Forecasting with Social Media: Evidence from Tweets on Soccer Matches *

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Abstract

Social media is now used as a forecasting tool by a variety of firms and agencies. But how useful are such data in forecasting outcomes? Can social media add any information to that produced by a prediction/betting market? In this paper we source 13.8m posts from Twitter, and combine them with contemporaneous Betfair betting prices, to forecast the outcomes of English Premier League soccer matches as they unfold. We find that the Tweets of certain journalists, and the tone of all Tweets, contain information not revealed in betting prices. In particular, Tweets aid in the interpretation of news during matches.

JEL Classification: G14, G17

Keywords: forecasting, social media, prediction markets, soccer

1 Introduction

Social media content – for example that produced on Twitter or Facebook – is increasingly used as a forecasting tool. For example, Hollywood studios use data from social media to forecast demand for new films.[1] Financial firms extract sentiment from Twitter to predict stock returns, and design funds to algorithmically trade based on this information[2]. And social media is now even used for economic forecasting: in 2012, the Australian Treasury department launched a division to harness social media data to forecast workforce participation and retail sentiment, among other things.[3]

But how useful and accurate a forecasting tool is social media? On the one hand, social media content can harness the opinions and beliefs of a wide group of participants. Thus the 'wisdom of the crowd' (Galton, 1907, Surowiecki, 2005) may produce accurate forecasts. On the other hand, the incentives for an individual on social media to provide accurate information for forecasting may arguably be weak. Unlike in markets, accurate social media

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[1]'Hollywood Tracks Social Media Chatter to Target Hit Films', Brook Barnes, *New York Times*, Dec 7th 2014.

[2]'Hey Finance Twitter, You Are About to Become an ETF', Eric Balchunas, *Bloomberg*, Oct 15th 2015.

[3]'Treasury to Mine Twitter for Economic Forecasts, David Ramli, *Financial Review*, Oct 30th 2012.

forecasts may enhance an individual's reputation, but are not directly profitable. And worse, there are many incidences of misinformation on social media. For example, a hoax Tweet on the Associated Press Twitter feed in 2013, misreporting an explosion at the White House in Washington, briefly wiped $136 billion off the S&P 500 Index.[4]

In this paper we evaluate the accuracy of social media forecasting in a fast-moving, high-profile environment: English Premier League soccer matches. We study 13.8 million Tweets, an average of 5.2 Tweets per second, during 372 matches that took place during the 2013/14 season. Our primary aim is assess whether information contained in these Tweets can predict match outcomes. Furthermore, we also aim to assess whether the forecasting capacity of social media is concentrated in the lead-up to large events (such as goals or red cards) – which would indicate that social media helps to 'break' news – or whether any forecasting capacity is to be found in the aftermath of such events, in which case social media helps in the interpretation of information.

One problem is that social media content does not easily translate to probability forecasts. For example, we cannot state that X number Tweets on a particular team, in a given interval, maps to a prediction that the team has a Y% chance of victory. Our solution, therefore, is to ask whether Twitter content can add information to probability forecasts produced by a prediction/betting market, Betfair. This is a very high bar, as prediction markets have been found to outperform tipsters in the context of sports (Spann and Skiera, 2009), and outperform polls and experts in the context of political races (Vaughan Williams and Reade, 2015). Prediction markets have even performed well when illiquid, as was the case in the corporate prediction markets studied by Cowgill and Zitzewitz (2015), and have also performed well when attempts have been made to manipulate prices, as was the case in the presidential betting markets studied by Rhode and Strumpf (2004) and Rothschild and Sethi (2015). In addition, and of particular relevance to our setting, prediction/betting markets have been found to accurately digest information on events (goals) almost immediately (Croxson and Reade, 2014).

We find that aggregate tweeting does contain information not in betting prices, and, surprisingly, this effect is concentrated in the aftermath of events (e.g. goals, red cards).

[4]'A Fake AP Tweet Sinks the Dow for an Instant', Jared Keller, *Bloomberg*, April 23rd 2013

Rather than breaking news faster than the betting market, activity on social media aids in the interpretation of information. To be specific, pronounced social media activity for a given team in a given match (identified by the hashtag), after a goal has been scored (or indeed conceded), implies that that team is 4.27% more likely to win than contemporaneous betting market prices suggest. We also find that the predictive power of social media activity is concentrated amongst a subset of tweeters: the Tweets of British Broadcasting Corporation (BBC) journalists, in particular, are highly predictive of a team's fundamental probability of winning, and not just after a significant match event has occurred. Finally, we find that instances of positive tweeting (measured using the micro-blogging dictionary of Nielsen, 2011) – for a given team in a given second – also strongly suggest that the team in question is more likely to win than betting market prices imply. (We label our measure of Tweet content the 'tone' of the Tweet, as the label 'sentiment' is more often than not used to capture non-fundamental information, e.g. as in Edmans *et al.*, 2007). In short, aggregate information taken from Twitter is not noise, and does not purely reveal sentiment, but is actually a useful predictor of outcomes.

We also examine the speed with which social media information is subsequently incorporated into betting prices. We find that stale Tweets, particularly stale BBC Tweets and stale positive tone tweeting, still have information not in betting prices 60 seconds after the Tweet and later. Only when a Tweet follows a significant market event – such as a goal or a red card – is this social media information quickly digested by the market (approximately 10 seconds later). In other words, when social media output is not a response to a salient market event, its informational content often does not find its way into betting prices.

What are the returns to a strategy that exploits social media information? This will give us a rough idea of the magnitude of fundamental information that is embedded in social media content, but not in betting prices. To calculate returns, we first need an an implementable strategy, which requires us to take two factors into account. Firstly, as evaluated in Brown and Yang (2015), Betfair operate a speed bump which creates a 5-9 second delay between the time at which an order is submitted and the time it is logged on the exchange. (This is to ensure that bettors in the stadia cannot adversely-select bettors at home watching the match with a delay). Secondly, we need to allow time for a hypothetical arbitrageur to execute their trade; this means scraping the information from Twitter, calculating the tone of the Tweets (if applicable), and then placing an automated trade on Betfair. Once we account for these two factors, we find that a simple strategy of betting when the BBC have tweeted about a team yields average returns of 2.56% from 1,615 bets, and a strategy of betting when aggregate tone for that team is positive yields average returns of 2.28% from 903,821 bets. These returns – for an investment duration of no more than 90 minutes each – compare very favourably with average returns for all bets of -5.41%, and indicate that the marginal information contained in social media data is substantial.

Before extrapolating these results to other settings, there are two important caveats to bear in mind. Social media in our setting is accompanied by a betting/prediction market. There may be other settings where such a market does not exist; in which case the forecaster must confront the original problem of constructing probability forecasts from social media output. Secondly, soccer matches are extremely popular topics of conversation on Twitter. The FIFA World Cup, which took place at the end of the season in our study, was at the time the most-tweeted about event in history.[5] In other words, this crowd is one of the largest to be found on social media, so may be wiser than most. Nevertheless, our results suggest that social media is a useful forecasting tool in fast-moving environments, and is particularly helpful in the interpretation of new information.

The rest of the paper is structured as follows. In Section 2 we briefly summarize more of the related literature. In Section 3 we introduce the Twitter and Betfair data, and in Section 4 we conduct our analysis. Section 5 concludes.

2 Related Literature

Our paper is most closely related to the work of Vaughan Williams and Reade (2016). Vaughan Williams and Reade combined Betfair and Twitter data in order to examine whether breaking news reached betting market prices or Tweets first. Their focus was the 'bigotgate' incident in 2010, when the then U.K. Prime Minister Gordon Brown was caught off-camera

[5]'World Cup was biggest event yet for Twitter with 672m tweets', Stuart Dredge, *The Guardian*, 15th July 2014.

insulting a prospective voter. News of that incident broke on Twitter first, and it was a number of hours before the news was incorporated into betting market prices. In the same vein, Asur and Huberman (2010) show that Twitter activity is a better predictor of box-office revenues, for 24 different movies, than market-based predictors. In our study we have many more significant events (goals/red cards) to analyse, and also many more (match) outcomes to forecast than in these two papers. Furthermore, Betfair trading on English Premier League matches is more liquid than prediction markets on political events or movie earnings outcomes; 666 million GBP is wagered on Betfair on the matches we study. This raises the bar for social media: can the output on Twitter predict outcomes even after accounting for prices in such a large and liquid market?

Our work is also related to the finance literature on the use of social media to predict stock returns. Chen *et al.* (2014), Sprenger *et al.* (2014), and Avery *et al.* (2015) find that opinions on three different social media sites – Seeking Alpha, Twitter, and CAPS respectively – predict subsequent cross-sectional stock returns, and, in the case of Seeking Alpha, posts also predict earnings announcement surprises. Zhang *et al.* (2011) find that Twitter content can even predict returns at the aggregate index level. The problem with such analysis, however, is that returns are only a proxy for fundamental information, and any effect is inevitably sensitive to the time-horizon chosen. The ability of social media to predict returns may be solely due to its capture of short-run sentiment, and not due to fundamentals. Furthermore, if market participants believe that social media can be mined for asset-relevant information, then the belief becomes self-fulfilling, as their buying and selling pressure drives asset prices and returns. Even earnings announcements – which may be less vulnerable to such endogeneity issues – are still only a noisy, and, to a degree, manipulable, measure of asset fundamentals. In our paper we are only interested in forecasting fundamentals, and for this we have a very clean measure: the outcome of the match.

3 Data: Twitter and Betfair

The Tweets for our analysis were provided by Twitter as part of their #datagrants programme. We were granted access to the data via Gnip, a firm that is now a subsidiary of

Twitter. Gnip provide both real-time access to Tweets, and also historical sweeps based on hashtags and tweeter IDs. We obtained Tweets for every English Premier League soccer match in the 2013/14 season. Many different hashtags are used for each team. For example, for Liverpool Football Club, the hashtags include #lfc and #ynwa (where ynwa stands for You'll Never Walk Alone). In addition to sourcing according to hashtags, we also obtained Tweets, and apportioned them to a team, based on the tag of well-known twitter accounts. In the case of Liverpool again, these include @thisisanfield, @liverpoolfc and others. Tweets on soccer teams can occur throughout the week, but we focus on Tweets that occur as the team in question is playing. There are some examples where more than one team is tagged in a particular Tweet. For example, when Liverpool play Chelsea Football Club you may observe a hashtag #lfcvcfc. These Tweets are dropped from our analysis as it is unclear which team the Tweet is focused upon. Our sweep of historical Tweets includes original Tweets, and the retweeting (sharing) of an original Tweet. Including retweets, we have 13.8 million Tweets in our sample.

Table 1 provides summary statistics on the number of Tweets per second. This is measured at the team-second level, so there are two observations, one for each team, each second. On average a team receives 2.6 Tweets per second. This distribution is highly positively skewed, with one instance of a team receiving 264 Tweets in a given second. Of these a slight majority are original, with an average number of original Tweets of 1.37 per team per second. (Retweets come in at an average of 1.23 per team per second). In the middle panel of Table 1 we also summarize an indicator variable, equalling 1 if there was at least one Tweet for that team in that second, and 0 otherwise. A look at this indicator variable tells us that teams receive at least one Tweet 44.1% of the time. A team receives an original Tweet 36.9% of the time, and a retweet 29.6% of the time. It is important to note that we only consider the inplay period (as matches are being played), so attention on these teams at that time is typically quite high. Having said that, the statistics we describe encompass all teams in the 372 matches in our sample, not simply the matches that are televised. Some matches, of course, receive much more attention on social media than others.

Although we are interested in the opinions of all Twitter users, there will undoubtedly be variation in the ability of different users to predict match outcomes. A natural subset of users to focus upon are professional journalists from the British Broadcasting Corporation (BBC). The BBC has both a national division, that will send journalists to the largest matches, but also regional divisions which will cover the majority of matches. Moreover, these individuals are easily identifiable from the BBC suffix in their Twitter names. We identified 148 distinct BBC twitter accounts, and cross-checked their identities online. In Table 1 we summarise the actions of these BBC tweeters. There is seldom more than one BBC Tweet per team per second. Only in 0.03% of team-second observations is at least one BBC Tweet observed, so while these Tweets might contain important information on likely match outcomes (by breaking news of goals etc.), they are relatively infrequent.

Although we assume that tweeting about a particular team is a positive signal about a team's prospects, this depends, of course, on the content of the Tweet. Tweeters may be using the Tweet to voice their dissatisfaction with the team's performance, and predict that they will lose the match. Therefore, we cannot argue that a Tweet – tagged to a team with their hashtag – is equivalent to a buy signal on a stock message board. With this in mind, we use the Nielsen (2011) dictionary for micro-blog content to establish the tone for each team each second. As mentioned in the Introduction, we label our resultant measure of Tweet content the 'tone' of a Tweet, as one alternative label, 'sentiment', often implies that the information is unrelated to fundamentals. It is precisely these fundamentals (match outcomes) that we want to capture. Within the Nielsen dictionary, the majority of positive and negative words receive a score of 2 and -2 respectively. The dictionary also captures obscenities, allowing for scores of -4 or -5.

In Table 1 we present summary statistics on this tone measure. We calculate the aggregate tone for each team in each second; this is the sum across all Tweets (which is itself the sum of all words within the Tweet). As captured in the top panel of Table 1, aggregate tone is, on average, positive. There is, however, great variation across teams and across time. Aggregate tone ranges from -144 to +471. We also create an indicator variable, equalling 1 if aggregate tone is positive and 0 otherwise. From here we can see that 20.9% of team-second observations have positive tone. Note, however, that there are only Tweets in 44.1% of team-second observations, so tone is positive in approximately 46.5% of cases when there are Tweets. Conditional on there being at least one Tweet, aggregate tone is negative in 18%

of cases and is neutral (i.e. aggregate tone=0) in 35.5% of cases. This variation justifies our reluctance to state that a Tweet tagged to a given team is an unambiguously positive signal about the team's prospects.

Perhaps the best way to describe this dictionary is to give a few examples. In April 2014, Liverpool played Chelsea in an important match for Liverpool's hopes of winning the Championship. At 0-0 in the first half, the Liverpool captain Steven Gerrard slipped, allowing the Chelsea forward Demba Ba to run through and score. The reaction on Twitter ranged from positive for Chelsea:

Hahahahahaha yes demba ! Chin up liverpool #CFC

This received a score of +1 in the Nielsen dictionary. Others focused more negatively on the outcome for Liverpool:

WTF #YNWA

This Tweet produces a tone score of -4, but is topped by the obscenities (censored in this paper but not on Twitter) in the next negative Tweet which gets a tone score of -9:

F*** u Steve u c*** #lfc

Like any dictionary, there will be instances when the meaning of the Tweet is not accurately captured. For example, the dictionary does not detect the sarcasm in the following Tweet:

Captain fantastic and all that... #LFC

This last Tweet got a score of +4.

The dictionary provided by Nielsen (2011) is appealing for our research setting, as it is primarily intended to classify micro-blog output. This means that it captures colloquialisms, such as 'WTF', and obscenities, which are often used in online soccer discussions. We do, however, recognise the problems that may arise when using a general dictionary in a specific context. As Loughran and McDonald (2011) illustrated in their study of financial text, words can have very different connotations in different settings. (One example of theirs was that the term 'liability' is negative in the majority of contexts, but less so in a financial context). An alternative is to devise our own dictionary specific for Twitter conversations on soccer. Our concern with this approach is that this inserts the researcher more closely into the data-generating process, and perhaps our classifications would subconsciously be biased in the direction of our prior hypotheses. Another point we can make is that, in this type of research, the success of a dictionary in capturing tone is, in part, revealed by the extent to which this tone tells us something that betting prices do not. As we will see in our later analysis, the dictionary of Nielsen is quite an accurate predictor of match outcomes.

We marry our social media data with betting price data from Betfair, a U.K. betting exchange. The exchange operates as a standard limit order book of the type used by most financial exchanges. Bettors can place limit orders, which act as quotes for other bettors, or place market orders, which execute at prices currently quoted by others. Bettors can wager that a particular team will win (via a 'back' bet), or bet that a team will lose (via a 'lay' bet). We obtained Betfair limit order book data from Fracsoft, a third-party provider of historical data. This data include the best back and lay quotes (and associated volumes), measured each second, throughout 372 matches in the 2013/14 season. 8 matches are missing from the Fracsoft database, so we discard the Twitter data on these.

Our main measure from the betting data is the implied win probability. This is defined as $(1/B_t + 1/L_t)/2$, where B_t are the best back quotes at time t, and L_t are the best lay quotes at time t. This is the midpoint of the back-lay (bid-ask) spread. We use this measure because we want to see whether Tweets can add information to the probability forecasts produced by the betting market. To be specific, we are asking, does the presence of a Tweet for a team indicate that the team is more likely to win than betting market prices imply? For our implied win probability measure we have 7.94 million observations (rather than 5.29 million), as data on the draw outcome in a match are included. The average implied win probability is 0.336, with a range from 0.01 to 0.99. If a team is certain to win or lose, there will be no quotes. Within the 372 matches in the Fracsoft database there are a few missing bets, which explains why the average implied win probability is 0.336 rather than 0.333. In Table 1 we also summarise an indicator variable equalling 1 if the team ultimately won. This also averages 0.336, so our implied win probability measure appears to be, even with the missing outcomes, an unbiased measure of actual win probability. For our later analysis, we discard the draw data as Tweets are seldom tagged #draw. Excluding the draw, we have 5.29 million order book observations, and quotes in 4.44 million cases.

To illustrate the Twitter and Betfair data together, we created Figure 1, which describes the aforementioned match between Liverpool and Chelsea in April 2014. In the left panel we have betting prices and the number of Tweets for Liverpool each minute of the match. In the right panel we have the same information for Chelsea. (We will examine prices and Tweets each second in our later analysis, but that level of granularity is too detailed for a plot). The Gerrard slip, and Demba Ba goal, occurred in the 48th minute (in stoppage time at the end of the first half). There is little indication from the number of Tweets that this goal was anticipated, but it did set off a spike in Tweets for both teams (albeit more for the scoring team Chelsea). Similarly, when we plot aggregate tone, instead of the number of Tweets, in Figure 2, we find a similar pattern. Aggregate tone did not appear to predict the goal, but tone certainly spiked for the scoring team Chelsea, who went on to win the match. There was a more modest uptick in tone, some of it perhaps defiant, for Liverpool, the team that conceded. In the next section, we will exploit the full granularity of the data to establish whether this pattern applies across the full set of goals and matches.

4 Analysis

Throughout the analysis section we predominantly estimate an equation of the following form:

$$y_i = \beta_0 + \beta_1 x_{it} + \beta_2 z_{it} + \epsilon_{it} \tag{1}$$

y_i is an indicator variable, equalling 1 if team i won the match, x_{it} is the implied win probability of team i winning as measured from the odds at time t, z_{it} is an indicator variable capturing some element of Twitter behaviour for team i at time t, and ϵ_{it} is an error term. This equation, minus the z_{it} term, is commonly referred to as the Mincer-Zarnowitz regression (Mincer and Zarnowitz, 1969), and is often used in the estimation of the favourite-longshot bias (see Vaughan Williams and Reade, 2015, for example). We are most interested in the

β_2 coefficient, as significance here would indicate that social media content can improve on the forecasts produced by the betting market. Put another way, a significant β_2 coefficient would indicate that the betting market forecasts are inefficient.

In our first regression, z_{it} is an indicator variable equalling 1 if there is at least one Tweet for that team in that second. We use an indicator variable, rather than count the number of Tweets in a second, as the latter would lead to a substantial number of predicted values outside the unit interval (recall that there was one instance of 264 Tweets for a team in one second), and potentially bias our estimates. The results of our first regression can be found in Table 2. Firstly, there is little evidence of a favourite-longshot bias, as the coefficient associated with implied win probability is insignificantly different from 1.[6] The coefficient associated with the Tweet indicator suggests that teams win more often than betting prices imply when there is a Tweet, but the difference is not statistically significant. In another words, for the full inplay period, there is little evidence that the mere presence of a Tweet conveys information not in market prices.

At present we have lumped together both original Tweets and retweets (the sharing of original Tweets). One way to break down our analysis is to separate these two types of Tweet out. It is possible that while original Tweets contain information on match outcomes, retweets do not. Alternatively, it may be that a Tweet is not relevant until validated by the another user who shares the information. In Table 2 we therefore repeat our first regression, but this time use an indicator variable for whether there was an original Tweet or a retweet, in regressions 2 and 3 respectively. We find little difference between the predictive power of original Tweets and retweets; neither have a significant effect across the full inplay data. There appears to be as much (or as little) information contained in the sharing of a Tweet as there is in the decision to tweet in the first place. This holds for all of our analysis, so, to save on space, for the remainder of the paper we only describe the results for all Tweets, not original Tweets and retweets separately.

Our next approach is to look at the predictive power of a subset of tweeters. An obvious group to consider are BBC journalists, who, in addition to their journalistic credentials, are

[6] Betting exchange prices typically exhibit less of a favourite-longshot bias than bookmaker prices, as shown in Smith *et al.* (2006).

stationed across a large number of matches. These journalists may lead the betting market in breaking news, particularly as they report on many Saturday 3pm matches that are not televised. In regression 4 we regress the win indicator variable on the implied win probability – as inferred from the betting odds – and an indicator variable equalling 1 if a BBC journalist tweeted about that team in that second. We find that teams are 3.29% more likely to win than their betting odds imply if a BBC journalist has contemporaneously tweeted and tagged that team.

Our last analysis in Table 2 is on the tone of Tweets. As outlined in Table 1, there is great variation in the tone of a Tweet, as measured by the Nielsen (2011) dictionary. We would expect that if a Tweet is to convey information not already in betting prices, then much of this information will be in the content of the Tweet and not simply in the existence of a Tweet. With this in mind we regress our win indicator variable on the implied win probability, and an indicator variable equalling 1 if aggregate tone – across all Tweets for that team in that second – is positive. Positive tone occurs in 20.9% of team-second observations and, conditional on there being at least one Tweet for that team, 46.5% of team-second observations. We find that positive tone does predict match outcomes in a way not fully captured by betting prices. Teams with positive tone tweeting in a given second are 3.39% more likely to win than a team without positive tone, after controlling for the implied win probability of contemporaneous betting prices. In other words, tone extracted from aggregate tweeting is a useful predictor of outcomes across the full inplay time period.

We summarise the main results from Table 2 in Figure 3. We estimate local polynomial regressions (of degree 3) of the relationship between the win indicator and the implied win probability (inferred from the midpoint of the bid-ask spread). The local polynomial estimation does not impose the linear structure assumed by our earlier regressions. In the top left, we display the relationship between actual and implied win probability for all seconds as a benchmark, and display a 45 degree line – which represents a perfectly efficient market – for comparison. From this we can see that teams win approximately as often as the betting prices imply in the full sample. (Note that we are using the midpoint of the bid-ask spread at this stage, so deviations from the 45 degree line do not demonstrate that there are profit opportunities; this will come later with our analysis of returns). Proceeding thorough the panels we can see that teams win slightly more often than prices imply when accompanied by a Tweet, and win even more often when accompanied by a BBC Tweet or positive tone in aggregate tweeting. In short, social media content can predict match outcomes even after accounting for betting prices.

Where does the predictive power of social media come from? Is social media quicker to predict or reveal information (goals, red cards) than betting markets? Or does social media help in the interpretation of information? We begin by analysing whether social media output predicts or reveals events. In the first regression of Table 3 we regress an indicator variable equalling 1 if a positive event occurs for team i in the next 5 seconds, on an indicator variable equalling 1 if there was at least one Tweet for that team (in the 5 seconds preceding the event). Positive events can be scoring a goal, receiving the award of a penalty, or the opposition having a player sent off. We also run the same analysis for events that occur in the next 60 seconds. The idea is that tweeters may either 1) break news quicker, if we find that Tweets predict events up to 5 seconds in advance, or 2) tweeters might be better at forecasting that something will happen, if we find that Tweets predict events up to 60 seconds in advance. We find that the presence of at least one Tweet for a team does not predict events either up to 5 seconds ahead or up to 60 seconds ahead. Looking across to regressions 3-6, BBC Tweets do not predict events either, and positive tone is actually a negative predictor of positive events (particularly up to 60 seconds ahead). Any ability of social media to predict match outcomes does not therefore stem from an ability to predict the occurrence of significant events such as goals and red cards.

Perhaps social media, and the tone that can be extracted from its content, is more useful in the interpretation of news, rather than in the breaking of news. In Table 4 we repeat the regressions of Table 2 but this time focus on the time period either up to 5 seconds after a market suspension, or up to 60 seconds after a market suspension. The aim is to establish whether social media content can help in the interpretation of news in its immediate aftermath (up to 5 seconds afterwards) or soon after (up to 60 seconds afterwards). We find that the existence of at least one Tweet for a team conveys information in the immediate aftermath (regression 1), but a Tweet up to 60 seconds after a market suspension does not (regression 2). Specifically, a team is 4.27% more likely to win, than betting market prices imply, if there is at least one Tweet tagged with that team in the immediate aftermath of the event (regression 1). In regression 3, there are even stronger effects for BBC Tweets (30.9% more likely to win than prices suggest), but this is, of course, concentrated around a very small number of Tweets. Positive tone also suggests that a team is 8.12% more likely to win than betting prices suggest immediately after an event (regression 5). Both BBC Tweets and positive tone convey information even if the Tweet occurs up to 60 seconds after the event (see regressions 4 and 6), though the magnitude of this effect is diminished relative to the immediate aftermath of the event (regressions 3 and 5).

We summarise the main Table 4 results in Figure 4. Figure 4 is a replication of Figure 3, except this time we only focus on the 5 seconds in the immediate aftermath of market suspensions. As detailed above, a team wins more often than betting prices imply, after a market suspension, when there is a Tweet for that team, and particularly when that Tweet comes from a BBC journalist or the aggregate tone of tweeting is positive. (Note that although BBC Tweets are highly predictive of fundamentals after a market suspension, there are relatively few observations of such Tweets, and therefore the confidence intervals are very wide for this panel in Figure 4).

In short, social media output aids in the interpretation of news. But is this because a Tweet signifies that a team is more likely to win, than prices suggest, after a positive event? This would imply that Tweets can point out when prices have under-reacted to information. Or does a Tweet signify that a team is more likely to win, than prices suggest, after a negative event? This would indicate that Tweets can point out when prices have over-reacted to information. Of course, Tweets could be useful for identifying mispricing in both positive and negative scenarios.

In Table 5 we break down our Table 4 analysis into instances when the news was positive and instances when the news was negative. (We only consider the 5 seconds after an event, as the effects in Table 4 were stronger in this time period). We find that Tweets predict a team is more likely to win than prices suggest after both positive and negative events. A team is 4.87% more likely to win than contemporaneous prices imply if there is at least one Tweet tagged with that team in that second, after a positive event (regression 1), and 5.31% more likely to win than prices imply if there is at least one Tweet tagged with that team in that second, after a negative event (regression 2). In other words, the mere presence of a tagged Tweet can inform us that the market has under-reacted to positive news, and/or over-reacted to negative news. Similar effects are found for BBC Tweets, and positive tone tweeting, though both of these are more predictive of under-reaction to positive news. The effect associated with the BBC indicator is particularly large (50.6%) but this, again, is based on a very small number of Tweets.

One issue with our results so far is that we have ignored the Betfair speed bump. Betfair impose an artificial delay between the time at which an order is submitted and the time at which it is logged on the exchange. This delay, put in place to protect bettors watching at home from being adversely-selected by bettors in the stadia, varies from 5-9 seconds depending on the match. The implications of the delay, for our study, are that betting prices may not be able to fully reflect information immediately, because of the time it takes for an order to reach the exchange. While bettors can cancel orders immediately, new orders – which reflect new information – will take 5-9 seconds to reach the exchange.

With this in mind, perhaps it is more accurate to compare prices with the Tweets that occurred 5-9 seconds into the past, with the precise adjustment depending on the duration of the order processing delay. In Table 6 we do something along those lines. We regress an indicator variable, equalling 1 if the team won and 0 otherwise, on the implied win probability, and an indicator variable equalling 1 if there was an executable Tweet for that team X+1 seconds in the past. X is the duration of the order processing delay for that particular match, and an extra 1 second is added to simulate the time it might take to source data from Twitter and execute a trade algorithmically. In effect, we are checking whether there is a mispricing on Betfair, pointed out by activity on Twitter, that could generate abnormal profits. The analysis in Table 6 mirrors the results in Table 2. There are executable BBC Tweets that indicate betting market mispricing, and executable tone (revealed in Tweets X+1 seconds in the past) that could also indicate betting market mispricing. The similarity between the coefficients in Tables 2 and 6 create the view that the type of mispricing that Twitter reveals decays, but does not decay rapidly. For example, a team is 3.39% more likely to win than contemporaneous betting market prices suggest if there is positive tone on Twitter (regression 5 Table 2), and is 3.38% more likely to win than prices at time $t + X + 1$ suggest if there is positive tone at time t (regression 3 Table 6).

A natural next step is to more generally assess the decay of social media information. We know that social media can still predict match outcomes – after accounting for betting prices – up to 10 seconds after the Tweet (or after the order processing delay has elapsed), but what about 60 seconds after the Tweet, for example? To answer this question, we regress an indicator variable, equalling 1 if the team won and 0 otherwise, on the implied win probability, and an indicator variable equalling 1 if there was an Tweet for that team precisely T seconds in the past. In Figure 6 we then plot these coefficients for $T = 0$ all the way to $T = 60$.[7] We display the results for all Tweets, BBC Tweets, and aggregate positive tone tweeting in the left, centre and right panels respectively. In blue we use all Tweets, and in red we display only Tweets after a market suspension/event (such as a goal or a red card). We find that social media information after a goal/red card decays quite rapidly, with much of the content in prices after 10 seconds. (Note that the most stark results, for BBC Tweets after market suspensions, are based on only a few observations). However, there is little or no decay in social media information if the Tweet did not follow a major market event. What is more, the coefficients are still positive after 60 seconds, and with little sign of decline, suggesting that some social media information may never find its way into prices.

Our final step is to estimate the returns that might be available to an arbitrageur looking to capitalise on the mispricing we describe. This arbitrageur could extract information from Twitter, calculate the tone of the Tweets (if necessary), and then algorithmically execute a bet on Betfair. These bets will be executed at the best back quote, not at the midpoint of the back-lay spread as previously analysed. In Table 7 we present summary statistics on the returns to four strategies. (All strategies allow X+1 seconds for execution, where X is the duration of the order processing delay). The first strategy is to bet on all teams, in all seconds. This is the benchmark return and gives us an idea of the margins on the exchange. The second strategy is to bet when there has been at least one Tweet tagged with the team in question in that second. The third strategy is to bet when there has been a BBC Tweet on that team in that second. And the fourth and final strategy is to bet when aggregate

[7] Only cases where the match was still ongoing, and back and lay quotes were still available, at $T = 60$ are used, so the coefficients for $T = 0$ differ slightly from those displayed in Table 2.

tone for that team in that second is positive. Betfair charge commission of 2-5% on profits within each market, with the rate depending on the historical activity of the bettor. We therefore present the returns to the four strategies for three different commission rates: 0% (a hypothetical rate), 2% (the minimum rate, available to the most active customers), and 5% (the maximum rate, available to a first-time user of the exchange).

There are substantial returns available for betting on the basis of BBC Tweets, and on the basis of positive aggregate tone. To take the highest commission rate of 5% as an example, the average returns to the BBC strategy are 2.55% (from 1,615 bets), and the returns to the positive tone strategy are 2.28% (from 903,821 bets). This compares with average returns of -5.41% across all 4.44 million bets. Given that the strategy returns are for, at most, a 90 minute investment, the magnitudes are quite striking. Of course, if we wanted to properly establish the economic significance of these returns, we would need to calculate the volume available for each of these bets, and use a model to predict the price impact of each of our trades. Nevertheless, even our back-of-the-envelope calculations illustrate the magnitude of information on social media that is not in betting prices.

5 Conclusion

The modern forecaster has a number of tools at their disposal. Two tools, in particular, allow forecasters to harness the 'wisdom of crowds': prediction markets and social media. We know that prediction markets generally lead to accurate forecasts, and outperform individual experts and polls in many settings. But does social media have anything to add? Can we combine probability forecasts from prediction markets with social media output to improve our predictions?

In this paper we analyse 13.8 million Twitter posts on English Premier League soccer matches, and compare them with contemporaneous betting prices available on Betfair, a popular U.K. betting exchange. We follow both throughout 372 matches in the 2013/14 season. We ask a series of simple questions: does social media activity predict match outcomes, after accounting for betting market prices? Are certain Tweeters, and their Tweets, particularly useful for forecasting? Does the aggregate tone of Tweets predict that a team is more likely to win than the market implies?

We find that Twitter activity predicts match outcomes, after controlling for betting market prices. The effect is concentrated amongst journalists from a large media organisation, the BBC, but can also be found in the general tone of all Tweets. Much of the predictive power of social media presents itself just after significant market events, such as goals and red cards, where the tone of Tweets can help in the interpretation of information. To give an idea of the magnitude of social media information not in betting prices, returns to strategies predicated on social media activity can generate returns of 2.28% to 2.55%, for less than 90 minute investments, on the betting exchange. In short, social media activity does not just represent sentiment or misinformation, but, if sensibly aggregated, can – when combined with a prediction market - help to accurately forecast outcomes.

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Figures and Tables

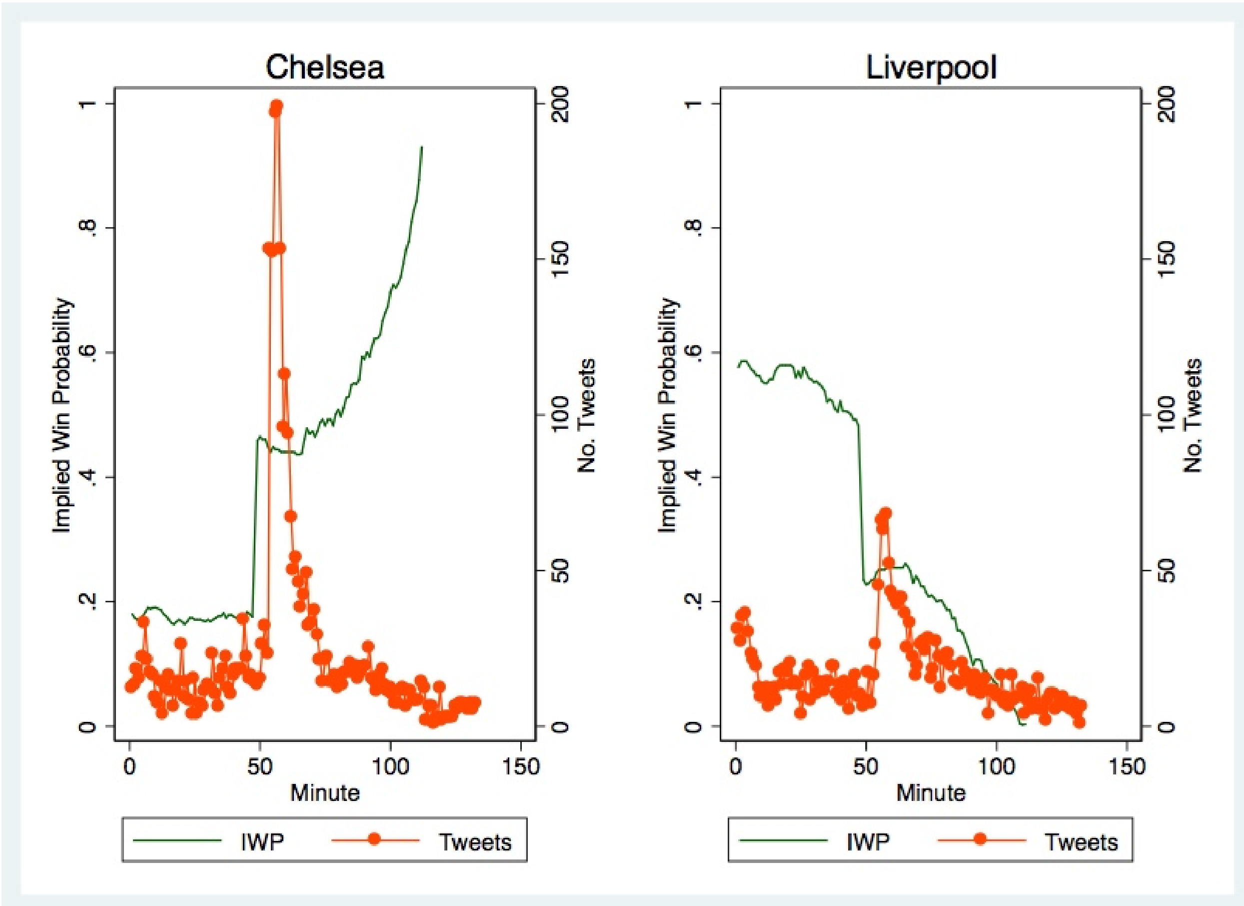

Figure 1: **Number of Tweets**. Plots of implied win probability and the number of Tweets for each team, calculated each minute, in a match between Liverpool and Chelsea played at Anfield on the 27th April 2014.

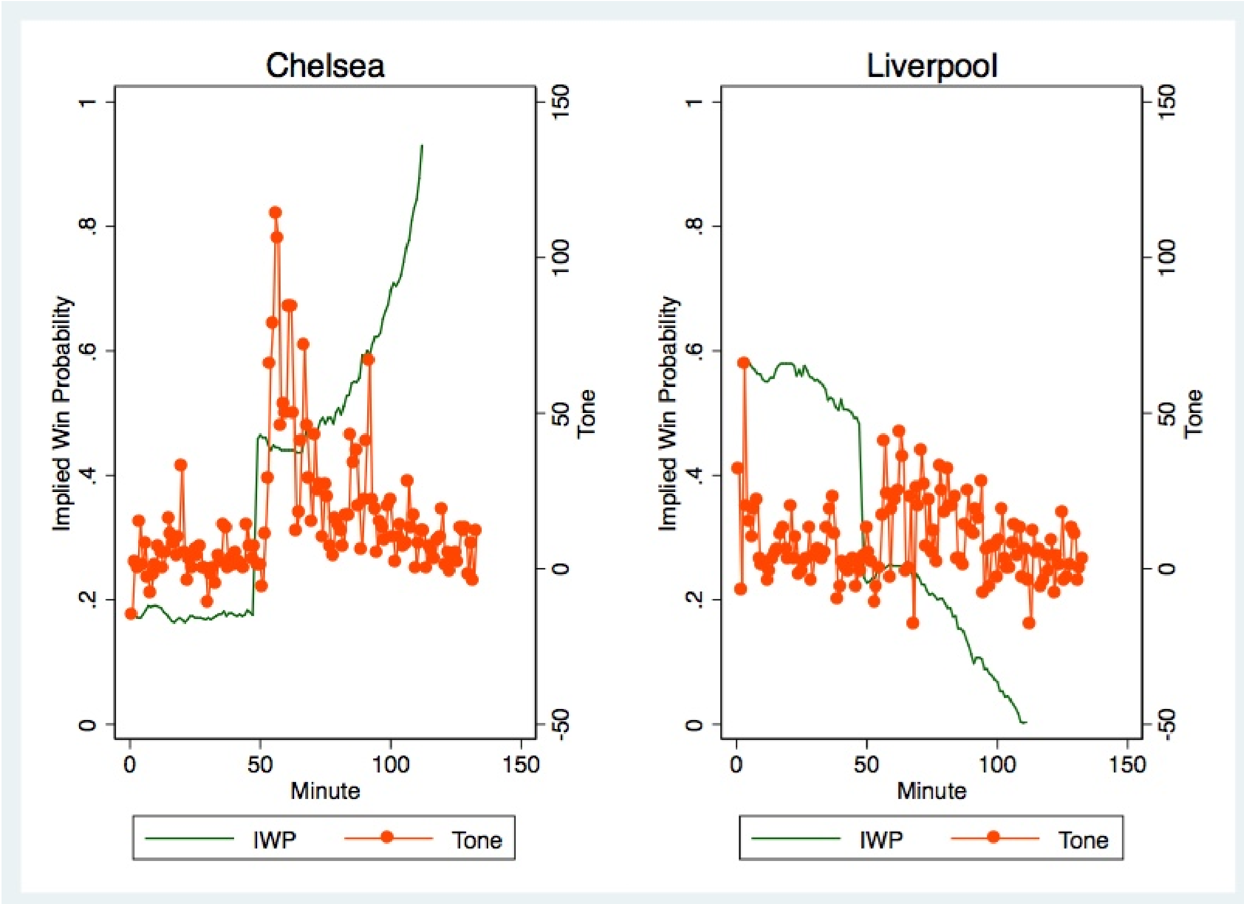

Figure 2: **Tone**. Plots of implied win probability and aggregate tone for each team, calculated each minute, in a match between Liverpool and Chelsea played at Anfield on the 27th April 2014.

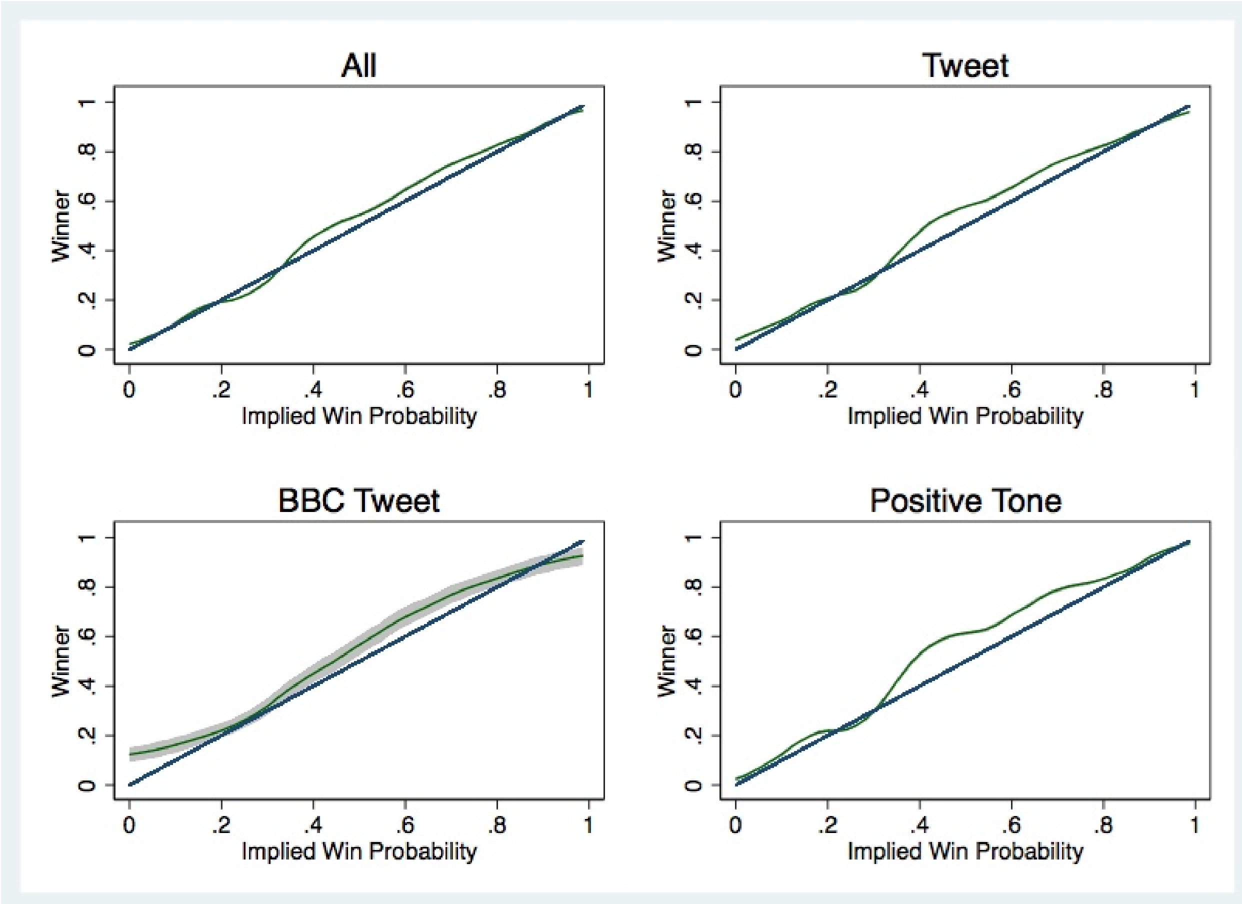

Figure 3: **Information Contained in Tweets**. Local polynomial regression estimations (of degree 3) of the relationship between the win indicator variable (equalling 1 if the team won the match), and the implied win probability (inferred from the midpoint of the bid-ask spread). The four panels include 1) all seconds, 2) just seconds where a Tweet for that team was observed, 3) just seconds where a BBC Tweet for that team was observed, and 4) just seconds where aggregate tone for that team was positive. A 45 degree line is added in blue for comparison, and 95% confidence intervals are displayed.

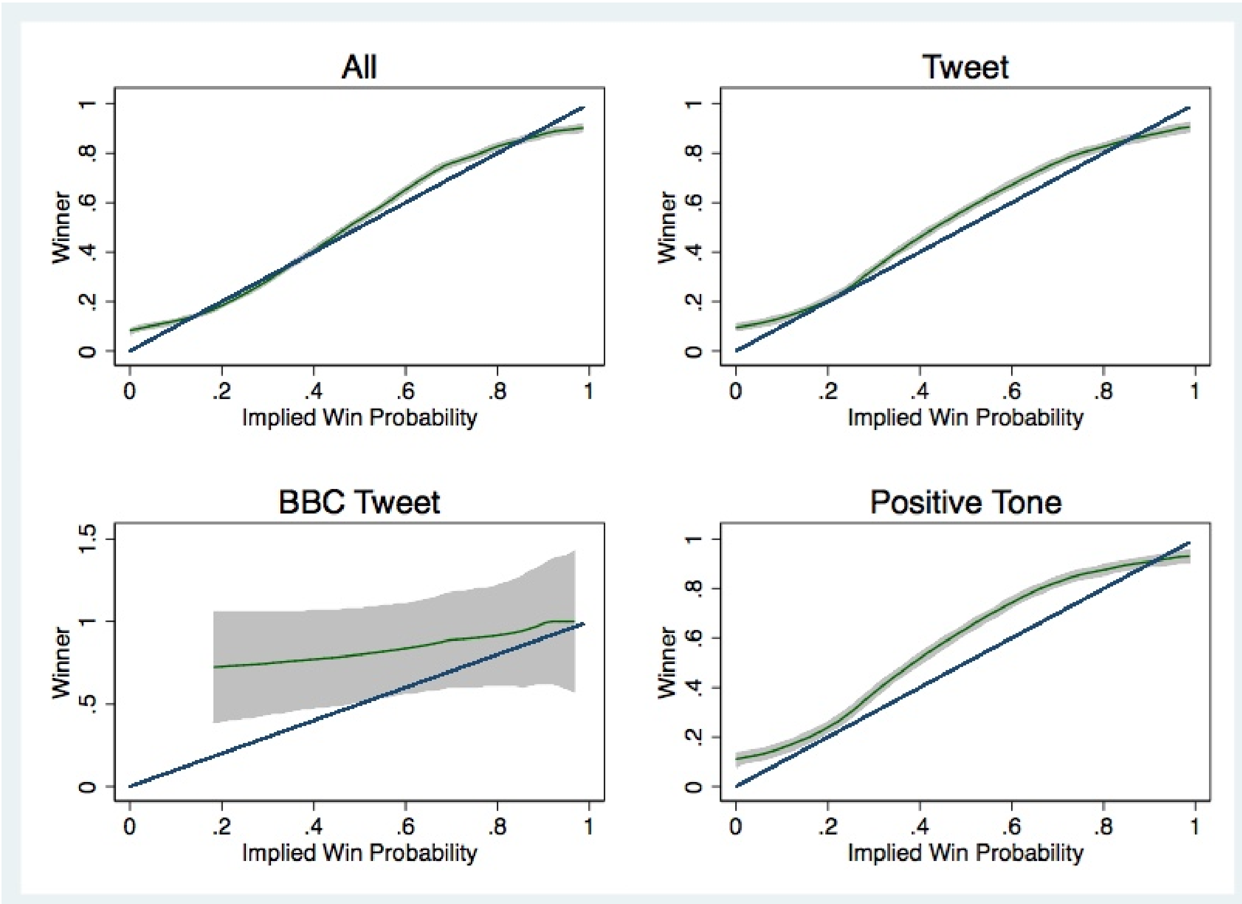

Figure 4: **Information Contained in Tweets after Events**. Local polynomial regression estimations (of degree 3) of the relationship between the win indicator variable (equalling 1 if the team won the match), and the implied win probability (inferred from the midpoint of the bid-ask spread). In this figure, data are only taken from the 5 seconds immediately after a market suspension (for a goal/red card etc.). The four panels include 1) all seconds, 2) just seconds where a Tweet for that team was observed, 3) just seconds where a BBC Tweet for that team was observed, and 4) just seconds where aggregate tone for that team was positive. A 45 degree line is added in blue for comparison, and 95% confidence intervals are displayed.

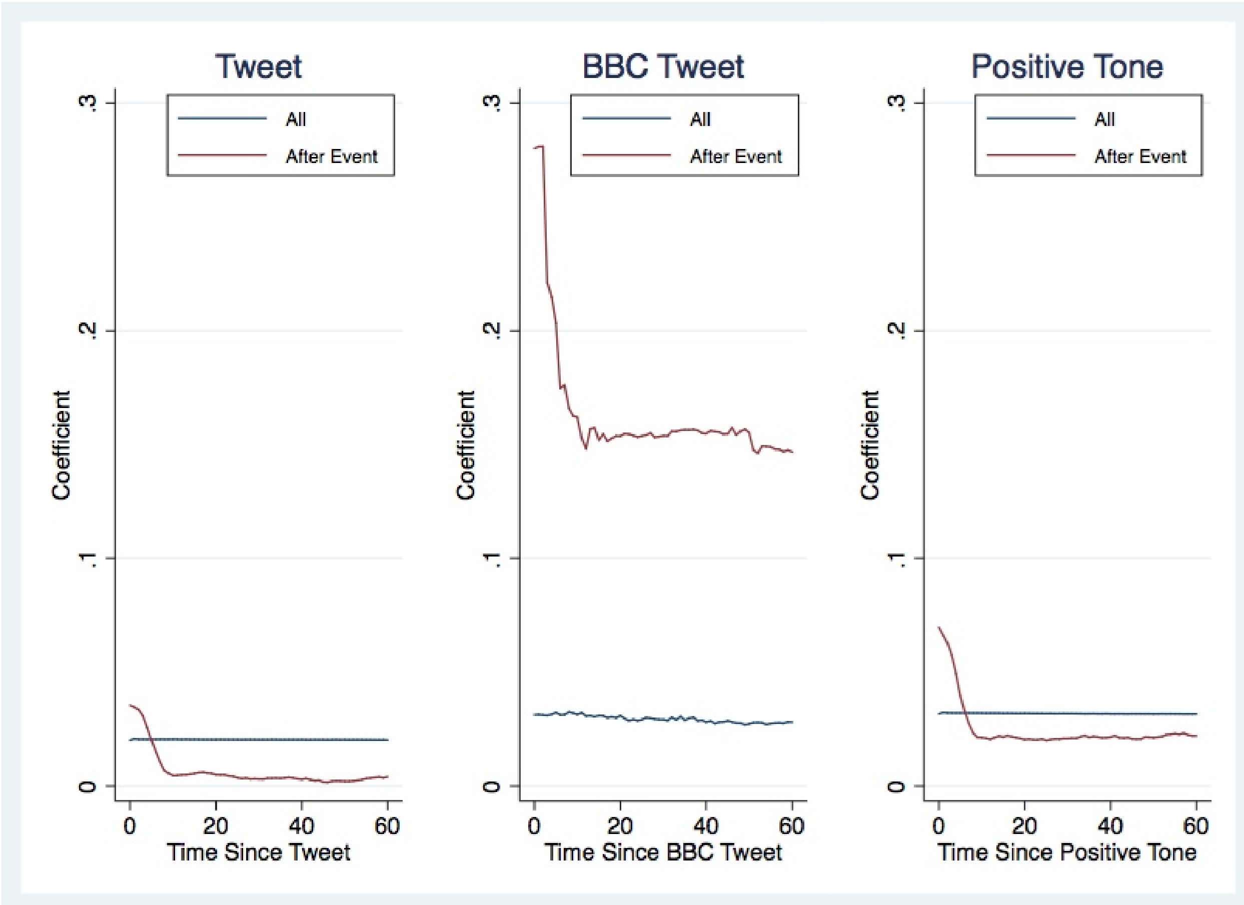

Figure 5: **Decay of Information in Tweets**. Estimates of the β_2 coefficient from Equation (1), this time varying the time (in seconds) since the Tweet(s). These plots indicate the decay in social media information as the Tweets become more stale. Results for all Tweets, BBC Tweets, and aggregate positive tone tweeting are displayed in the left, centre and right panels respectively. Separate plots are displayed for all inplay Tweets, and for Tweets in the aftermath of market suspensions/events (e.g. goals, red cards etc.)

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)
Variables	N	mean	sd	min	max
No. of Tweets	5,249,502	2.608	7.346	0	264
No. of Original Tweets	5,249,502	1.377	3.878	0	163
No. of Retweets	5,249,502	1.231	3.942	0	181
No. of BBC Tweets	5,249,502	0.000410	0.0210	0	2
Aggregate Tone	5,249,502	1.398	7.629	-144	471
Tweet	5,249,502	0.441	0.496	0	1
Original Tweet	5,249,502	0.369	0.483	0	1
Retweet	5,249,502	0.296	0.457	0	1
BBC Tweet	5,249,502	0.000396	0.0199	0	1
Positive Tone	5,249,502	0.209	0.406	0	1
Implied Win Probability	7,941,303	.336	.462	.001	.99
Win	7,941,303	.336	.472	0	1

In the top panel, we display summary statistics on the number of Tweets, the number of original Tweets, the number of retweets, the number of BBC Tweets, and aggregate tone of all Tweets, each second. In the middle panel we display indicator variables equalling 1 if, each second, there is at least one Tweet, equalling 1 if there is at least one original Tweet, equalling 1 if there is at least one retweet, equalling 1 if there is at least one BBC Tweet, and equalling 1 if aggregate tone is positive. In the bottom panel, we display summary statistics on implied win probability – inferred from betting prices – and a win indicator variable. Draws are included in the betting price data and the match outcome, but not in the Tweets (Tweets are seldom tagged #draw).

Table 2: Main Analysis

	(1)	(2)	(3)	(4)	(5)
Variables	Win	Win	Win	Win	Win
Implied Win Probability	1.028***	1.028***	1.026***	1.033***	1.025***
	(0.0280)	(0.0280)	(0.0281)	(0.0280)	(0.0281)
Tweet	0.0218				
	(0.0149)				
Original Tweet		0.0219			
		(0.0147)			
Retweet			0.0233		
			(0.0172)		
BBC Tweet				0.0329*	
				(0.0168)	
Positive Tone					0.0339**
					(0.0148)
Constant	-0.00355	-0.00214	2.10e-05	0.00423	0.000169
	(0.0161)	(0.0157)	(0.0155)	(0.0149)	(0.0151)
Observations	4,447,057	4,447,057	4,447,057	4,447,057	4,447,057
R-squared	0.416	0.416	0.416	0.415	0.416

Robust standard errors – clustered at the bet/team level – in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The main analysis in the paper. An indicator variable equalling 1 if the bet/team won, is regressed on the implied win probability inferred from the betting prices, and five different indicator variables in five different regressions. These indicators equal 1 if, in that second, there is at least one Tweet, or equal 1 if there is at least one original Tweet, or equal 1 if there is at least one retweet, or equal 1 if there is at least one BBC Tweet, or equal 1 if aggregate tone is positive, respectively.

Table 3: Predicting Positive Events

Variables	(1) +Event+5	(2) +Event+60	(3) +Event+5	(4) +Event+60	(5) +Event+5	(6) +Event+60
Tweet	-4.09e-05	-0.000429				
	(5.67e-05)	(0.000335)				
BBC Tweet			-0.000186	-0.000846		
			(0.000677)	(0.00192)		
Positive Tone					-0.000137**	-0.00116***
					(5.55e-05)	(0.000312)
Constant	0.00116***	0.00724***	0.00114***	0.00705***	0.00117***	0.00729***
	(4.85e-05)	(0.000302)	(3.59e-05)	(0.000237)	(4.10e-05)	(0.000263)
Observations	5,294,202	5,294,202	5,294,202	5,294,202	5,294,202	5,294,202
R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Robust standard errors – clustered at the bet level – in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Analysis to examine whether Tweets, for a particular team, predict positive events, either in the next 5 seconds (+Event+5) or in the next 60 seconds (+Event+60). Both '+Event+5' and '+Event+60' are indicator variables. These indicator variables are regressed on three other indicator variables, which equal 1 if, in that second, there is at least one Tweet, or equal 1 if there is at least one BBC Tweet, or equal 1 if aggregate tone is positive, respectively.

Table 4: Processing Information

Sample	Event-5	Event-60	Event-5	Event-60	Event-5	Event-60
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Win	Win	Win	Win	Win	Win
Implied Win Probability	1.056***	1.032***	1.066***	1.036***	1.049***	1.029***
	(0.0413)	(0.0307)	(0.0410)	(0.0303)	(0.0414)	(0.0311)
Tweet	0.0427**	0.0167				
	(0.0217)	(0.0198)				
BBC Tweet			0.309**	0.0434*		
			(0.121)	(0.0259)		
Positive Tone					0.0812***	0.0300*
					(0.0195)	(0.0170)
Constant	-0.0244	-0.0104	-0.00796	-0.00328	-0.0177	-0.00714
	(0.0238)	(0.0195)	(0.0212)	(0.0164)	(0.0214)	(0.0167)
Observations	17,339	198,577	17,339	198,577	17,339	198,577
R-squared	0.343	0.462	0.342	0.461	0.346	0.462

Robust standard errors – clustered at the bet level – in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Analysis to examine whether Tweets aid in the interpretation of information. Subsamples of the data are examined, either up to 5 seconds after a market event/suspension (Event-5), or up to 60 seconds after a market event/suspension (Event-60). An indicator variable equalling 1 if the bet/team won, is regressed on the implied win probability inferred from the betting prices, and three different indicator variables in three different regressions. These indicators equal 1 if, in that second, there is at least one Tweet, or equal 1 if there is at least one BBC Tweet, or equal 1 if aggregate tone is positive, respectively.

Table 5: Processing +/- Information

Sample	+Event-5	-Event-5	+Event-5	-Event-5	+Event-5	-Event-5
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Win	Win	Win	Win	Win	Win
Implied Win Probability	1.062***	1.039***	1.073***	1.051***	1.055***	1.035***
	(0.0508)	(0.0461)	(0.0511)	(0.0460)	(0.0512)	(0.0465)
Tweet	0.0487*	0.0531**				
	(0.0268)	(0.0247)				
BBC Tweet			0.506***	0.0990		
			(0.156)	(0.377)		
Positive Tone					0.0957***	0.0733***
					(0.0243)	(0.0229)
Constant	-0.0631**	-0.00188	-0.0430*	0.0178	-0.0564**	0.00950
	(0.0285)	(0.0263)	(0.0245)	(0.0235)	(0.0251)	(0.0238)
Observations	6,230	7,609	6,230	7,609	6,230	7,609
R-squared	0.301	0.382	0.299	0.379	0.305	0.383

Robust standard errors – clustered at the bet level – in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Analysis to examine whether Tweets aid in the interpretation of positive or negative information, or both. Subsamples of the data are examined, either up to 5 seconds after a positive market event (+Event-5), or up to 5 seconds after a negative market event (-Event-5). An indicator variable equalling 1 if the bet/team won, is regressed on the implied win probability inferred from the betting prices, and three different indicator variables in three different regressions. These indicators equal 1 if, in that second, there is at least one Tweet, or equal 1 if there is at least one BBC Tweet, or equal 1 if aggregate tone is positive, respectively.

Table 6: Executable Tweets

	(1)	(2)	(3)
Variables	Win	Win	Win
Implied Win Probability	1.028***	1.033***	1.025***
	(0.0280)	(0.0280)	(0.0281)
Executable Tweet	0.0218		
	(0.0149)		
Executable BBC Tweet		0.0324*	
		(0.0166)	
Executable Tone			0.0338**
			(0.0147)
Constant	-0.00356	0.00423	0.000166
	(0.0161)	(0.0149)	(0.0151)
Observations	4,447,057	4,447,057	4,447,057
R-squared	0.416	0.415	0.416

Robust standard errors – clustered at the bet level – in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Analysis to examine whether information contained in Tweets still has predictive power even if we take the Betfair speed bump into account. The speed bump varies from 5-9 seconds. If the speed bump is X seconds, we link Tweets to betting prices X+1 seconds into the future. This allows time to cross the speed bump, and an extra 1 second to source Twitter data, calculate tone if applicable, and place a bet. An indicator variable equalling 1 if the bet/team won, is regressed on the implied win probability inferred from the betting prices, and three different indicator variables in three different regressions. These indicators equal 1 if there is at least one Tweet, or equal 1 if there is at least one BBC Tweet, or equal 1 if aggregate tone is positive, respectively.

Table 7: Betting Returns (%)

	(1)	(2)	(3)	(4)	(5)
Variables	N	mean	sd	min	max
0% Commission					
All Returns	4,447,057	-2.504	368.1	-100	64,900
Tweet Returns	1,970,960	0.740	209.5	-100	7,900
BBC Tweet Returns	1,615	5.472	188.8	-100	2,500
Positive Tone Returns	903,821	4.908	195.9	-100	7,400
2% Commission					
All Returns	4,447,057	-3.667	361.1	-100	63,602
Tweet Returns	1,970,960	-0.365	205.8	-100	7,742
BBC Tweet Returns	1,615	4.307	185.7	-100	2,450
Positive Tone Returns	903,821	3.858	192.5	-100	7,252
5% Commission					
All Returns	4,447,057	-5.411	350.5	-100	61,655
Tweet Returns	1,970,960	-2.023	200.3	-100	7,505
BBC Tweet Returns	1,615	2.558	180.9	-100	2,375
Positive Tone Returns	903,821	2.282	187.4	-100	7,030

Summary statistics on betting returns. Returns are for back bets for four different strategies: bet on all teams at all times (every second), bet when there is a Tweet for that team, bet when there is a BBC Tweet for that team, and bet when aggregate tone for that team is positive. The strategies allow X+1 seconds for a X second speed bump; the extra second is to allow for extraction of Twitter data and execution of the bet. Returns are displayed for 0% commission (a hypothetical rate), 2% commission (the minimum rate), and 5% commission (the maximum rate).