

Wisdom of the Crowds:

Modeling Real-Time Win Probabilities With Twitter

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Abstract

Past research has considered the ... We ...

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1 Introduction

The wisdom of the crowds is not a new phenomenon. Economists treat the collective opinion of independent rational agents as sacrosanct; efficient market hypotheses are, at their core, expressing a fundamental belief in the wisdom of the crowds. Statisticians can explain the idea as the reduction of systemic risk—the variance of the sum of n independent and identically distributed random variables is smaller than the variance of any individual r.v. by a factor of $\frac{1}{n}$. In politics, prediction markets have quickly become a better predictor of election results than polls or the opinions of the experts¹.

The last example evidences the importance of being able to properly assess the wisdom of the crowds. While betting on political elections is illegal in the United States, the number of bets on the current presidential race is up fourfold since 2012 in Ireland.² Betfair, the largest online betting exchange for U.S. presidential elections, has nearly one million users and records nearly seven million transactions a day, which it claims is “more than all European stock exchanges combined”.³ In this cutthroat industry, any edge a gambler can get matters.

The betting market on politics pales next to the worldwide sports betting market—a colossal enterprise whose size experts ballpark at around \$1 trillion dollars a year. In a market with roughly the GDP of Indonesia, understanding the underlying statistics (in this case, the relative quality of the teams) is fundamental. Any bettor who can consistently outperform the crowds can turn a predictable profit; one has to win only 52.4 percent of his bets to break even in Vegas.

In our paper, we tackle the common questions about the wisdom of the crowds from a different angle: instead of asking whether crowds or experts, alone or in aggregate, can predict games before they happen, we look at their ability to understand and predict games that are ongoing. We consider Twitter data from 43 games in the National Collegiate Athletic Association (henceforth, “NCAA”) Men’s Basketball Tournament (henceforth, “March

¹<http://www.wnd.com/2016/01/prediction-markets-more-accurate-than-polls>

²<http://abcnews.go.com/Politics/las-vegas-bets-hillary-clinton-literally/story?id=30897911>

³<http://corporate.betfair.com/about-us/betfair-facts.aspx>

Madness”) to identify metrics that gauge the level of interest and the sentiment of the crowd at any point in time.

The justification for using Twitter as a predictive mechanism is simple: it can update far quicker than standard predictors like the margin of the game. If a star player goes down with injury or picks up a fourth or fifth foul—forcing him out of the game—the immediate effect will not be seen in the margin, but Twitter users will be able to accurately process the effect it will have on the game. Likewise, while Twitter can distinguish margins that are unsustainable (e.g. leads built on fluky plays or low-percentage shots) and those that are not, standard statistical models have a difficult time doing so.

Prior research has taken a cursory look at these questions; previous studies of National Football League (henceforth, “NFL”) games identified that the volume of Tweets before a game is predictive of the final outcome and that Twitter is reactive to big plays in the game. Our work builds upon these analyses, not only by substantiating prior results for a different sport⁴ but also by distinguishing between Tweet volume and Tweet sentiment. Prior papers considered only the volume of Tweet in each contest to measure the wisdom of the crowd; we use a sentiment classifier to determine how Twitter feels about both teams and how that evolves over the course of the game. In our Empirical Results section, we demonstrate that Twitter sentiment has predictive power that Twitter volume does not.

Our paper has three main results. First, to establish a baseline for our future analysis, we demonstrate empirically that Twitter is responsive to important game events—Twitter volume and sentiment will increase in response to salient changes in the score. This provides evidence for our initial claim that Twitter is responsive to the events currently going on in the game.

After showing that Twitter can capture what has happened in the past, we argue that Twitter is a useful predictor of what happens in the future. Our second result demonstrates

⁴Given the differences between football and basketball, this is a non-trivial contribution. Since basketball has far fewer breaks than football, one might imagine that Twitter would be significantly slower to reach to big events (fewer timeouts and breaks of play with which to process what happened). We show this not to be true in the Empirical Results section.

that Twitter sentiment and Twitter volume is a statistically significant predictor of future changes in margin; the aggregate Twitter sentiment in any period⁵ is predictive of the change in margin in the next period. Here we find evidence for our prior claim about unobservable data—while margins tend to show mean reversion (i.e. teams that are up by a lot in period t tend to see their margin shrink in period $t + 1$) as a whole, Twitter sentiment helps to distinguish which leads will continue to increase.

Our final result tests whether Twitter data can be used as an effective predictor of the final result at any point during the game. We use logistic regression models to incorporate the sentiment in a given period. We find that the Twitter sentiment is only statistically significant for about the final quarter of the game, but models that include Twitter sentiment outperform standard models⁶ at every single minute of the game. We conclude by showing that incorporating Twitter sentiment is more valuable than simply incorporating raw Twitter volume, as other papers have done.

The remainder of the paper proceeds as follows. In Section 2, we review the brief literature on the subject, demonstrating both the advances and the gaps in prior research. In Section 3, we detail our data collection process, explaining how we matched gametime data (e.g. “7:30 remaining in first half”) to real-time data (e.g. “9:30 PM”) and discussing the construction of both our relevance and sentiment classifiers. In Section 4, we provide an overview of our empirical results and a thorough discussion of the aforementioned three main results and their significance. In Section 5, we conclude and discuss the important caveats and extensions to our work.

2 Overview of Related Literature

Previous literature has established that useful modeling information can be derived from Twitter data, some including work using sentiment analysis, with the body of work mostly

⁵This is roughly measured as the support for one team minus the support for another team.

⁶For the purposes of our analysis, we cite the logistic prediction models rolled out by FiveThirtyEight during this year’s March Madness as the standard model for predicting the end of the game

focused on the NFL.

A real-time system was built in 2012 using volumes of tweets related to National Football League (NFL) games to isolate significant game events=. That project characterized a difference between human- and machine-generated tweets based on posting rates, and, by discriminating between different varieties of users, the system could identify events in near real-time. The event detection system leveraged pre-selected sets of hashtags to isolate relevant tweets as input to the system. (Zhao et al, 2012)⁷.

Sentiment analysis has also been previously applied to Twitter data to a predictive model for NFL games. In 2013, Sinha et al. found that Twitter data collected in advance of weekly NFL games could be used effectively to predict the outcomes of games more successfully than methods using other traditional statistical models. Their work used a dataset of tweets collected over periods in advance of games and also collected tweets by building sets of hashtags related to participant teams (Sinha et al., 2013).⁸

3 Data Overview

Our dataset consists of approximately 1 million Tweets made during the 2016 National Collegiate Athletic Association (henceforth, “NCAA”) Men’s Basketball Tournament (henceforth, “March Madness”). Before describing how we acquired and classified Tweets, we briefly describe March Madness and the basketball-related data we collected.

3.1 Game Data

March Madness, the largest single-elimination tournament in major American sports, is one of the most important events on the U.S. sporting calendar. The tournament takes place from mid-March to early April, with the 68-team field shrinking to sixteen after the first weekend. On the following weekend, the so-called “Sweet Sixteen” compete for a spot in the

⁷<http://arxiv.org/pdf/1205.3212v1.pdf>

⁸<https://www.cs.cmu.edu/~nasmith/papers/sinha+dyer+gimpel+smith.mlsa13.pdf>

“Final Four”—the given name for the national semifinals. The 67-game tournament, which takes teams from across the country,⁹ is the NCAA’s primary source of revenue—in 2015, it comprised 90 percent of the organization’s total revenue.

We chose to look at March Madness game data because of the level of excitement surrounding the event. Unlike other sports that share the same athletic calendar—most prominently, the National Basketball Association (henceforth, “NBA”)—there are rarely more than two March Madness games occurring at once and so the entire focus is on the current game.

The level of interest surrounding an average March Madness game is much higher than that for a regular season mid-week NBA contest; the tournament encourages fans, regardless of their level of expertise, to fill out a bracket predicting the outcome. This cultural phenomenon has exploded in recent years, with ESPN receiving 13 million brackets this year. From the brackets arises an intense gambling market (more than \$9 billion in 2016), raising interest and attention in the games.

⁹In fact, nearly every major school is eligible to compete in March Madness. The tournament reserves 33 spots for the winners of each major Division I athletic conference, leaving an automatic berth available for 351 colleges and universities across the nation

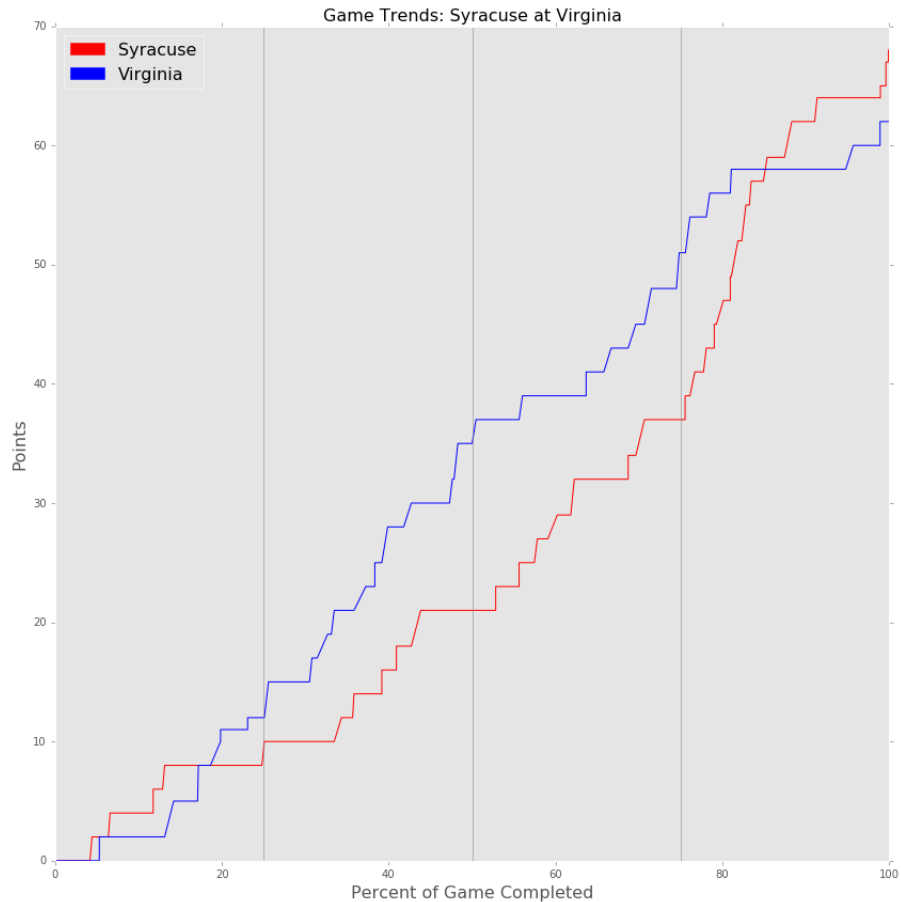


Figure 1: Score over time for Syracuse-Virginia Elite Eight contest

For each 2016 March Madness contest, we scraped ESPN.com to secure play-by-play data for each contest. From the website, we were able to get the scores for each team at every point in time, as well as a description of every event (i.e. “Paige, Marcus hits a three-pointer”). Figure 1 above shows the evolution of a Syracuse-Virginia Elite Eight contest, with Syracuse coming back from a 14-point deficit to take a late lead and storm into the Final Four.

3.2 Twitter Data

After obtaining our game data, we sought to collect a series of Tweets for each event to gauge public sentiment while the game was happening. In order to do this, we set up a Tweet listener while the game was actually going on, recording the Tweets as they were sent

for an hour before and an hour after each game.

In order to detect which Tweets were relevant, we only pulled Tweets that had a certain set of hashtags. Following the blueprint of Sinha et al. (2013), we constructed a set of Tweets associated with each game manually, scrolling through the official Twitter accounts of each individual team and adding the most commonly used hashtags to our list.

#NCAATournament #MarchMadness #LetsDance
#NCAATOURNAMENT #CBB #NCAAB
#SyracusevsVirginia #Syracuse #Cuse
#OrangeCrush #CuseMode #Virginia
#UVA #GoHoos #Cavaliers

Figure 2: Set of NBA hashtags for UVA-Syracuse Elite Eight game.

Figure 2 above demonstrates the set of hashtags used for the UVA-Syracuse game. Hash-tags in black are hashtags that were not related to either team and common to all sets of tags.¹⁰ The other hashtags were taken directly from the official Twitter accounts of the two schools and are colored in relation to which school they refer to.

To get a sufficient cross-section of data, we took Tweets corresponding to 43 separate games. Fifty-four of the 68 teams participated in at least one game in our dataset. All in all, we collected over 1 million Tweets, with an average of roughly 21,000 Tweets per game.

¹⁰With the caveat that the final Tweet, "#SyracusevsVirginia", was altered in each case to refer only to the teams playing in the game.

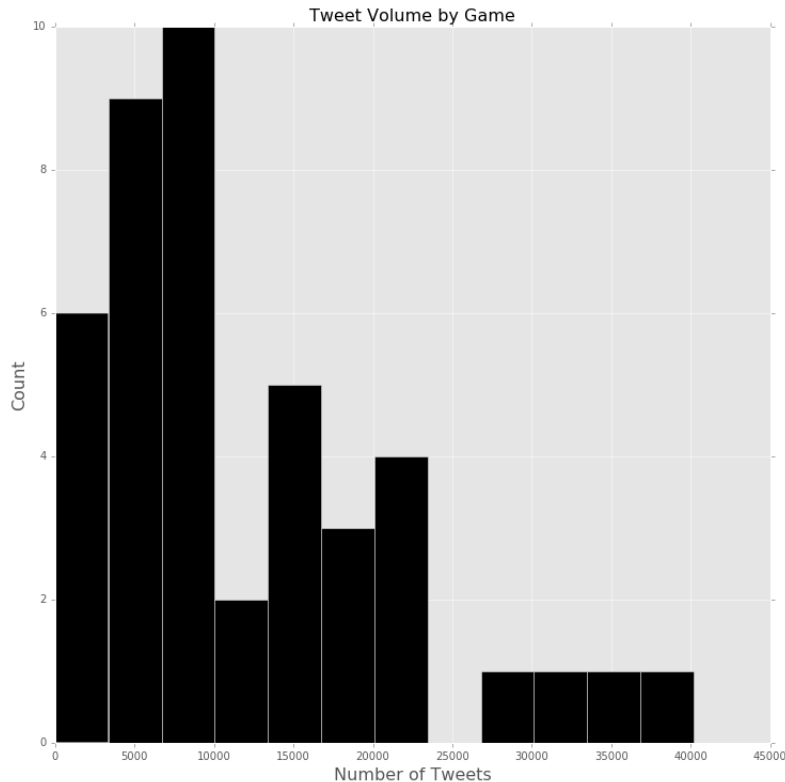


Figure 3: Tweet volume by contest

Figure 3 above shows the distribution of Tweets per game. The number of Tweets increased as the tournament went on; while first-round games had an average of just about 12.7 thousand Tweets a contest, there were an average of 15.8 thousand Tweets about each Sweet Sixteen contest in our dataset. Figure 3 excludes the national title game between Villanova and the University of North Carolina, which garnered just under 160,000 total tweets—by far the most in the dataset.

Once we had the two datasets, we set out to match the two to one another. Our source for game data did not log the exact moment at which each event occurred in real time, just in game time. To map game time (i.e. “11:30, first half”) to real time (“9:30 PM”), we used a rough approximation algorithm. For each game, we manually took the beginning and end times of each game from ESPN.com and @marchmadness, the official Twitter handle of the NCAA Tournament and used that information to estimate the length of each half. From

that data, we estimated the time each event happened as a function of the length of each half and the time remaining in each half, using a modified uniform approximation to match game times to real times.

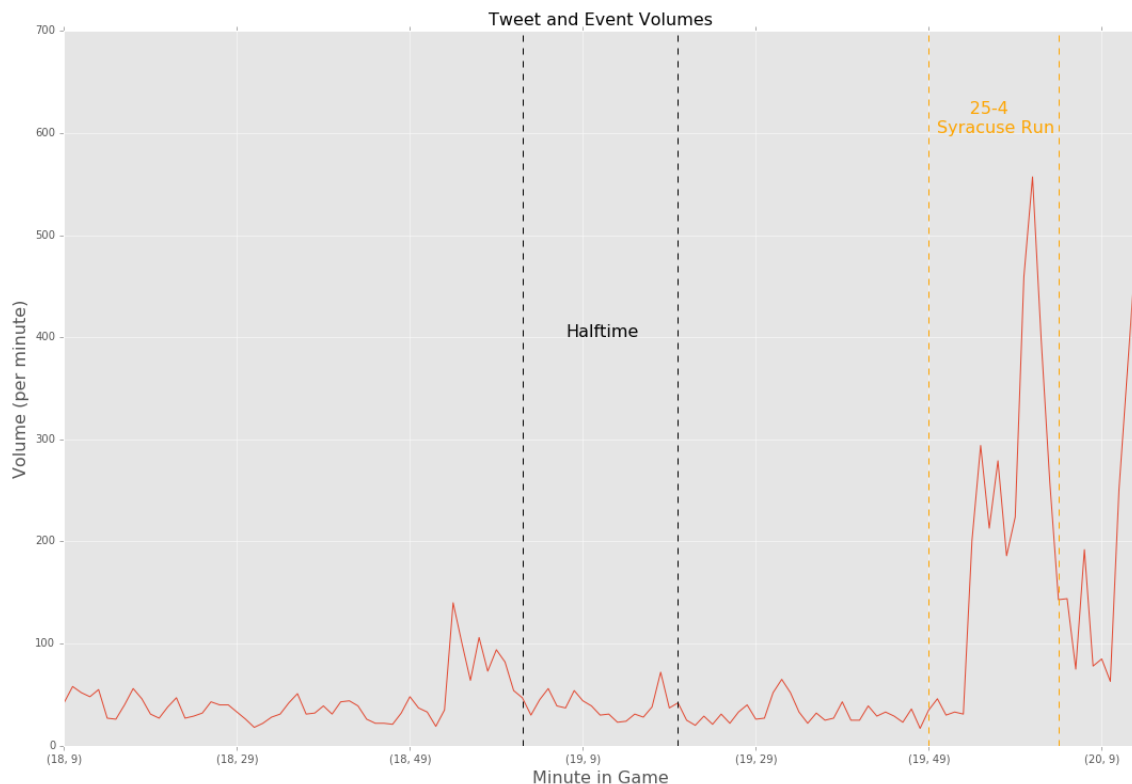


Figure 4: Tweet counts over time for UVA-Syracuse

Figure 4 above demonstrates the results of the mapping, which allowed us to identify exactly when halftime and key game events occurred in real time. As seen in the above graph, there was a significant spike in Twitter traffic during the pivotal moments of the game—a 25-4 run by Syracuse that brought the team from 14 points down into the lead. The associated large spike in Twitter traffic seen in the above figure reflects a common trend across the data: when the game got more exciting, Tweet volume spiked.

The next classification we made to the data was to classify each Tweet according to which team it related to. Since the eventual goal of the project was to be able to classify public sentiment towards any given team at any point in time, our intermediate step was to

associate each Tweet with a team based on the content of its message.

To classify the subject of each Tweet, we created a list of relevant tags¹¹ for each time and identified how often they showed up in the Tweet. From this, we computed a weighted relevance score for both teams, dividing the Tweets according to their relevance score for each team (i.e. those with a higher relevance score for Syracuse were tagged as ‘Syracuse-related’ Tweets).

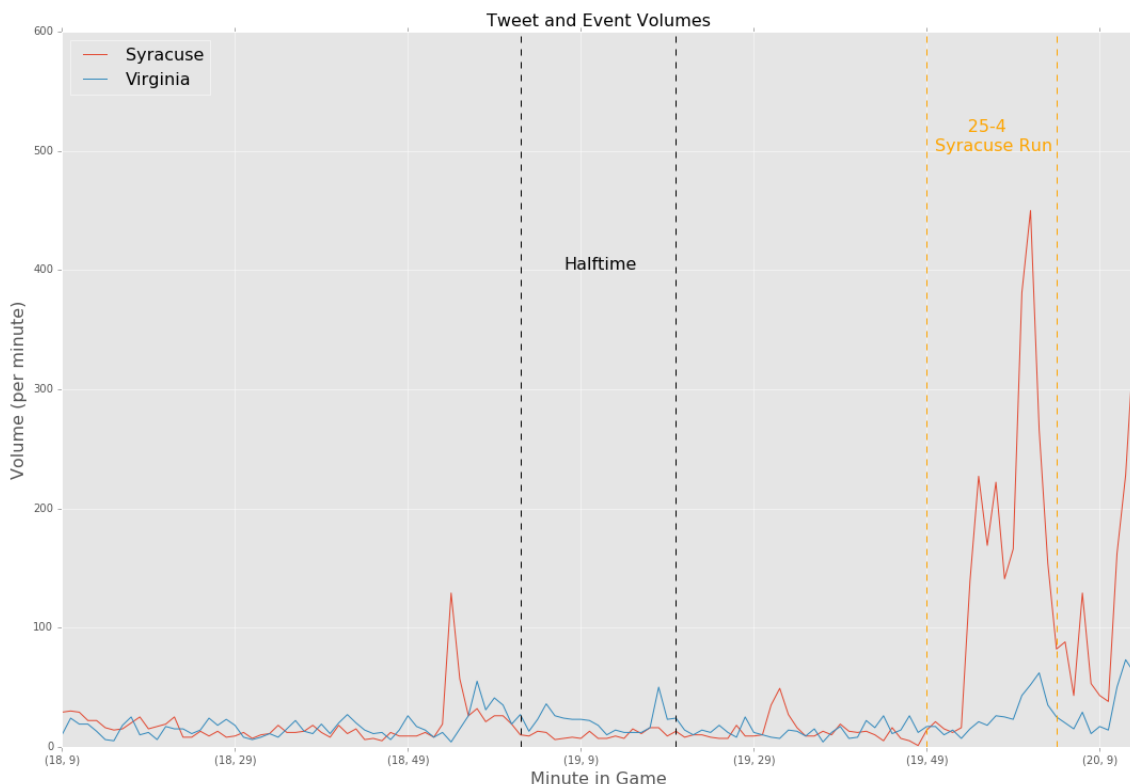


Figure 5: Tweets counts by subject over time for UVA-Syracuse

Figure 5 above breaks down the Tweet volume data by team, demonstrating that the spike in traffic during Syracuse’ run comes almost entirely from people Tweeting about their comeback. We can see that when trailing early in the game, very few people were Tweeting about Syracuse; likewise, when Virginia opened up at a 14-point lead at halftime, they saw

¹¹In addition to using the tags shown in Figure 2, we scraped the last names of the seven best players for each team and the coach of the team. In many cases, we found that Tweets included both team names (i.e. “ ... #Virginia #Syracuse”) but were actually about one team or the other. Including the last names of the players increased the accuracy of our classifier, since it better differentiated amongst these Tweets.

a brief bump in traffic during the 20-minute intermission.

The final step in our data collection was to classify the sentiment of each Tweet. In order to tell whether public opinion was positive or negative for each team over time, we constructed a sentiment classifier for individual Tweets. We chose a linear-kernel Support Vector Machine as our primary classifier, using a standard bag-of-words methodology and training the model on a prior labeled corpus of over 4000 words¹².

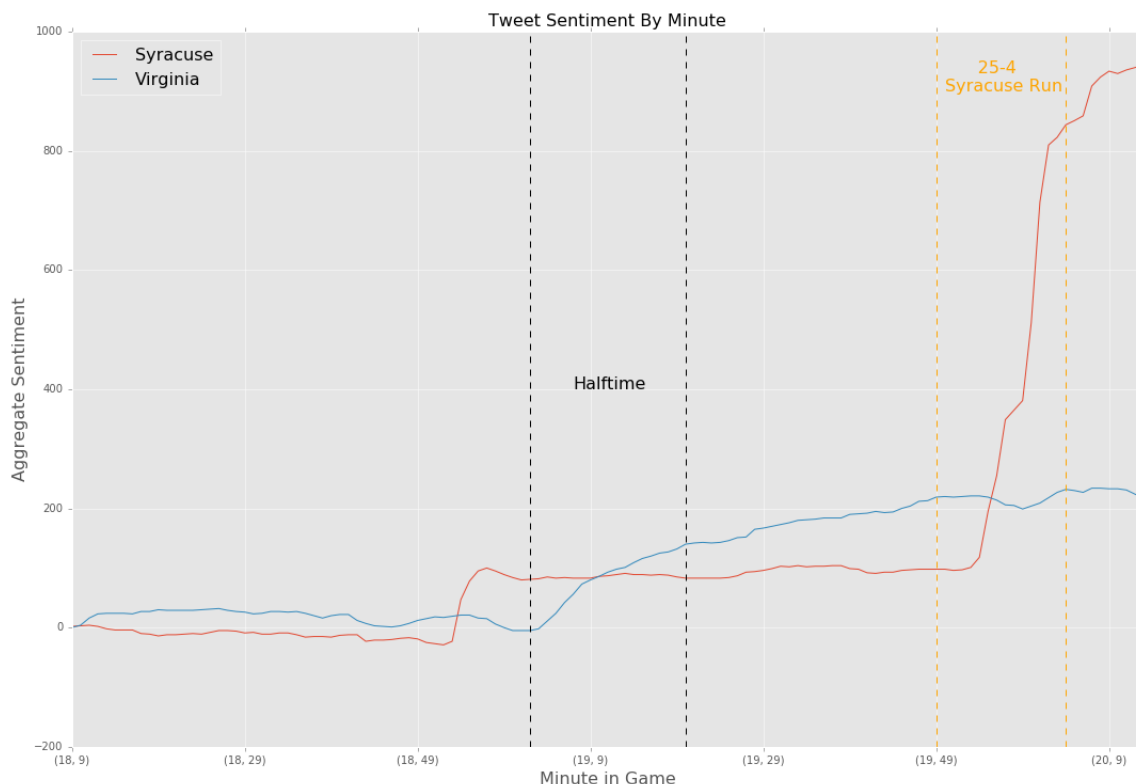


Figure 6: Tweet sentiment over time for UVA-Syracuse

Figure 6 above demonstrates the results of our classifier. We grouped Tweets into three categories: positive, negative, and neutral. In order to come up with an aggregate sentiment at any point in time, we took a simple linear combination of the three numbers—with our weights determined by the relative sensitivity of our classifier.¹³

¹²We had to make minor mechanical adjustments to the model due to the oddities of the language surrounding basketball; while words like ‘dirty’, ‘filthy’, and ‘disgusting’ would be classified as negative sentiments in almost any social context, they are the highest of compliments that can be paid on a basketball court

¹³Since our classifier was more sensitive to positive speech than negative speech, we gave a higher coefficient

The results, demonstrated above, were fascinating. During the Syracuse-UVA game, we can clearly see that as Syracuse falls behind, public sentiment drops into the negatives. An 8-0 run during the latter stages of the first half generates a lot of positive public sentiment, but during the half, the public begins to support Virginia (who has a 14-point lead). As Syracuse makes its comeback in the second half, however, Virginia plateaus and sentiment on Twitter shifts very strongly towards the Orange. As demonstrated in the forthcoming sections, this is evidence of the reactionary public sentiment to changes in the box score.

4 Empirical Results

This section lays out support for the theoretical hypotheses presented earlier. Section 4.1 demonstrates that Twitter is responsive to large swings in the game and can effectively incorporate information about game events. Section 4.2 demonstrates that both Twitter volume and aggregate Twitter sentiment can predict future events in the game. After showing the predictive power of our variables, we conclude in Section 4.3 by demonstrating that they constitute an improvement on prior models. We compare standard logistic regression models with those incorporating Twitter information, showing the latter is more predictive of the final outcome at each point in the game.

4.1 Twitter’s Ability to Process Prior Events

The first idea that we want to assess is whether Twitter is able to process game events as they happen. As discussed in the previous section, we use a modified uniform approximation to map game times to real times, allowing us to capture subsets of Tweets that occurred in the time surrounding an event. To empirically test this result, we divided up our dataset for each game into a series of one-minute intervals. For each interval, we not only measured the change in margin (i.e. how Team 1’s lead/deficit changed over the course of the minute) but also the change in Twitter sentiment and change in Twitter volume for both teams.

to the amount of negative Tweets, assuming that they were an under-representation of the general sentiment

If Twitter is responsive to events in the game, then Twitter sentiment and volume for a given team should spike as their play improves. We have already seen evidence of this in previous figures, which showed that Tweet sentiment and volume about Syracuse increased drastically as they made their comeback against Virginia. Over the same time, sentiment and volume plateaued for the Cavaliers.

In Table 1, we look at whether the difference in margin in period t can predict the sentiment difference in period t . The variable `Margin_Period_Lag_1` represents the change in the lead/deficit in the prior period, while `SentDiff_Period` shows how Twitter sentiment changed in the current period.¹⁴ In Columns (1) and (2), we find that the margin in period t is a significant positive predictor of sentiment different in period $t + 1$ even after controlling for time fixed effects and measures of team quality and popularity.¹⁵ In Column (3), we find that even if we lag the margin by two time periods, it remains significant even with our standard controls.

The coefficients on all the lagged margins are positive, indicating that the better Team 1 does in the prior period, the more Twitter responds in the next period. This is exactly what we would have expected to see. In Table 2, we see very similar results by regressing `Margin_Period_Lag_1` on `VolDiff_Period`, a measurement of Twitter volume.¹⁶ We find the exact same results as we did in Table 1, demonstrating that Twitter both gets increasingly

¹⁴Specifically, this measures the difference in sentiment scores between the two teams in the current period. If the public assigns Syracuse a sentiment score of 130 and Virginia a sentiment score of 110, then `SentDiff_Period` will equal 20. The higher the metric, the more the public favors one team over the other. We find this metric to be correlated with the actual margin.

¹⁵Our time fixed effects variable, `Min_End`, refers to the end of the current interval. We have two measures of team quality. The first is `Vegas_Line`, which refers to the pre-game betting line in Las Vegas (as sourced from ESPN). The second metric is `Quality_Diff`, which refers to the difference in Ken Pomeroy scores for the two teams. Ken Pomeroy scores are a widely accepted advanced statistical measurement of team quality, so here they are used as a proxy for any quality differences that the betting lines do not account for. Last, we use `TwitterDiff`, or the difference in the number of Twitter followers for each team's official Twitter account, as a measure of the spread of popularity between the two teams. Since both of our Twitter metrics (volume and sentiment) are aggregate numbers, this helps control for the size of the fan base.

¹⁶We evaluate changes in volume in the same way we do changes in sentiment: on a relative basis. Instead of looking at how volume for Team 1 increases over time, we de-trend for increases in volume for Team 2 to isolate shifts in opinion on Twitter. Without de-trending the data, we would find that at the end of close games (where Twitter volume naturally increases as viewers tune in to watch the final minutes) volume could increase substantially for a team that is falling farther and farther behind.

positive about a team as it does better and begins to Tweet more about that team. We measure volume in thousands of tweets, so we can interpret the coefficient at the top of Column (2) as saying that for every additional point that Team 1 pulls ahead, there will be, on average, nearly six thousand more Tweets sent in the next period about Team 1.

One interesting question is how this responsiveness changes at the end of close games, when game events have a significantly larger impact on the final outcome of the game. In Table 3, we limit our dataset to one-minute intervals in the final 10 minutes of the game and find some interesting results. Columns (1) and (2) indicate that as the game winds down, Twitter is responsive not to past events, but to current events. The coefficient on `Margin_Period` in Column (1) is more than three times as large as any of the coefficients in Table 1, indicating that not only does Twitter process events at the end of the game quicker, but its reaction is far stronger. Columns (3) and (4) provide reinforcing evidence for this claim, demonstrating that Twitter responds quicker and more vigorously to margin changes at the end of the game.

4.2 Twitter’s Ability To Predict Near-Term Events

After showing that Twitter can incorporate information about what is happening in the game, we next want to demonstrate that it is incorporating predictive information. If Twitter is just incorporating information about the margin in period $t - 1$ —which is very uncorrelated with the margin in period t —then it will be a poor predictor of future performance. However, if we think that Twitter is incorporating some unobservable information, then it should be predictive of results that we see in the future.

In Table 4, we test this by regressing the sentiment difference in period $t - 1$ on the change in margin in period t . We find in Columns (1) and (2) that the sentiment difference is statistically significant and positive in predicting the margin in future periods. We can interpret this result as saying that the more bullish Twitter is on a team, the better it will perform in future periods. In Column (3), we see that Twitter sentiment in the most

recent period is the only sentiment that matters, but that it remains significant even after controlling for prior sentiment differences.

Table 5, which tests the same concept with a lagged difference in Twitter volume instead, reinforces the same idea: Twitter’s reaction in period $t - 1$ tends to be predictive of changes in the game in period t .¹⁷ Given that the margin in period $t - 1$ is not predictive, this appears to argue that Twitter contains some predictive ability beyond what we see in the game.

There is an obvious counterpoint: Twitter is picking up not only the margin in period $t - 1$, but the total margin for the game. If a team is up by 16 and then is outscored by 4 points in a one-minute interval, Twitter will “understand” that it is still up by 12, while simply regressing on the margin in period $t - 1$ will not capture that information. To test whether Twitter is just picking up the effect of the total margin, in Table 6 we investigate how the regression changes when we control for the total margin in period $t - 1$.

The results appear to indicate that Twitter does have additional predictive ability. In Column (1), we find an interesting tendency for mean reversion—since `Margin_TOT_Lag1`, our measure of the total margin in the previous period, has a negative coefficient, we can infer that teams that are ahead overall are projected to give back part of the lead in the next period. Even more than that, we can say that the larger the lead, the more the lead will shrink in the next period—an interesting result that holds up in Column (3) even if we control for the quality of the team.¹⁸

Our most interesting results come in Columns (2) and (4) however, which appear to indicate that even after controlling for the margin, Twitter sentiment has a statistically significant positive coefficient. This implies that Twitter is picking up information that is not already baked into the total margin, giving it some additional predictive power into the future. One way to write the result is that Twitter can differentiate between sustainable and unsustainable leads—while the total margin does not demonstrate whether a team will

¹⁷Column (3) would appear to indicate that Twitter volume is a better predictor than Twitter sentiment, which could be explained by the problems with our sentiment classifier (see Discussion).

¹⁸One might have hypothesized that this reflects a tendency for weaker teams to give back leads that they get early, since the talent of a better team will ‘win out’ over a longer time period.

keep its lead into the future, the aggregate Twitter sentiment does. Said another way, if a team is ahead and Twitter sentiment is positive, it can expect to lengthen its lead in future periods. However, if a team is ahead but Twitter sentiment is negative, then its lead is likely to regress.

For obvious reasons, this result is very interesting. It implies that the crowd is able to sort between early leads that are built on fluky shots or unsustainably high levels of play and leads that are generated by teams that are simply better than their opponent. While our dataset is not large enough for us to evaluate whether this is due to the presence of unobservables (an avenue for future research mentioned in Section 5), it does indicate that Twitter can read information from the game that standard box score metrics cannot.

4.3 Twitter’s Ability To Predict Game-End Winners

Given that we have established Twitter’s ability to predict events in the immediate future, we now want to attack the question that practitioners (read: gamblers) care about: is Twitter useful in predicting the outcome of games?¹⁹

To find the answer to this question, we first look at when Twitter sentiment becomes significant in predicting the final outcome of the game.

¹⁹From a practical standpoint, while the majority of betting markets involve ex ante bets (i.e. those cast before the game begins), a growing subset of international markets incorporate during-game betting and Betfair recently rolled out an ‘in-play’ betting service, indicating that there is an opportunity for practitioners to potentially put these results into action.

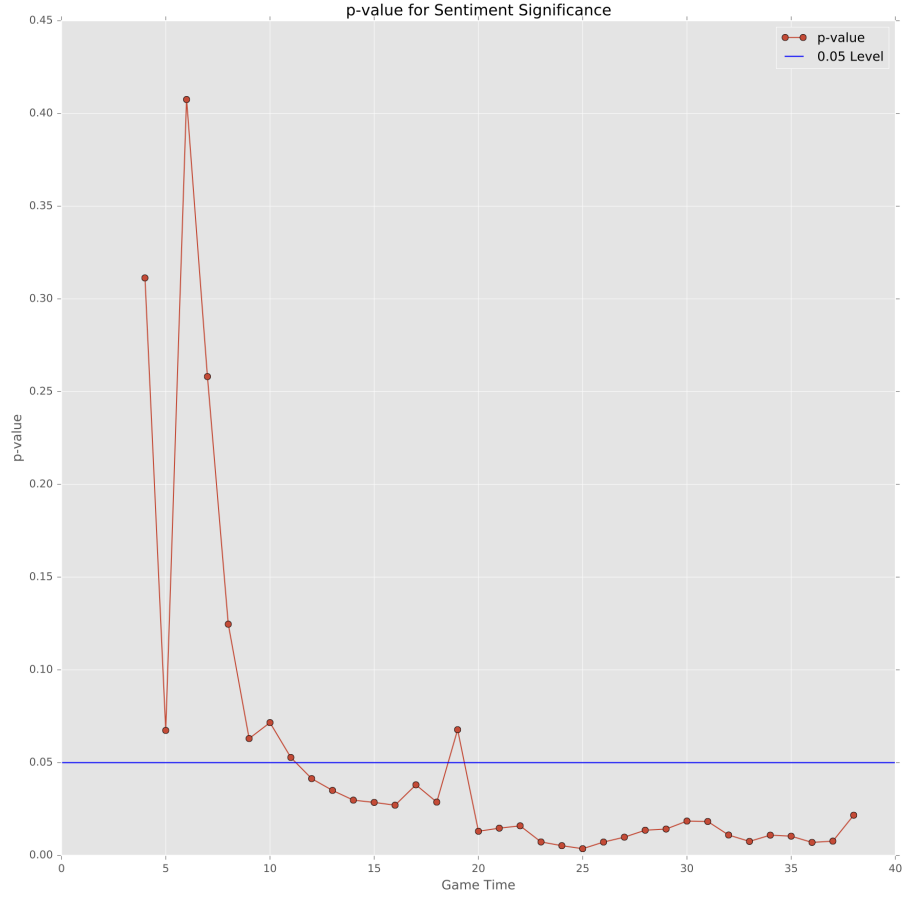


Figure 7: Predictive power of sentiment difference over time

To create Figure 7 above, we ran logistic regressions for the winner of the game with varying amounts of time remaining. We found that the total sentiment difference between the two teams only started being consistently significant at the 0.05 percent level in the second half, where it was an important predictor of the final outcome. We can see from the graph that in the early stages of the game, Twitter’s opinion about a team is not nearly as effective at predicting the final outcome.

From this, we can infer that Twitter does have some predictive power to evaluate the winner of each game from an intermediate stage. To properly assess this, we compare the

standard in-game prediction models to those that utilize Twitter sentiment. The canonical mid-game models consist of logistic regressions that use just two variables: the current margin and an ex ante predictor of team quality (typically the betting line provided by Vegas before the game). This was the basis of the models that FiveThirtyEight popularized during the 2016 tournament while creating their in-game prediction models.

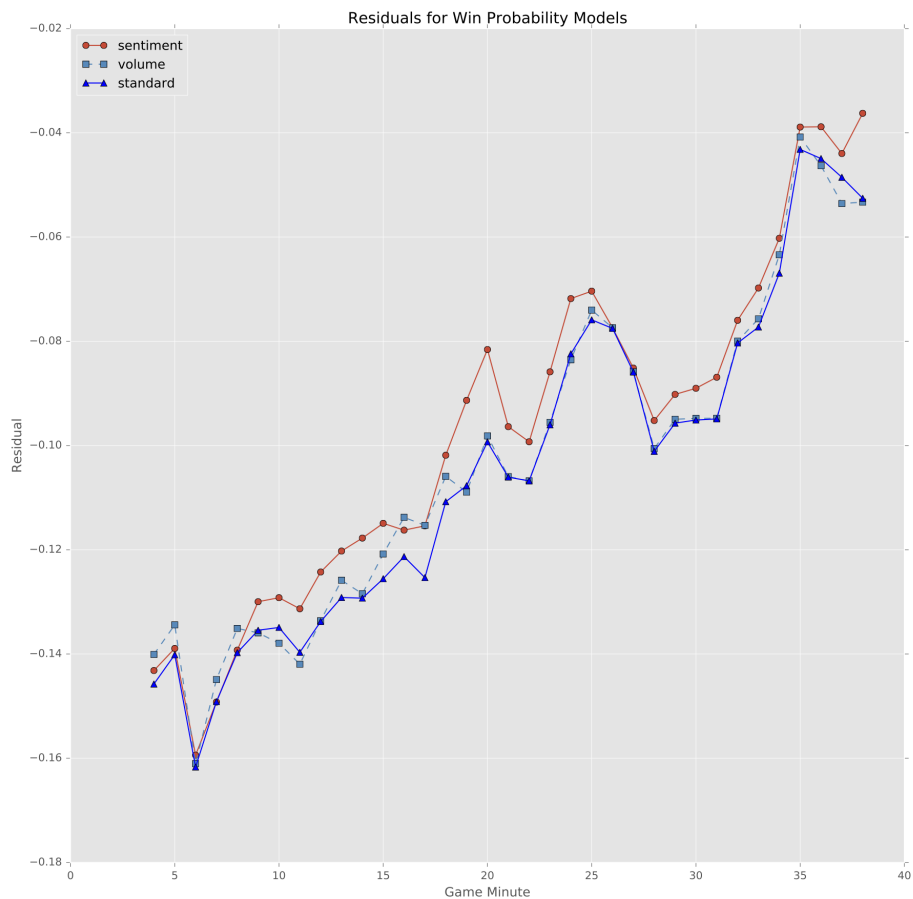


Figure 8: Relative quality of standard and updated models at each minute of the game

In Figure 8 above, we look at how the standard models measure against logistic regression models that include Twitter sentiment and Twitter volume as other explanatory factors. As can be inferred from the above graph, a logistic regression model that adds in Twitter

sentiment outperforms the standard model at every point in the game—the residual for the updated model is consistently smaller than the residual for the standard model. We note that these results do appear to reinforce a result we first saw in Table 5, which indicates that Twitter sentiment carries more predictive power than Twitter volume.²⁰

These results provide more substantial evidence for what we had inferred before: Twitter captures important predictive information that previous models did not. Table 9 shows the results of global regressions that merely confirm the relevance of both Twitter sentiment and volume. In Columns (2), (3), and (4) the two metrics are statistically significant at the 0.01 percent significance level and carry positive coefficients, implying that the higher Twitter is on a team, the more likely they are to eventually come out victorious.

²⁰Recall that in section 4.1 we had shown that Twitter volume is more responsive to past events, however.

5 Discussion

6 Tables and Figures

Table 1: Twitter Responsiveness to Game Events (pt. 1)

	<i>Dependent variable:</i>		
	SentDiff.Period		
	(1)	(2)	(3)
Margin_Period_Lag1	0.891** (0.367)	0.881** (0.366)	0.910** (0.370)
Margin_Period_Lag2			0.864** (0.377)
Vegas_Line		−1.008*** (0.231)	−0.973*** (0.237)
QualityDiff		35.390*** (10.041)	32.811*** (10.304)
TwitterDiff		−0.004 (0.011)	−0.006 (0.011)
Min_End		0.068 (0.075)	0.061 (0.079)
Observations	1,306	1,306	1,266
R ²	0.005	0.021	0.023
Adjusted R ²	0.004	0.017	0.018
Residual Std. Error	30.443	30.238	30.562
F Statistic	5.897**	5.548***	4.972***

Table 2: Twitter Responsiveness to Game Events (pt. 2)

	<i>Dependent variable:</i>		
	VolDiff_Period		
	(1)	(2)	(3)
Margin_Period_Lag1	6.253*** (1.259)	5.877*** (1.237)	6.028*** (1.246)
Margin_Period_Lag2			4.779*** (1.268)
Vegas_Line		-1.454* (0.781)	-1.416* (0.797)
QualityDiff		129.964*** (33.914)	122.143*** (34.662)
TwitterDiff		0.165*** (0.036)	0.168*** (0.037)
Min_End		-0.630** (0.253)	-0.679** (0.267)
Observations	1,306	1,306	1,266
R ²	0.019	0.063	0.073
Adjusted R ²	0.018	0.060	0.069
Residual Std. Error	104.377	102.132	102.812
F Statistic	24.685***	17.550***	16.599***

Table 3: Twitter Responsiveness to Game Events (Closing Minutes)

	<i>Dependent variable:</i>			
	SentDiff_Period		VolDiff_Period	
	(1)	(2)	(3)	(4)
Margin_Period	3.080*** (0.898)		9.598*** (2.980)	
Margin_Period_Lag1		1.325 (0.934)		7.570** (3.071)
Vegas_Line	-1.691*** (0.585)	-1.802*** (0.594)	1.061 (1.941)	0.671 (1.953)
QualityDiff	54.306** (25.706)	61.013** (26.013)	44.282 (85.282)	60.681 (85.559)
TwitterDiff	-0.012 (0.028)	-0.012 (0.028)	0.451*** (0.092)	0.447*** (0.092)
Min_End	-0.526 (0.740)	-0.719 (0.751)	-2.755 (2.455)	-3.466 (2.470)
Observations	316	316	316	316
R ²	0.068	0.039	0.133	0.121
Adjusted R ²	0.053	0.024	0.119	0.107
Residual Std. Error	37.840	38.427	125.537	126.387
F Statistic	4.535***	2.520**	9.490***	8.531***

Table 4: The Accuracy of the Crowds (pt. 1)

	<i>Dependent variable:</i>		
	Margin_Period		
	(1)	(2)	(3)
SentDiff_Period_Lag1	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
SentDiff_Period_Lag2			0.001 (0.003)
SentDiff_Period_Lag3			−0.003 (0.002)
Vegas_Line		0.009 (0.018)	0.003 (0.019)
QualityDiff		0.983 (0.780)	1.239 (0.809)
TwitterDiff		0.0003 (0.001)	0.0002 (0.001)
Min_End		0.004 (0.006)	0.007 (0.006)
Observations	1,306	1,306	1,226
R ²	0.006	0.012	0.015
Adjusted R ²	0.005	0.008	0.009
Residual Std. Error	2.342	2.338	2.344
F Statistic	7.250***	3.106***	2.638**

Table 5: The Accuracy of the Crowds (pt. 2)

	<i>Dependent variable:</i>			
	Margin_Period			
	(1)	(2)	(3)	(4)
VolDiff_Period_Lag1	0.002*** (0.001)	0.002*** (0.001)	0.002** (0.001)	0.003*** (0.001)
SentDiff_Period_Lag1			0.004 (0.002)	
VolDiff_Period_Lag2				0.0004 (0.001)
VolDiff_Period_Lag3				−0.002** (0.001)
Vegas_Line		0.006 (0.018)	0.009 (0.018)	0.0004 (0.018)
QualityDiff		0.902 (0.780)	0.837 (0.781)	1.224 (0.806)
TwitterDiff		−0.00003 (0.001)	0.0001 (0.001)	0.00005 (0.001)
Min_End		0.005 (0.006)	0.005 (0.006)	0.008 (0.006)
Observations	1,306	1,306	1,306	1,226
R ²	0.009	0.014	0.016	0.021
Adjusted R ²	0.008	0.010	0.011	0.015
Residual Std. Error	2.338	2.335	2.334	2.337
F Statistic	11.852***	3.686***	3.435***	3.675***

Table 6: Reversion to the Mean

	<i>Dependent variable:</i>			
	Margin_Period			
	(1)	(2)	(3)	(4)
Margin_TOT_Lag1	−0.018** (0.008)	−0.023*** (0.008)	−0.019** (0.008)	−0.024*** (0.008)
SentDiff_Total_Lag1		0.001** (0.0004)		0.001** (0.0004)
VolDiff_Total_Lag1			0.00004 (0.0001)	0.00005 (0.0001)
Vegas_Line	0.005 (0.018)	0.016 (0.019)	0.005 (0.018)	0.017 (0.019)
QualityDiff	1.679** (0.802)	1.364* (0.815)	1.631** (0.805)	1.303 (0.819)
TwitterDiff	0.0004 (0.001)	0.0005 (0.001)	0.0003 (0.001)	0.0003 (0.001)
Min_End	0.002 (0.006)	0.001 (0.006)	0.002 (0.006)	0.002 (0.006)
Observations	1,306	1,306	1,306	1,306
R ²	0.011	0.014	0.011	0.015
Adjusted R ²	0.007	0.010	0.007	0.009
Residual Std. Error	2.339	2.336	2.340	2.337
F Statistic	2.865**	3.111***	2.454**	2.744***

Table 7: Generalized Linear Model

	<i>Dependent variable:</i>			
	Winner			
	(1)	(2)	(3)	(4)
Vegas_Line	−0.041*** (0.014)	−0.034** (0.014)	−0.044*** (0.014)	−0.038*** (0.014)
Margin_TOT	0.173*** (0.012)	0.166*** (0.012)	0.168*** (0.012)	0.160*** (0.012)
SentDiff_Total		0.001*** (0.0005)		0.001*** (0.001)
VolDiff_Total			0.0002** (0.0001)	0.0002** (0.0001)
Observations	1,346	1,346	1,346	1,346
Log Likelihood	−594.303	−590.365	−591.049	−587.436
Akaike Inf. Crit.	1,194.606	1,188.730	1,190.097	1,184.873

7 Bibliography

8 Appendices