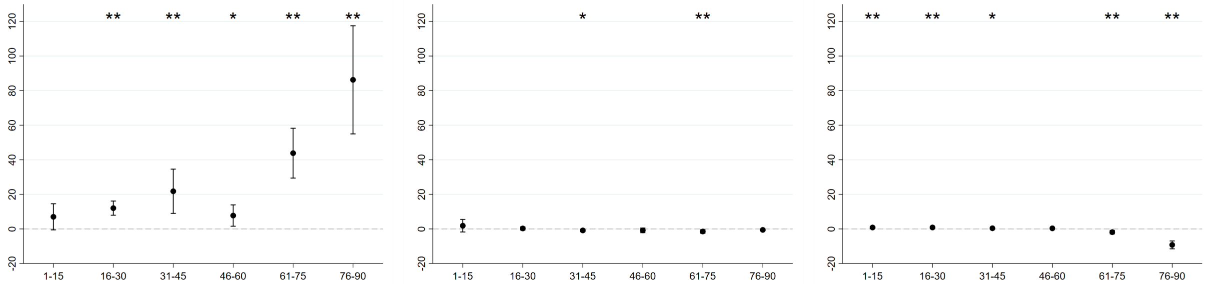
Team A hitting the post trailing by one goal

(d) Asset "*Team B wins*" (e) Asset "*Team B wins*" (f) Asset "*Draw*"



Scoreline is tied

(g) Asset "*Team A wins*" (h) Asset "*Team B wins*" (i) Asset "*Draw*"



Team A hitting the post leading by at least one goal

(j) Asset "*Team A wins*" (k) Asset "*Team B wins*" (l) Asset "*Draw*"

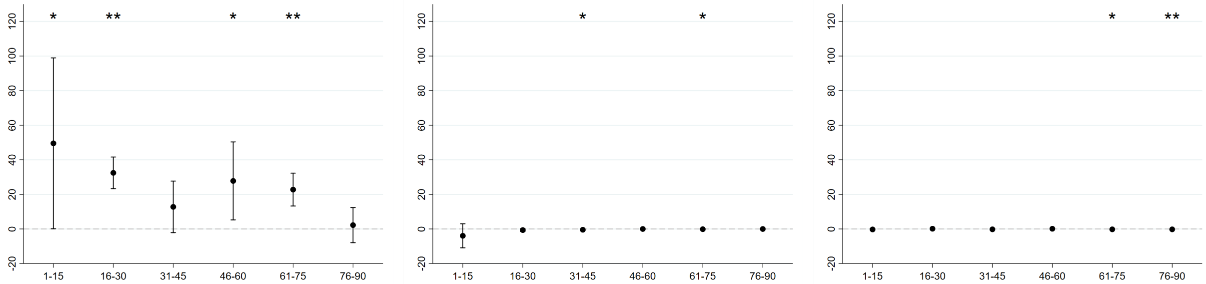


Figure L.1: Estimate of volume matched (in 1,000 £) in the 60 seconds following a post. Kernel matching estimator, matching on x-y with Euclidean distance. std errors computed by 1,000 bootstraps. * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level for sharpened q-values.

Asset *Team A wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
17,419	14,973	18,340	9,551	17,647	15,674	11,094	23,432	26,683
(< 0.001)***	(< 0.001)***	(< 0.001)***	(0.043)*	(< 0.001)***	(< 0.001)***	(0.001)**	(< 0.001)***	(< 0.001)***
[0.001]**	[0.001]**	[0.001]**	[0.044]*	[0.001]**	[0.001]**	[0.002]**	[0.001]**	[0.001]**
5,174	2,323	2,851	662	778	883	852	899	1,100
Team A hitting the post trailing by at least two goal								
670	426	686	.	−260	1,412	1,882	330	20
(0.120)	(0.654)	(0.056)†	(.)	(0.082)†	(0.499)	(0.112)	(< 0.001)***	(0.171)
[0.087]†	[0.244]	[0.051]†	[.]	[0.065]†	[0.206]	[0.082]†	[0.001]**	[0.105]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
3,072	3,723	2,646	4,067	3,927	3,205	2,243	4,161	2,065
(< 0.001)***	(0.221)	(0.015)*	(0.505)	(0.137)	(0.056)†	(0.032)*	(0.007)**	(0.002)**
[0.001]**	[0.129]	[0.020]*	[0.207]	[0.095]†	[0.051]†	[0.034]*	[0.011]*	[0.004]**
880	312	568	31	121	160	162	173	233
Scoreline is tied								
24,426	13,515	40,549	7,014	12,032	21,791	7,744	43,825	86,242
(< 0.001)***	(< 0.001)***	(< 0.001)***	(0.069)†	(< 0.001)***	(0.001)**	(0.014)*	(< 0.001)***	(< 0.001)***
[0.001]**	[0.001]**	[0.001]**	[0.060]†	[0.001]**	[0.002]**	[0.019]*	[0.001]**	[0.001]**
2,362	1,461	901	576	475	410	307	298	296
Team A hitting the post leading by at least one goal								
17,532	24,359	14,773	49,521	32,444	12,771	27,776	22,775	2,221
(< 0.001)***	(< 0.001)***	(< 0.001)***	(0.049)*	(< 0.001)***	(0.093)†	(0.016)*	(< 0.001)***	(0.668)
[0.001]**	[0.001]**	[0.001]**	[0.048]*	[0.001]**	[0.072]†	[0.020]*	[0.001]**	[0.245]
1,549	492	1,057	53	165	274	302	333	422

Table L.1: Estimate of volume matched (in £) in the 60 seconds following a post. Kernel matching estimator, matching on − with Euclidean distance. pvalues computed by 1,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Team B wins*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
-836	-260	$-1,058$	848	86	$-1,671$	506	-702	$-2,744$
$(0.023)^{*}$	(0.658)	$(0.086)^{\dagger}$	(0.341)	(0.869)	$(0.001)^{**}$	(0.544)	(0.634)	$(< 0.001)^{***}$
$[0.027]^{*}$	[0.244]	$[0.068]^{\dagger}$	[0.167]	[0.295]	$[0.002]^{**}$	[0.222]	[0.239]	$[0.001]^{**}$
5,174	2,323	2,851	662	778	883	852	899	1,100
Team A hitting the post trailing by at least two goal								
$4,693$	$-4,065$	$7,605$	.	$-1,873$	$-6,478$	$11,835$	$10,088$	$2,654$
(0.166)	(0.731)	$(0.010)^{*}$	(.)	(0.927)	$(0.028)^{*}$	$(0.044)^{*}$	(0.181)	(0.555)
[0.105]	[0.268]	$[0.015]^{*}$	[.]	[0.305]	$[0.032]^{*}$	$[0.044]^{*}$	[0.109]	[0.225]
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
$-4,942$	-711	$-7,281$	$-6,988$	$1,015$	$-1,548$	$-3,503$	$-3,253$	$-10,336$
$(0.011)^{*}$	(0.706)	$(< 0.001)^{***}$	(0.375)	(0.662)	(0.168)	(0.102)	(0.581)	$(< 0.001)^{***}$
$[0.015]^{*}$	[0.259]	$[0.001]^{**}$	[0.175]	[0.244]	[0.105]	$[0.077]^{\dagger}$	[0.226]	$[0.001]^{**}$
880	312	568	31	121	160	162	173	233
Scoreline is tied								
-214	417	-953	$1,859$	280	-860	-819	$-1,476$	-545
(0.490)	(0.497)	$(< 0.001)^{***}$	(0.314)	(0.558)	$(0.027)^{*}$	(0.229)	$(0.005)^{**}$	$(0.070)^{\dagger}$
[0.206]	[0.206]	$[0.002]^{**}$	[0.159]	[0.225]	$[0.031]^{*}$	[0.129]	$[0.008]^{**}$	$[0.060]^{\dagger}$
2,362	1,461	901	576	475	410	307	298	296
Team A hitting the post leading by at least one goal								
-181	-854	-65	$-3,956$	-641	-460	-3	-128	-8
$(0.006)^{**}$	$(0.048)^{*}$	$(0.096)^{\dagger}$	(0.265)	(0.130)	$(0.051)^{\dagger}$	(0.983)	$(0.051)^{\dagger}$	(0.606)
$[0.010]^{*}$	$[0.048]^{*}$	$[0.074]^{\dagger}$	[0.142]	$[0.091]^{\dagger}$	$[0.049]^{*}$	[0.315]	$[0.048]^{*}$	[0.236]
1,549	492	1,057	53	165	274	302	333	422

Table L.2: Estimate of volume matched (in £) in the 60 seconds following a post. Kernel matching estimator, matching on − with Euclidean distance. pvalues computed by 1,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

Asset *Draw*								
All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
1,381	512	1,831	704	575	267	860	636	2,825
(< 0.001)***	(< 0.001)***	(0.104)	(< 0.001)***	(< 0.001)***	(< 0.001)***	(0.004)**	(0.104)	(0.062)†
[0.001]**	[0.001]**	[0.077]†	[0.001]**	[0.001]**	[0.001]**	[0.007]**	[0.077]†	[0.056]†
5,172	2,323	2,849	662	778	883	851	899	1,099
Team A hitting the post trailing by at least two goal								
605	−121	714	.	−200	62	1,520	540	198
(< 0.001)***	(0.517)	(< 0.001)***	(.)	(0.190)	(0.807)	(0.019)*	(0.030)*	(0.076)†
[0.001]**	[0.211]	[0.001]**	[.]	[0.114]	[0.291]	[0.025]*	[0.033]*	[0.063]†
383	58	325	.	17	39	81	95	149
Team A hitting the post trailing by one goal								
10,744	826	18,693	1,351	888	531	2,739	7,467	33,146
(< 0.001)***	(0.003)**	(< 0.001)***	(0.097)†	(0.001)**	(0.001)**	(0.010)*	(0.003)**	(0.003)**
[0.001]**	[0.005]**	[0.001]**	[0.074]†	[0.002]**	[0.003]**	[0.015]*	[0.006]**	[0.006]**
880	312	568	31	121	160	162	173	233
Scoreline is tied								
−897	686	−3,527	843	848	399	353	−1,857	−9,218
(< 0.001)***	(< 0.001)***	(< 0.001)***	(0.002)**	(< 0.001)***	(0.020)*	(0.078)†	(< 0.001)***	(< 0.001)***
[0.001]**	[0.001]**	[0.001]**	[0.004]**	[0.001]**	[0.025]*	[0.063]†	[0.001]**	[0.001]**
2,362	1,461	901	576	475	410	307	298	296
Team A hitting the post leading by at least one goal								
−113	−88	−148	−275	142	−202	114	−212	−217
(0.011)*	(0.250)	(< 0.001)***	(0.235)	(0.303)	(0.155)	(0.341)	(0.029)*	(< 0.001)***
[0.015]*	[0.139]	[0.001]**	[0.131]	[0.155]	[0.100]	[0.167]	[0.033]*	[0.001]**
1,547	492	1,055	53	165	274	301	333	421

Table L.3: Estimate of volume matched (in £) in the 60 seconds following a post. Kernel matching estimator, matching on − with Euclidean distance. pvalues computed by 1,000 bootstraps in bracket (second line). Sharpened q-values in square brackets (third line). † significance at the 10% level, * significance at the 5% level, ** significance at the 1% level, *** significance at the 0.1% level.

M Minimum Detectable Effect

Following Djimeu and Houndolo (2016), we compute the MDE as:

$$MDE = (t_{1-\frac{\alpha}{2}} + t_{1-\beta})\sigma\sqrt{\frac{1}{p(1-p)n}}$$

Where σ is the standard deviation of the outcome r, p the proportion of posts going in, and n the sample size. We choose the standard values of $\alpha = 0.05$ and $\beta = 0.2$, for a test of significance at 5% and 80% statistical power.

M.1 Parametric MDEs

To start with, we can use the standard error from our estimates to measure the MDEs, assuming that the critical thresholds are obtained from a Student distribution. We then compute $t_{1-\frac{\alpha}{2}}$ and $t_{1-\beta}$.[31] Table M.1 shows the MDE for each of our subsamples:

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[31] The degree of freedom is $n-1$, where n is the subsample's sample size.

All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
Asset *Team A wins*								
0.037	0.064	0.042	0.132	0.110	0.096	0.090	0.083	0.049
Asset *Team B wins*								
0.034	0.058	0.040	0.115	0.100	0.091	0.087	0.076	0.048
Asset *Draw*								
0.038	0.062	0.048	0.118	0.105	0.101	0.096	0.095	0.064
Team A hitting the post trailing by at least two goal								
Asset *Team A wins*								
0.028	0.129	0.023	.	0.073	0.214	0.033	0.073	0.002
Asset *Team B wins*								
0.095	0.377	0.089	.	0.615	0.539	0.217	0.209	0.069
Asset *Draw*								
0.093	0.376	0.086	.	0.617	0.542	0.216	0.192	0.066
Team A hitting the post trailing by one goal								
Asset *Team A wins*								
0.071	0.139	0.079	0.450	0.239	0.185	0.185	0.160	0.080
Asset *Team B wins*								
0.106	0.185	0.129	0.539	0.303	0.264	0.259	0.261	0.172
Asset *Draw*								
0.103	0.171	0.128	0.481	0.264	0.255	0.252	0.256	0.179
Scoreline is tied								
Asset *Team A wins*								
0.067	0.089	0.099	0.146	0.158	0.163	0.180	0.191	0.143
Asset *Team B wins*								
0.058	0.078	0.086	0.128	0.135	0.147	0.168	0.161	0.112
Asset *Draw*								
0.066	0.083	0.107	0.129	0.148	0.162	0.177	0.210	0.174
Team A hitting the post leading by at least one goal								
Asset *Team A wins*								
0.057	0.120	0.062	0.449	0.204	0.156	0.151	0.123	0.061
Asset *Team B wins*								
0.033	0.080	0.030	0.295	0.157	0.090	0.080	0.054	0.028
Asset *Draw*								
0.052	0.105	0.057	0.388	0.172	0.141	0.139	0.116	0.058

Table M.1: Minimum Detectable Effect for each sub-sample studied in the paper. We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case.

M.2 Bootstrap MDE

The parametric assumption is valid overall. As shown in Figure M.1 our estimates are normally distributed. The use of a Student distribution to measure MDEs is therefore suitable.

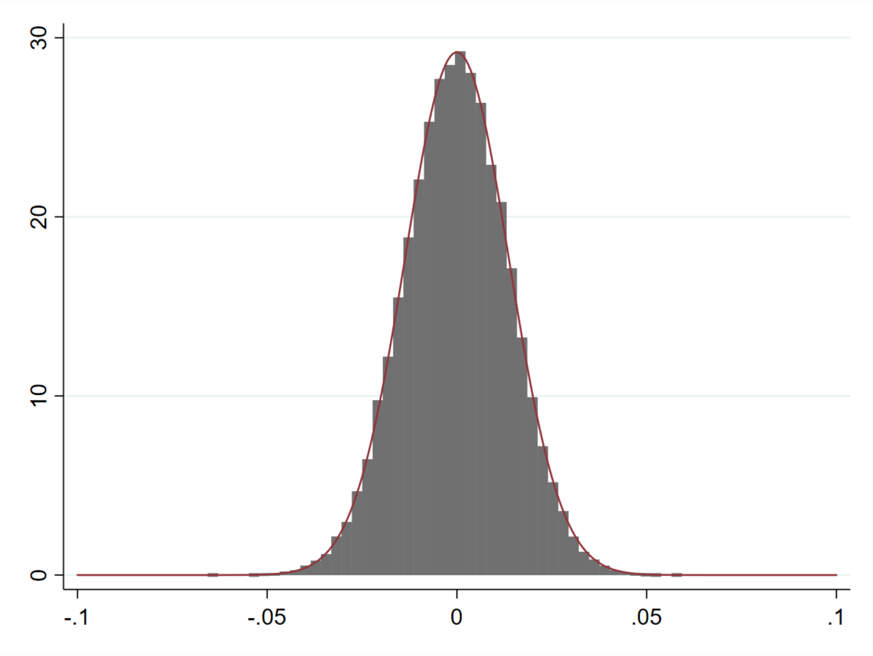

Figure M.1: Distribution of τ^* for the overall sample on the market team A hit the post.

However, the previous calculation is problematic for corner solutions. At corners MDEs cannot be symmetric by design. We therefore use our bootstrap distributions to estimate MDEs. In each situations, two MDEs are estimated instead of just one: one MDE for underreaction (MDE_{upper}) and one for overreaction (MDE_{lower}).

$$MDE_{upper} = (c_{0.975} + c_{0.80})$$

$$MDE_{lower} = (c_{0.025} + c_{0.20})$$

where $c_{0.025}$, $c_{0.20}$, $c_{0.8}$ and $c_{0.975}$ are defined in point (7) of Appendix F.

Table M.2 shows the MDE for each of our subsample. The results are overall similar to those of Table M.1.

All	0-45	46-90	1-15	16-30	31-45	46-60	61-75	76-90
All situations								
−0.039, 0.038	−0.066, 0.064	−0.044, 0.044	−0.135, 0.133	−0.108, 0.107	−0.104, 0.102	−0.094, 0.094	−0.086, 0.084	−0.056, 0.054
−0.032, 0.032	−0.054, 0.054	−0.036, 0.036	−0.119, 0.116	−0.092, 0.091	−0.080, 0.077	−0.078, 0.076	−0.066, 0.064	−0.041, 0.040
−0.039, 0.039	−0.061, 0.061	−0.047, 0.048	−0.120, 0.124	−0.100, 0.102	−0.096, 0.099	−0.095, 0.097	−0.088, 0.090	−0.064, 0.066
Team A hitting the post trailing by at least two goal								
−0.065, 0.074	−0.203, 0.267	−0.062, 0.076	., .	−0.268, 0.270	−0.249, 0.388	−0.154, 0.188	−0.123, 0.194	−0.018, 0.049
−0.119, 0.124	−0.351, 0.375	−0.124, 0.133	., .	−0.469, 0.554	−0.450, 0.505	−0.269, 0.286	−0.276, 0.293	−0.119, 0.153
−0.110, 0.119	−0.296, 0.343	−0.114, 0.125	., .	−0.421, 0.534	−0.340, 0.489	−0.240, 0.266	−0.235, 0.273	−0.110, 0.147
Team A hitting the post trailing by one goal								
−0.096, 0.098	−0.171, 0.177	−0.108, 0.113	−0.477, 0.483	−0.266, 0.276	−0.255, 0.264	−0.232, 0.237	−0.218, 0.233	−0.132, 0.155
−0.105, 0.104	−0.185, 0.182	−0.130, 0.125	−0.512, 0.509	−0.307, 0.301	−0.264, 0.254	−0.249, 0.240	−0.254, 0.243	−0.171, 0.156
−0.113, 0.114	−0.179, 0.184	−0.145, 0.145	−0.472, 0.524	−0.286, 0.305	−0.264, 0.272	−0.265, 0.268	−0.279, 0.283	−0.214, 0.207
Scoreline is tied								
−0.069, 0.069	−0.092, 0.090	−0.106, 0.105	−0.151, 0.150	−0.155, 0.154	−0.173, 0.170	−0.190, 0.186	−0.198, 0.189	−0.156, 0.152
−0.053, 0.051	−0.073, 0.073	−0.069, 0.066	−0.133, 0.130	−0.129, 0.124	−0.125, 0.117	−0.140, 0.134	−0.122, 0.112	−0.083, 0.077
−0.065, 0.064	−0.084, 0.081	−0.105, 0.103	−0.138, 0.134	−0.145, 0.137	−0.162, 0.153	−0.183, 0.176	−0.197, 0.187	−0.163, 0.159
Team A hitting the post leading by at least one goal								
−0.050, 0.050	−0.113, 0.109	−0.053, 0.050	−0.387, 0.363	−0.210, 0.192	−0.146, 0.138	−0.131, 0.119	−0.113, 0.105	−0.060, 0.055
−0.027, 0.025	−0.065, 0.060	−0.025, 0.023	−0.275, 0.238	−0.118, 0.103	−0.084, 0.074	−0.068, 0.056	−0.049, 0.042	−0.021, 0.017
−0.047, 0.045	−0.104, 0.098	−0.049, 0.047	−0.348, 0.308	−0.180, 0.165	−0.135, 0.125	−0.120, 0.111	−0.107, 0.097	−0.060, 0.054

Table M.2: Minimum Detectable Effect for each sub-sample studied in the paper. For the market “Team A wins” (first row), “Team B wins” (second row) and "‘Draw"’ (third row). We only observe two posts for situations when Team A hits the post while trailing by at least two goals in the first 15 minutes. We, therefore, cannot perform our estimation in that case.