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Twitter and Elections: are tweets, predictive, reactive, or a form of buzz?

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Abstract:

The popular microblogging social media platform Twitter has been prominently covered in the press for its perceived role in activism, disaster recovery, and elections amongst other things. In the case of elections, Twitter has been used actively by candidates and voters alike in a diverse range of elections around the world including the 2010 UK elections, the 2012 US presidential elections, and the 2013 Italian elections. However, Twitter has often been found to be a poor predictor of electoral success. This article investigates what role tweets play during elections and whether they are more reactive than predictive. Using the specific case of the 2012 US Republican presidential primary elections, this article explores how candidate's Twitter presence affects electoral outcomes and whether the sentiment and frequency of candidate-related tweets is related to campaign success and offline success at the ballot box. This study finds that tweets were more reactive rather than predictive. Additionally, sentiment analysis revealed that tweets were generally neutral towards candidates. An interesting finding of our study is how candidates used Twitter to generate 'buzz', political capital that did not translate to success at the ballot box. We specifically explore how Huntsman's daughters used YouTube videos and tweets that were perceived as a 'backstage' look into the campaign and ultimately generated high levels of buzz. Though tweets do not seem to be reflective or predictive of an election campaign offline, they are being used for social media campaigns which can and do get covered by traditional media.

Keywords: Twitter, elections, buzz, political sentiment, social media, Republican, social media strategy

Introduction

Twitter, the popular microblogging, social media platform, has been prominently covered in the press for its perceived role in activism, disaster recovery, and elections amongst other things. In the case of elections, Twitter was used actively by candidates to campaign (especially in terms of directly reaching out to voters) in the 2010 UK elections (Kiss 2010), the 2012 US presidential elections (Hong and Nadler 2012), and the 2013 Italian elections (Caldarelli, Chessa et al. 2014).

This article examines the specific case of the 2012 US Republican primary elections, the primary elections for selecting the Republican presidential candidate. Given the high profile of this national election, the primaries were a popular topic on Twitter, spanning hashtags such as #gop, #gop2012, and #republicanprimary. The candidates, news media, citizen journalists, and voters were key participants in these and other primary-related hashtags. Primary debates, elections, media coverage, and candidates dropping out of the race were the factors most shaping tweeting patterns. However, this was not always in congruence with popular opinion. For example, Twitter users mentioned Ron Paul, a former Congressman from Texas, was more than any other candidate during several debates. However, during the same time, Paul lagged rather than led in popular polls. In other words, his prominence on Twitter seemed to be disconnected from his overall popularity ratings. The purpose of this article is to evaluate the impact of social media such as Twitter on election campaigns and electoral outcomes. Specifically, this article evaluates whether election-related tweet volume and sentiment is related to offline success at the ballot box; and if tweets are not related or predictive, what purpose are they serving?

The 2012 US Republican Presidential Primaries

The US Republican presidential primary season began in Fall, 2011. Key issues regarding the primary on Twitter and on other media included income distribution, complete withdrawal from Iraq, education, Israel, unemployment, and home mortgages amongst other things. In the wake of the deaths of Anwar al-Awlaki and Osama bin Laden, Republican candidates sought to make clear their position on the ‘War on Terror’. The candidates represented a variety of political opinions and major talking points. For example, Jon Huntsman, after his experience as

Ambassador to China, focused on foreign policy and Michele Bachmann criticized her opponents on social issues, including vaccination and abortion policy. Rick Perry, campaigned against Obama's stimulus package and 'Big Government'; media and audience responses indicated that he performed poorly in primary debates (Zeleny and Parker 2012). Herman Cain focused on his 9-9-9 economic plan (9 percent sales tax, a 9 percent income tax, and a 9 percent corporate tax), but a personal scandal forced him to end his campaign in December, 2011. Newt Gingrich campaigned on monetary reform, strong immigration policies, and family values; he had a steady increase in popularity after his early setbacks. Gingrich's avoidance of negative campaigning tactics boosted his popularity. Santorum suspended his campaign on April, 2012, which most attributed to his low delegate count and his daughter's fatal chromosomal disease (Cohen 2012). Romney campaigned on a pro-business, foreign-policy aware, center-right platform (honed from his 2008 presidential campaign). Gingrich reluctantly dropped out in May, 2012, after the Republican National Committee (RNC) declared Romney the presumptive nominee. The elections came at an important time in terms of new media and American politics as the right-wing Tea Party had invested significant time, energy, and money into social media campaigns (Qualman 2011).

Republicans and Social Media

Twitter has been deployed regularly in recent American conservative campaigns, with John Culberson (cited in Lassen and Brown 2011) stating that '"Twitter posts have been a big part of driving" news about the Republican effort'. As Qualman (2011) observes, the "#TCOT (top conservatives on Twitter) hashtag […] has fueled the Tea Party movement". Conover et al.

(2011) found Republicans engaging with a diverse array of hashtags, including #teaparty, #GOP, #OCRA, #tlot, #sgp. YouTube is credited with virally circulating a right-wing video by Rick Santelli on the Chicago Mercantile exchange (Boykoff and Laschever 2011), which jumpstarted the Tea Party movement. However, Twitter was also important to gathering support for the inaugural 2009 Tea Party rally (Ratkiewicz, Conover et al. 2011). Cogburn and Espinoza-Vasquez (2011) highlight how social media has been used by both Democrats and Republicans alike due to its low cost, but potential high-yield (both in terms of campaigning, but also, importantly, for fundraising). This is a view not specific to elections and campaigning, but rather a trend seen with social movements and Twitter (Earl and Kimport 2011).

Twitter and Elections

Twitter has been studied in the context of elections across a variety of disciplines. In computer science, machine learning has been applied for topic classification during elections (Livne, Simmons et al. 2011, Skoric, Poor et al. 2012) as well as used for election forecasting (Tumasjan, Sprenger et al. 2010). Most of this work has found tweets are poor predictor of electoral success. In the social sciences, Twitter has been examined as a 'public sphere' where democratic political engagement occurs (Ausserhofer and Maireder 2013; Author A 2013). Lassen and Brown (2011) explored Twitter usage amongst US members of Congress. They explored the connection between highly competitive seats and Twitter use as well as the connection between members who ideologically differ from their district. They found that new members of Congress were more likely to use Twitter. This was particularly the case if their constituents were urban, young, and racial/ethnic minorities, common demographic attributes of Twitter users (Duggan and Brenner 2013).

Twitter data has also been used for studying political polarization. Conover et al. (2011) examined approximately 250,000 tweets from during the 2010 US congressional midterm elections. They found that political networks showed a homogeneity of network ties; particularly, there is 'limited connectivity between left-and right-leaning users' (Conover, Ratkiewicz et al. 2011). This supports the notion that Twitter preaches to the choir rather than being able to convince on the fence swing voters. Important work has also been done on the influence of political tweets in the US (Hong and Nadler 2011) as well as their (lack of) forecasting power of election results (Gayo-Avello 2012). Livne et al. (2011) found that Republican Twitter networks were denser, mentioned one another more often than Democrats, and their tweets were more topically similar.

In some cases, Twitter has been found to increase voter engagement. In Korea, for example, candidate and voter engagement on Twitter is relatively high, with Korean politicians having fairly dense Twitter networks (Hsu and Han Woo Park 2011). In the case of tweets from Korean politicians in the 2009 Korean National Assembly, Hsu and Han Woo Park (2011) found that politicians on Twitter were not endogamous by party affiliation. Rather, they followed and interacted with a range of South Korean politicians across party lines. Kim and Park (2012) found that Korean politicians/candidates were more likely to be active on Twitter and could muster meaningful discourse on the medium, even with a 'small number of users'. Other studies have shown that Twitter can reflect public perception of candidates. Specifically, Skoric et al.

(2012) found that during the 2011 Singapore general election, the 'Twitter sphere represents a rich source of data for gauging public opinion'.

Tumasjan et al. (2011) explored the role of Twitter as a vehicle for political engagement in Germany. They evaluated whether tweets reflected political preferences and party bias. They studied 104,003 tweets relating to the 2009 German federal election (via mentions of the six main German parties). Automatic sentiment analysis grouped the tweets into positive and negative categories. They determined that tweets can predict elections and that Twitter 'comes close to traditional election polls' (Tumasjan, Sprenger et al. 2010). This is in congruence with Williams' and Gulati's (2008) and Caldarelli et al.'s (2014) findings that Facebook and Twitter, respectively, are predictive of offline vote outcomes . Tumasjan et al. (2011) also concluded that Twitter can be used as a platform for political deliberation. However, most scholarship in the area disagrees with Tumasjan et al. (2011) and finds that tweets are not predictive of election results (Chung and Mustafaraj 2011, Gayo-Avello 2012). Jungherr et al. (2012) found that Twitter 'allows no prediction of election results' and Metaxas et al. (2011) argue that using Twitter data to predict US Senate and Congressional races is 'not better than chance'. One gap in the literature this article seeks to address is whether tweets are reactive if they are not predictive.

Methods

We collected 347,538 tweets from December, 2011 to February 2012 which were election-related (either by relevant hashtags, such as #gopprimary, #gopdebate, and #election or explicit candidate mentions). Only geolocated tweets from urban American-based Twitter users were collected. These tweets were not specific to the candidates, but rather part of a larger Twitter data set we collected using Twitter's spritzer stream Application Programming Interface (~1% of tweets). We implemented a restrictive framework to achieve a high level of relevance. For a tweet to be counted as referring to a particular candidate, the tweet was required to contain the candidate's first and last name separated by a space (e.g. "Herman Cain") or the candidate's official campaign Twitter account or the account name (e.g.@THEHermanCain). Tweets which contained more than one candidate name were counted as mentions for both candidates. Though stringent, these rules prevented tweets which include 'Perry', but refer to the American pop singer Katy Perry to be counted as mentions for Rick Perry. The resulting, robust data set included 7,974 tweets containing 135,582 words. We do acknowledge that this method has limitations in that it restricts the data we can study. Though the frequency of the tweet count in our data is low because of this, all tweets studied have been verified as referring to the primary candidates and correspond to American-based Twitter users. Gayo-Avello's (2012) argument that much of Twitter research on elections is based on problematic Big Data analyses inspired our approach to use a smaller, more robust filtered data set.

Many of the methods for measuring sentiment and Twitter have leveraged machine learning algorithms. These methods have been successfully applied in a range of topical areas outside of Twitter data. For example, Yu et al. (2008) used a predefined dictionary of positive and negative words to predict sentiment. Fahrni and Klenner (2008) argue that the target impacts the polarity of the adjective, using their example that warm wine is negative and warm beer is positive. Likewise, old wine has a positive target polarity and old beer has a negative target polarity. Their and other methods argue for a combination of a subjectivity dictionary (words with positive and negative polarity) (Lin and He 2009) and context specific analysis. Whitelaw et al. (2005) implemented appraisal words during classification and determined that an individualized sentiment dictionary best classifies sentiment for individual studies. Because of the large corpus of tweet data we collected, we only employed a subjectivity lexicon, the Lexicoder Sentiment Dictionary (LSD) (Young and Soroka 2012), an established political sentiment dictionary. In terms of sentiment scoring, we followed Benamara et al. (2007) and assigned a number *t* between -1 and 1 where -1 is maximally negative and 1 is maximally positive.

Event	Acronym Assigned	Location	Results
December 15th, 2011 Debate	IAD	Sioux City, Iowa	Bachmann, Perry, and Romney were seen as successful (Cillizza 2012).
January 3rd, 2012 Iowa Caucus	IAC	Iowa	Santorum wins by a small margin.
January 7th, 2012 Debate	NHD1	Manchester, New Hampshire	Romney was perceived as successful in the media.
January 8th, 2012 Debate	NHD2	Concord, New Hampshire	
January 10th, 2012 New Hampshire primary	NHP	New Hampshire	Romney won.
January 16th, 2012 Debate	SCD1	Myrtle Beach, South Carolina	Gingrich and Perry were perceived as successful. Paul was seen as weak on foreign policy (Cillizza 2012).
January 19th, 2012 Debate	SCD2	Charleston, South Carolina	Gingrich was the perceived winner by most media sources.
January 21st, 2012 South Carolina primary	SCP	South Carolina	Gingrich won.
January 31st, 2012 Florida primary	FLP	Florida	Romney won
February 4th, 2012 Nevada caucus	NVC	Nevada	Romney won.
February 11th, 2012 Maine caucus	MEC	Maine	Romney won.

Table 1: Primary Events Studied

A variety of primary events were included in our data (see Table 1). Events were chosen to reflect diversity geographically and by type of event (debates, primaries, and caucuses). We did this to better evaluate the role of Twitter as a political 'networked public' (Varnelis 2008), in which diverse individuals meaningfully engaged within a public space, where engagement on Twitter may vary by event type. For example, the January 19th South Carolina Debate was a critical juncture in the primary contest as it occurred immediately after Gingrich's ex-wife was interviewed about their open marriage (a highly covered media event). The effects of Gingrich's strongly combative response affected the sentiment of news articles and perhaps the Twitter data. Interestingly, Gingrich won South Carolina in a surprise turn. Therefore, including events regarding the debates prior is important and the January 16th South Carolina Debate was also included in our data. New Hampshire is a critical primary state and is historically the first primary. Although New Hampshire has little predictive ability and often votes for candidates who do not win the nomination, the New Hampshire primary is important as it is a major media event and was thought to perhaps translate to increased activity on Twitter. Thus, we included the January 7th New Hampshire Debate, January 8th New Hampshire Debate, and the January 10th New Hampshire primary. Similarly, the Iowa caucus has more media than electoral influence. The Iowa caucus actually has no bound delegates, so the winner of the Iowa caucus does not technically gain anything the day after the Iowa caucus. However, the Iowa caucus is a symbolic start to the caucus and primary season, and it attracts major media coverage. Therefore, the December 15th Iowa Debate and the January 3rd Iowa caucus were included in our data. Although Romney was initially declared the winner, Santorum was eventually declared the winner of the Iowa Caucus. 11 primary events were included in our data (as detailed in Table 1).

We used the Lexicoder Sentiment Dictionary (LSD) (Young and Soroka 2012), a subjectivity lexicon which was developed specifically for discovering sentiment within political texts. LSD is optimized for sentiment-indicating words within processed text documents. Young and Soroka (2012) also created a negated version of their dictionary to capture grammatical constructions such as negated positive sentiment (i.e. 'I was not impressed'), and double negative sentiment (i.e. 'That speech was not bad!'). Additionally, tweets often contain high percentages of non-standard grammars, spelling, jargon, and vocabulary (e.g. "Ron paul ripped that debate last night #getem !")). To facilitate better sentiment accuracy, we followed Young and Soroka's (2012) advice that the LSD methods work best when the sentiment analysis program has more text to work with. Therefore, rather than relying on the classification of individual tweets, we developed 'documents' for consideration which consisted of collecting all tweets related to a given candidate over a given period of time and combining them into a single document. Thus, tweets during 3 events, wherein 4 candidates participated in each event, would yield 12 documents.

We implemented our own text preprocessing based on some of the core recommendations of the LSD model. This included removing punctuation and cleaning up some of the common peculiarities of 'Twitter language', including @-mentions, hashtags, and links. We scored sentiment using the method described in the LSD Codebook (Daku, Young et al. 2011). For each document, we counted the number of terms that were marked as positive and subtracted from that value the number of negative terms as identified in the LSD dictionary. These scores were then normalized proportional to the total number of words in each document. The resulting value was used as a variable we called the 'TweetSenti' score for each candidate-event.

Results

Of the 347,538 geo-located tweets we collected from December 2011 to February 2012, tweets with 135,582 words were verified to be relevant to the 2012 US Republican presidential primaries. Because the tweets constituted a sizable corpus of text, sentiment analysis was able to be successfully run. Of note, the average sentiment score across all tweets for all events was

0.00696, an almost neutral overall sentiment score. In terms of candidate distribution, 41.05% of words in the tweet data referred to Paul, with Romney, and Gingrich trailing behind (see Table 2). Sentiment by candidate differs slightly, with Paul leading overall Twitter sentiment, followed by Huntsman and then Romney (see Figure 1). Of note, Gingrich, and Bachmann both have overall average tweet sentiment scores which are negative.

[Pie chart above deleted]

Candidate	Tweet word frequency (by percentage)
Paul	41.05%
Romney	21.67%
Gingrich	16.20%
Santorum	10.48%
Perry	6.15%
Huntsman	3.16%
Bachmann	1.28%

Table 2: Tweet word frequency (percentage) by candidate

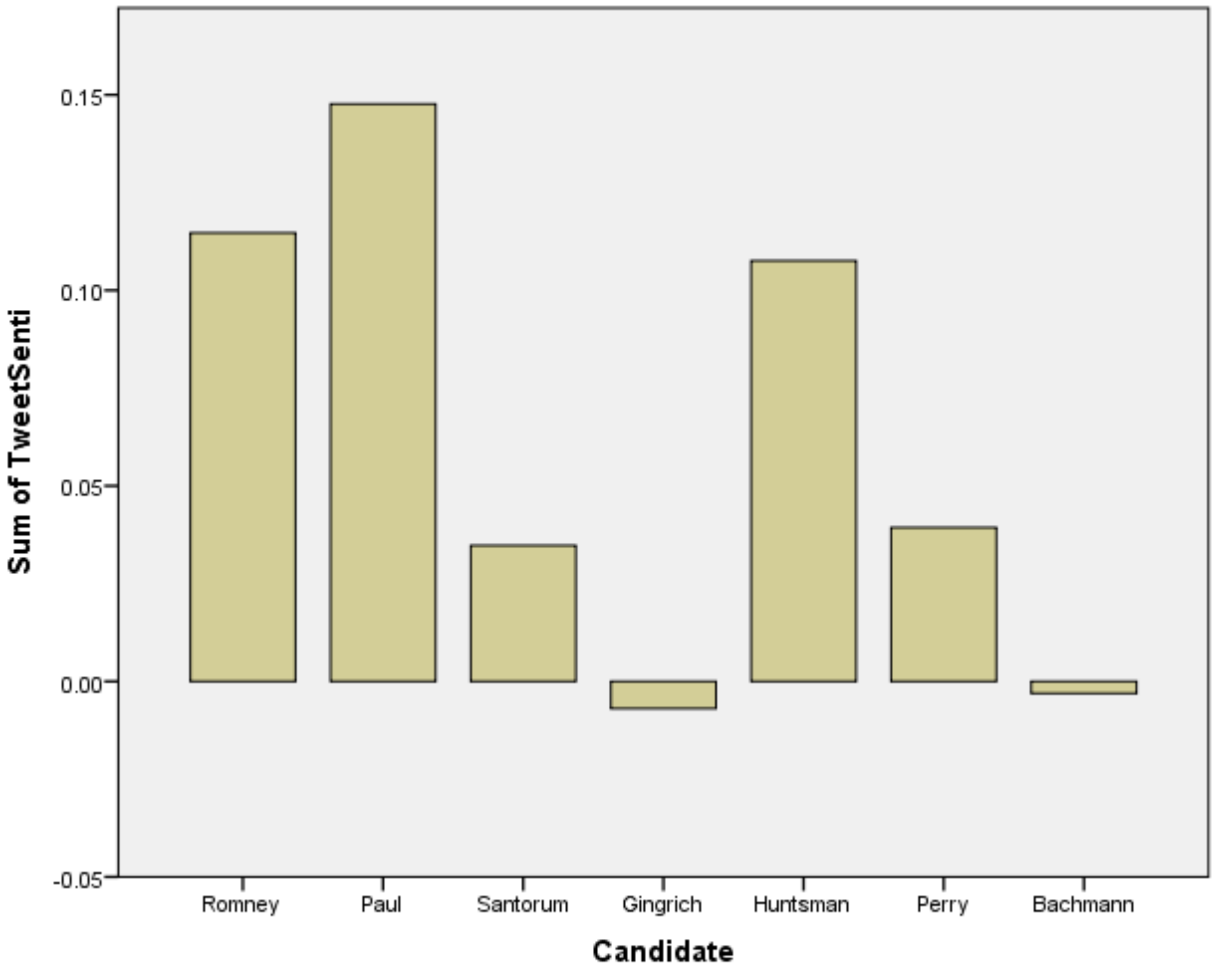

Figure 1: Overall Sentiment by Candidate

Lexical frequency is also consistent across tweets. Table 3 indicates that word, positive word, and negative word frequency are all highly correlated ($p<.01$). As tweet word frequency grows, the proportion of positive versus negative words also scales. Given the almost neutral sentiment of the corpus as an overall average, this is not surprising. Additionally, as Table 4 indicates, candidate and tweet sentiment (TweetSenti) show no statistically significant correlation, which is consistent with our data. This specifically highlights the 'flip-flop' pattern of tweet sentiment noticed with candidates (see Figure 3). Across all events, Paul is the only candidate with a consistent candidate-tweet sentiment score. For Huntsman, this was the case for the first half of events. The other candidates vary considerably in score.

		Positive	Negative	Words
Positive	Pearson Correlation	1	.963**	.984**
	Sig. (2-tailed)		.000	.000
	N	57	57	57
Negative	Pearson Correlation	.963**	1	.977**
	Sig. (2-tailed)	.000		.000
	N	57	57	57
Words	Pearson Correlation	.984**	.977**	1
	Sig. (2-tailed)	.000	.000	
	N	57	57	57

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3: Frequency Correlations

		TweetSenti	Candidate
TweetSenti	Pearson Correlation	1	-.158
	Sig. (2-tailed)		.240
	N	57	57
Candidate	Pearson Correlation	-.158	1
	Sig. (2-tailed)	.240	
	N	57	57

Table 4: Correlation of TweetSenti and Candidate

Twitter as reactive, not predictive

Primary elections, unlike debates, have definitive winners and losers. However, Twitter frequency and sentiment are hardly measures of 'victory'. They are better indicators of the social media 'buzz' around a candidate. Twitter also tends to act as a reactive rather than predictive media platform. For example, in the South Carolina primary, Gingrich was receiving significantly more positive sentiment on Twitter (see figure 4) , However, given previous work on the lack of predictive power of Twitter and elections (Chung and Mustafaraj 2011, Gayo-Avello 2012), it is important to examine these data at a granular level that is sensitive to time (Jungherr, Jürgens et al. 2012). What emerges is that usually - though not always - when a candidate is proclaimed winner by other media outlets (especially television networks and major newspapers), there is a spike in positive sentiment on Twitter. The exception is Paul, who garners positive sentiment on Twitter regardless of the health of his offline campaign. In other words, Paul's data is generally highly positive across all events (which will be discussed subsequently).

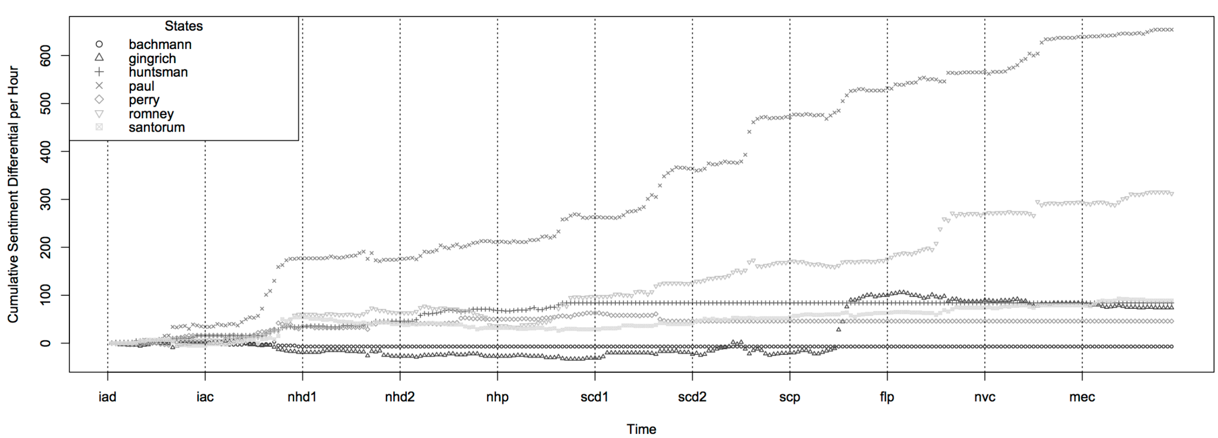

Figure2: TweetSenti across all events by candidate

Notably, Santorum's sentiment score by event varies quite widely and does not mirror other media outlets. Huntsman also has relatively large spikes in tweet sentiment despite having generally poor success at the polls. This is likely attributable to the fact that Huntsman received a disproportionately high level of positive media coverage (Mackowiak 2011).. It is possible that the media buzz surrounding Huntsman led to the spikes in positive sentiment on Twitter (though another explanation will be discussed later). Ultimately, our Twitter sentiment data provides some insights into the pulse of a candidate during an election (but this is not inherently reflective of electoral position - like Huntsman)

By examining each primary event by time rather than looking at the data as an aggregate by event, we are able to discern some interesting patterns on Twitter (see Figures 2 and 3). In the case of the South Carolina primary, the polls closed at 7 PM Eastern Standard Time, with exit polls putting Gingrich ahead of Romney. At 7:20 PM, television networks proclaimed Gingrich the winner. By 7:25 PM, the *Washington Post* proclaimed Gingrich the winner and shortly afterwards he made his victory first known via Twitter by tweeting, ‘Thank you South Carolina! Help me deliver the knockout punch in Florida. Join our moneybomb and donate now [...]’ (Sonmez, Jennings et al. 2012). If we track the primary’s timeline on Twitter, a reactive rather than predictive trend emerges. Figure 4 illustrates that Gingrich’s positive sentiment spike only surges from 7 PM onwards, the time when the polls closed and the television networks and press began proclaiming Gingrich the winner. Therefore, rather than indicating some level of predictive power, Twitter is echoing other media forms. Figure 4 also reveals that Paul’s sentiment during the same period is strong (albeit at significantly lower sentiment levels). This is despite Paul placing last in the polls (with a mere 13% of the vote). In terms of tweet-sentiment, Paul is the runner-up, a position taken at the polls by Romney. In this case, Twitter’s predictive and reflective ability are both weak.

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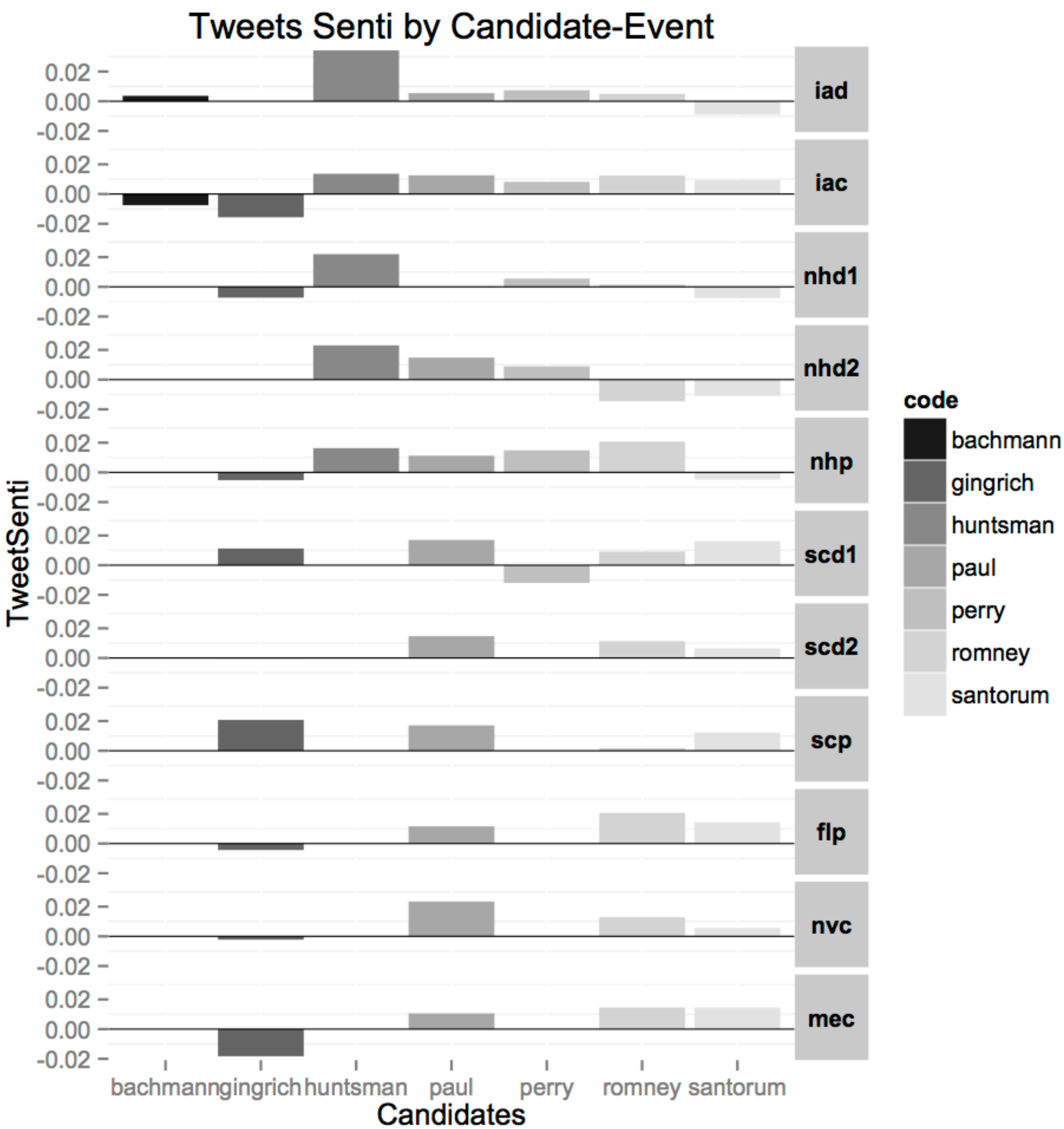

Figure 3

Indeed, if we explore the second South Carolina debate (see Figure 4), Twitter sentiment indicates Perry (who was not even a participant in the debate) spiking the morning of the debate. This is most likely attributable to Perry dropping out of the race. However, Perry's surge continues throughout the day rather than ebbing. Indeed, Gingrich, who was said to have delivered a 'show-stopper' performance actually dropped to negative Twitter sentiment levels the evening of the debate, while Perry held comfortable positive sentiment levels. Like most primary events, Paul surged with positive Twitter sentiment before and after the January 19 South Carolina debate. As runner-up in the South Carolina debate, Romney's lower sentiment is reflective of his performance (though he is placed third by Twitter, scoring lower than the dropped-out Perry). Indeed, if Paul's sentiment curve was actually Gingrich's, there would be data to better support Twitter's relevance as a predictive data source in elections. Twitter does partially reflect how candidates are being perceived offline on the campaign trail. However, the correlation is too weak to be significant. Paul's highly positive Twitter sentiment makes this particularly clear.

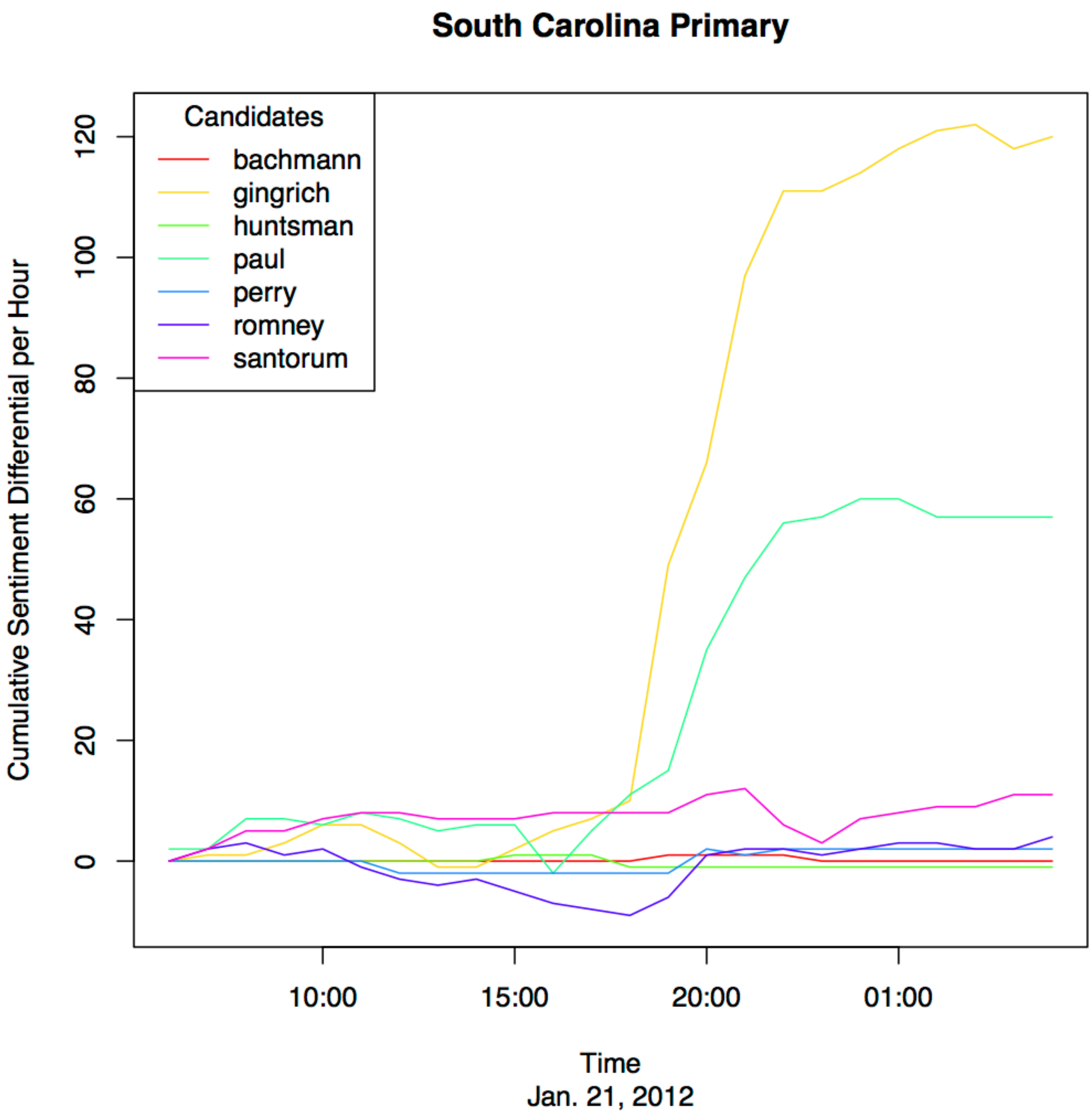

Figure 4: South Carolina primary by tweet sentiment

Romney, though significantly lower than Paul, does also have a significant upward sentiment trend (see Figure 2). Gingrich won South Carolina, but only experienced a sentiment jump once the election outcome was called. Of note, he managed to retain this positive sentiment across subsequent events, even though Romney won them. However, as Figure 5 illustrates, Twitter puts Paul and Romney neck and neck. Of note, Twitter sentiment actually experiences a small negative downturn for Romney after he won the New Hampshire primary (see Figure 5). Santorum, Perry, Bachmann, and Huntsman had much lower frequencies of tweets and the sentiment results do not reliably reveal much. Of course, Twitter is not wholly mutually exclusive as Romney, the GOP primary nominee, built a steady increase in sentiment on Twitter over time (see Figure 2). Overall, these data highlight the disjunctures between electoral success and candidate-related tweet frequency and sentiment. Our study confirms the tweet forecasting literature in that Republican primary-related tweets were a poor predictor of vote outcome.

The 'buzz model' of Twitter and Elections

Our data also reveals that Paul and Huntsman were 'successful' on Twitter over a sustained period, despite a lack of support in other media and offline at the ballot box. We conclude that this is due to a level of social media savvy by these candidates in developing a sustained or growing 'buzz' around them on Twitter. These findings suggest that the frequency of tweets mentioning a candidate and the positive sentiment conveyed in them is most attributable to a campaign strategy on social media. Both Paul's and Huntsman's campaigns seem to have borrowed social media tactics from 'buzz marketing', where companies generate buzz through novel or eye-catching (Freeman and Chapman 2008) attempts to generate viral sharing, liking, and commenting on social media. Though not replicating 'buzz marketing', successful primary candidates on Twitter adopted elements of buzz marketing to generate a buzz-like presence on social media around them which even seemed resilient to losses offline on election day or negative media coverage. This suggests that their success is built upon a certain level of Twitter savvy or 'Twitter capital' akin to Bourdieu's (1977) 'cultural capital'.

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A key finding of tweets studied was that Paul not only had the highest tweet frequency levels, but made a steadily upward rise in terms of sentiment, event by event (see Figure 2), accumulating buzz and Twitter capital. Importantly, this social media presence was not significantly correlated with winning a debate or a primary. Despite Romney winning the New Hampshire and Florida primaries and Gingrich winning the South Carolina primary, Paul's Twitter sentiment not only remained generally above both candidates across all events (though not in primaries), but did not experience noticeable downward trends. Rather, the pattern exhibits a staircase effect, where Paul reaches a higher level of sentiment (i.e. stair) event on event (see Figure 2). Figure 3 illustrates sentiment on Twitter by candidate and event. Like Figure 2, Paul has a consistent positive valence across events. Because Figure 3 details sentiment by event, it is able to highlight the high variance of Gingrich, for example, who 'flip-flops' from positive to negative. Romney's sentiment by event is particularly useful for comparing his Twitter sentiment to that of Paul.

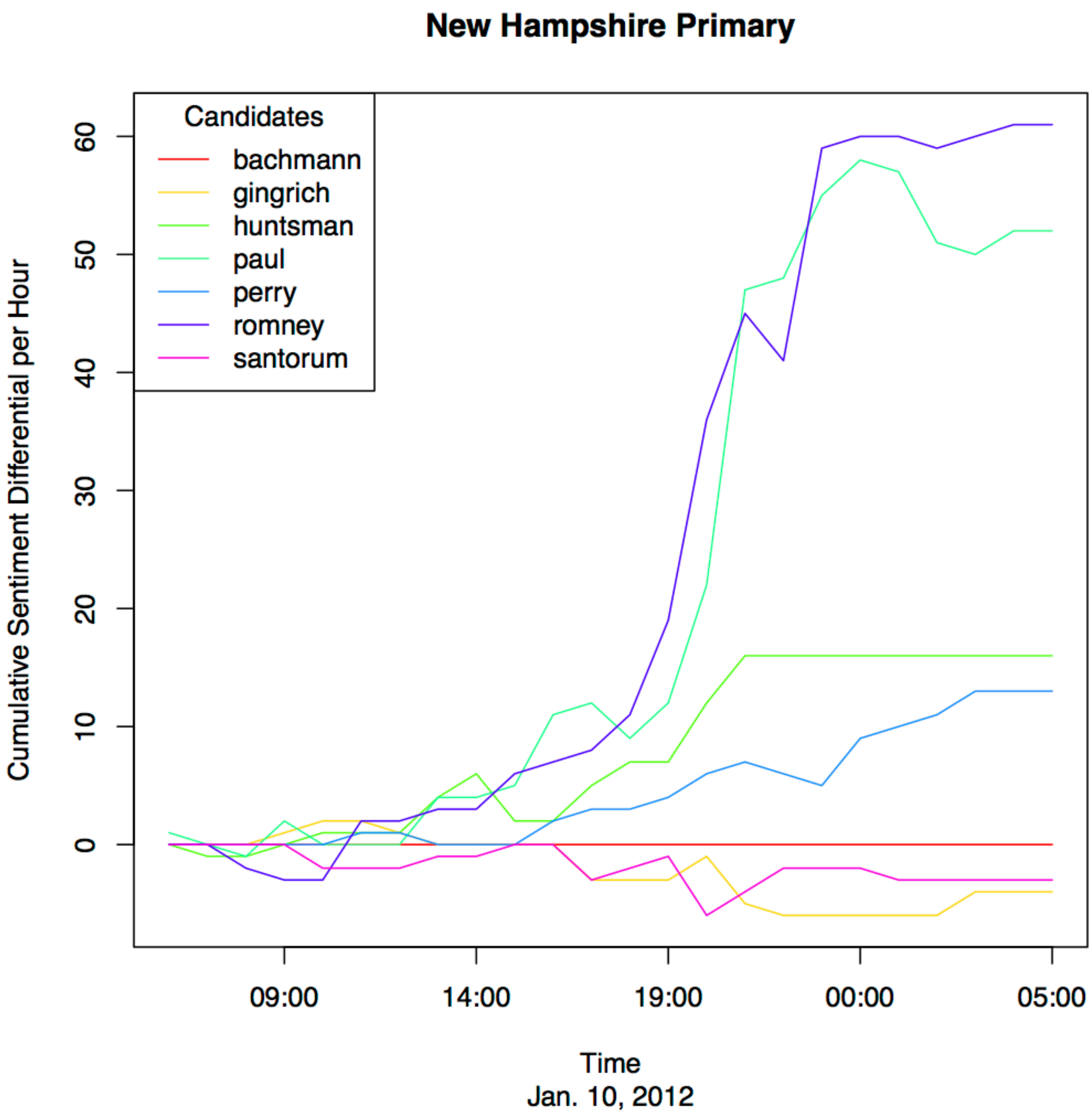

Figure 5

The sum of Twitter sentiment (see Figure 1) indicates that Paul had a high Twitter sentiment score across all events with Huntsman as runner-up and Romney in third. However, the mean puts Huntsman in the lead. This is better understood by Figure 3, which clearly illustrates that in the first five events, Huntsman not only has the highest Twitter sentiment, but his sentiment is higher by a considerable margin over Paul (and Romney). Twitter has been correlated in previous work with media sentiment (Tumasjan, Sprenger et al. 2011) and has been found to be an important journalistic space (Hermida 2010). Journalists are thought to regularly take 'cues from politicians' tweets' (Hong and Nadler 2012). Given Huntsman's disproportionately high media coverage, the surge in Twitter sentiment could perhaps be attributed to this. However, it is more likely that his high level of positive sentiment is attributable to the popularity of a social media campaign strategy launched by his older daughters, Mary Anne, Liddy, and Abby Huntsman, who tweeted under the alias @Jon2012girls. Huntsman's daughters produced a viral YouTube video and had a successful Twitter strategy which made them 'Twitter celebrities' in their own right (ABC News 2011). Indeed, Huntsman's daughters had nearly 3 times more followers than their father and, on Google, were searched for 3 times more as well (Orsini 2011). Their tweets about music, gossip, and, 'cheerleading' for their father led to a high level of visibility for Huntsman himself (Sakaria, Singer et al. 2012). Though both Romney's and Huntsman's social media strategies were very different, they both garnered noticeable success on Twitter, but did not see similar success at the polls. Importantly, this also highlights the need for thinking about the idea of Twitter buzz, which is somewhat akin to the socio-cultural processes which give rise to 'YouTube stars' and other Internet 'micro-celebrities' (Burgess and Green 2009).

Limitations

As with any automated sentiment analysis algorithm, there are methodological drawbacks. After reviewing several of the candidate-event documents and the term-coding within them, we noted some sentiment 'misses' for individual tweets. What one sees is that a human reading of these tweets would count the majority as containing negative sentiment towards a candidate, yet most of the final sentiment was positive (albeit minimally above neutral). Possible reasons for this are the fact that a noteworthy behavior on Twitter relating to political discussion includes parody accounts as well as general comedy, what Wilson (2011) terms 'affective play'. Specifically, Wilson found that many 'news junkies' on Twitter employ forms of parody in their tweets or set up parody accounts (Wilson 2011). The fact that the Twitter sentiment scores come out weighted on the positive part is likely due to several factors. One is that critical, comedic tweets often use sarcasm. Many tweets contain language, which LSD understands as positive, while a human reader can often see the negative intentionality which may be derived from the overall context of a tweet as opposed to individual words. This type of sentiment is much more difficult to test in an automated way on Twitter (González-Ibáñez, Muresan et al. 2011). Another common tweet practice is to speak to a subject using neutral or sentiment-weighted language and then include a hashtag which puts previous statements in a new or reversed sentiment context (e.g. 'Great job!! At the debate last night @governerperry #nowgotohell). Most natural language processing algorithms are not optimized for these types of linguistic nuances. However, regardless of algorithmic limitations, these cases raises the issue that the brevity of tweets can encourage flippant comments and that the insights tweets such as the #nowgotohell example can provide would be limited in terms of impact and meaning when interpreted by humans as well.

Many hashtags are also formed from the concatenation of a phrase. The words in hashtags then avoid being coded by the sentiment dictionary. Although some hashtags exist that have consistent definition and usage, there are just as many new hashtags created daily without known contexts or meanings. Aside from the fact that the LSD library is not designed to parse or understand concatenated hashtags, the development of a dictionary to account for the wide and varied use of such hashtags was not feasible in our study. Despite these issues, we believe that the Twitter sentiment score still tracks with actual sentiment. This is because tweets with difficult to interpret hashtags or content due to comedy and sarcasm are the minority. Tweets without complicated sentiment reversals (i.e. 'easily' coded tweets) were the overwhelming majority of tweets in our data set.

Conclusion

This article has explored tweets surrounding the 2012 US Republican presidential primaries. Studies of Twitter in elections have been conclusive in the lack of the medium's predictive power to call an election (Gayo-Avello 2012). So what role do election-related tweets play? This article found that tweets are reactive rather than predictive in this election context. By examining the timeline of specific primary debates, and elections, we found that tweets were reacting to offline campaign results rather than predicting them. In the case of the South Carolina primary, the polls closed at 7 PM Eastern Standard Time, with exit polls putting Gingrich ahead of Romney. At 7:20 PM, television networks proclaimed Gingrich the winner. 5 minutes later, the *Washington Post* proclaimed Gingrich the winner and shortly afterwards he made his victory first known via Twitter. By tracking the primary's timeline on Twitter, we found that a reactive rather than predictive trend emerges. Specifically, Gingrich's positive sentiment surges from 7 PM onwards, the time when the polls closed and the television networks and press began proclaiming Gingrich the winner. Therefore, rather than indicating some level of predictive power, Twitter is echoing other media forms.

We also found that some candidates engaged in social media-specific campaigning that tended to revolve around 'buzz'-style marketing. Twitter, YouTube, and other social media platforms were used to generate buzz around a candidate. Huntsman's daughters were particularly active in incorporating this strategy. However, the level of this buzz is not tied to offline vote outcomes. This study used the frequency and sentiment of tweets during and after a primary/debate in order to gauge what purpose tweets serve during elections. Using tweets collected from December 2011-February 2012 from urban American Twitter users, we found the presence of candidates who, regardless of offline primary results, maintained a high-frequency of tweets with positive sentiment levels. These data support the argument that Twitter is not predictive of offline vote outcomes. We also found that some candidates (especially Ron Paul) were able to maintain levels of 'buzz' which sustained or increased the volume of tweets as well as the levels of positive sentiment expressed by those tweets. In other words, the tweets served more as a positive marketing tool as part of a campaign strategy, but did not make up for shortcomings in other parts of their campaigns. This buzz resembles marketing strategies where the actual ad campaign is more popular and interesting than the product itself (e.g. the Huntsman daughters' viral videos).

We found that Ron Paul had built a significant Twitter presence and retained a high level of buzz throughout the campaign season. Paul had the most tweets with the most words and the highest positive sentiment. Both Figures 2 and 3 illustrate how, across all events, Paul held high positive sentiment on Twitter. And, as Figure 2 illustrates, he built that positive sentiment event on event. Huntsman's sentiment scores during the first five primary events were higher than Paul's in terms of positive Twitter sentiment by a significant margin. This was due to the social media buzz garnered by Huntsman's three older daughters tweeting under the highly successful @Jon2012girls Twitter handle.

Our study provides evidence of Twitter as part of a larger a 'media ecology' (McLuhan, McLuhan et al. 2003), wherein mediums are not inherently reflective of each other or oppositional. Rather, they have their different places and are suited to particular types of activities; McLuhan (2003) gives the example that television might be better for teaching languages then radio. In the context of this article, certain candidates may be more successful on Twitter because they are well suited to the medium or have strategized particularly for communication on the medium, building higher levels of Twitter savvy as they go along. This is not to say that Twitter success does not and cannot translate to electoral success (after all, Gingrich and Romney both purchased promoted tweets during the events). However, most studies have found no correlation between tweet frequency/sentiment and electoral results (Jungherr, Jürgens et al. 2012). Television continues to dominate the American election-related media ecology and Twitter is more peripheral.

We also found that conservative candidates are not, as Vergeer et al. (2013) found, 'virtually absent' from Twitter. In the case of the 2012 US Republican presidential primaries, it was actually the underdog candidate, Paul, who attracted a regular, high-volume Twitter presence with positive sentiment that was significantly above other candidates. Paul's supporters claim that traditional news media was not adequately covering him and that social media was the outlet the campaign would use in lieu (The Project for Excellence in Journalism 2012). We concluded that new models incorporating notions of social media capital, including buzz-like marketing, are needed to better understand how Twitter operates during elections. Like others (e.g. The Project for Excellence in Journalism 2012), we found that Paul had the highest volume and sentiment of tweets. However, it is Huntsman's clear success on Twitter in the first half of events that strongly supports the notion of Twitter campaign strategy as nuanced and complex. In the case of Huntsman, buzz around his campaign was generated through tweets and linked YouTube videos that were perceived as an earnest, backstage look into his campaign trail. This seems to parallel brand marketing in social media (Zarrella 2009) and celebrities who are successful on Twitter employ this strategy of the intimate social media confession room. Success on Twitter by politicians could require the same if Huntsman's Twitter response is any reliable indication. Twitter's environment during elections is less about predicting election outcomes or tracking campaign popularity, but, in the American context, more a niche media environment. That being said, the buzz built on social media can and did spill over to traditional media coverage as was the case with Huntsman. However, as the case of Paul illustrates, an aggressive social media profile did not substitute for a lack of visibility in traditional media and trailing in the polls.

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No potential conflict of interest was reported by the author.

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