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Trump versus Clinton – Twitter Communication During the US Primaries

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Abstract. When Donald Trump won the Republican nomination and subsequently beat Hillary Clinton in the presidential elections, his success came as a surprise to most observers. This research contributes to understanding the dynamics of this unusual campaign, in which social media played a prominent role. We collected 6,099 tweets by both nominees during the presidential primaries and identified the 21 most frequently discussed issues through computer-assisted content analysis. Secondly, we used time series analysis to investigate whether the candidates influenced each other’s political agendas. Most tweets by the candidates were found not to be about policy but about parties, other politicians, and the media. Of the political issues that were discussed, the most prominent ones were employment, family, minorities and terrorism. For tweets about minorities, we found possible evidence of agenda setting. We conclude that social media are mainly being used to reach out to supporters, instead of interacting with the opponent.

Keywords: microblog analysis, Twitter, agenda setting, inter-policy agenda setting, content analysis, time series analysis

1 Introduction

The results of the United States presidential primaries in 2016 were highly unexpected. Donald Trump, a businessman with no prior experience in political office, was first seen as an outsider with no real chance at winning the nomination. “If Trump is nominated, then everything we think we know about presidential nominations is wrong”, researchers at the University of Virginia Center for Politics said on their blog in August 2015 [1]. Trump was nominated and ultimately elected president, so what do we know?

The 2016 primaries were exceptionally polarizing and emotional. Donald Trump insulted the other Republican candidates, the Democratic candidates, politicians from all over the world, the media, women and ethnic groups [2]. Researchers have argued that Trump offers the masculine image of a “tough guy” [3] and anti-politician who channels dissatisfaction [4]. It has also been argued in the media that Trump has been successful at using social media to rally his supporters [5]. However, conclusive scientific evidence for this assertion is so far missing.

It is clear, however, that both Trump and Clinton, or their respective campaign staff, are prolific and influential Twitter users. Clinton has more than 8 million followers and has written about 7,000 short messages, or tweets, since 2013. Donald Trump has more than 10 million followers and has written more than 32,000 tweets since the creation of his account in 2009 (as of August 6, 2016). Both candidates are evidently able to reach millions of people on Twitter. Their tweets reflect their standpoints on political issues and their style of campaigning. In an analysis by the Washington Post of more than 6000 tweets posted by Donald Trump between June and December 2015, 11 % were found to be insulting [5].

The last decade has seen the emergence of social media and its acceptance as a new useful tool for researchers to examine a wide array of phenomena in domains such as politics and business [6–8]. In particular, it has helped researchers understand the dynamics of electoral campaigns [9–12]. It has been studied how social media data can be used to predict voter behaviour [13], how new technologies have shaped political campaigning [14] and which role social media appearances play in campaigns [15]. We contribute to this body of research by examining which issues were discussed on Twitter by the nominees in the run-up to the 2016 election, and how political issues were discussed.

To do so, we draw on agenda setting theory. This theory distinguishes three different agendas: the public agenda, the media agenda, and the policy agenda. For example, in this framework, the communication by the candidates on Twitter could be viewed as a reflection of the future policy agenda. Moreover, since communication on Twitter is generally public, candidates could influence each other in their communication and respond to one another. Therefore, this research addresses the following questions:

1. What is the nature of the Twitter communication by the main presidential candidates during the 2016 US primaries?
2. To what extent does agenda setting take place on Twitter between these candidates?

These research questions are addressed using a combination of content analysis and time series analysis. Content analysis is used to identify the most prominent topics discussed during the primaries by both eventual nominees (i.e. the first research question). Time series analysis is then used to address the second research question by examining the interrelations between the topic mentions over time. Prior research has investigated agenda setting on Twitter [16,17], but the application of this combination of methods and a social media data source to study inter-candidate agenda setting is new.

In the remainder of the article, we give a theoretical overview and introduce the present literature on agenda setting. We especially focus on the policy agenda and Twitter. Our hypotheses are derived from the literature. The third section describes the methods used, and section four presents the empirical results. Section five contains a discussion of the results and our conclusions. We finally consider the limitations of this study and its implications for future research.

2 Related Work

Agenda setting theory concerns the idea that people do not only learn about a certain topic by media consumption, they are also learning about its importance by evaluating the place and space of this specific topic [18]. In the words of Cohen [19, p. 13], media don't tell people "what to think", but "[...] what to think about". According to agenda setting theory, there are three different agendas: The public agenda, the media agenda and the policy agenda. These agendas are interrelated and influence each other. Personal experience, interpersonal communication and the "real world" have been found to influence all three agendas [20]. In the context of this study, the policy agenda is the most relevant.

2.1 The Policy Agenda

The policy agenda describes the actions taken by the government. The agendas of political parties, the bureaucracy, the President, the Committees and the Lower and Upper House belong to the policy agenda [21]. In the policy agenda, issues are of great importance. It is crucial for the candidates to find the majority-efficient position for a certain issue to convince voters [22]. Candidates will give more salience to issues for which they get broader support from voters [23]. Studies about policy agenda setting pay attention to the dynamics in the political system and answer the question of how a new idea, policy or problem is accepted in the political system [24].

The relationship between the media agenda and the policy agenda is reciprocal, that is, both agendas influence each other: Policy makers are not independent of the media – and the media are rarely independent of members of political institutions [25]. On the one hand, the president has been shown to influence the media agenda on foreign policy issues. In particular, issues with lower salience concerning foreign policy are most likely to be taken up by the media [26]. Moreover, the president has been found to be cited regularly during news about a press conference [27]. On the other hand, the media also influence the policy agenda by giving more attention to certain issues than to other issues. Media attention is often seen as "an agent of change" [25, p. 110] that has a stabilizing power for the policy-making process.

Politicians can take up issues from others and voice their opinions about these issues to distinguish themselves from other politicians. Soroka [21] calls these dynamics within political institutions *inter-policy agenda setting*. Studies regarding these dynamics found such effects between the President of the United States and Congress, with the former setting the agenda of the latter in most cases. Only for the issue of international affairs, Congress sets the President's agenda [28]. Moreover, the agenda setting process between candidates during election times has gained the attention of researchers during the last years. Inter-candidate agenda setting takes place for both issue salience and attribute salience relationships, but the results are stronger for attribute salience. The authors defined salience "by the frequency of issue and attribute mentions within campaign messages" [29].

2.2 Agenda Setting and Twitter

Campaign messages today are not only disseminated through traditional media, but also through social media such as the microblogging service Twitter. One can use the service to publish a status (*tweet*) with a maximum length of 140 characters. Users can also *follow* each other, that is, be notified when someone else publishes a tweet. Since its launch in 2006, Twitter has become a very popular medium in the US, with 66 million monthly active users in June 2016 [30].

Even in times of a more fragmented media landscape, agenda setting takes place [31], but in a different way: Traditional media have become less powerful in the agenda-setting process, as their former power is now divided between traditional media and citizen media [32]. Since the election of Obama in 2008, Twitter has been widely used by politicians, especially during election periods [33]. Obama used Facebook and Twitter to collect donations and to connect to the community [34]. Politicians are known to have an influential role on Twitter in terms of retweets [9].

Research regarding agenda setting and Twitter has particularly focused on possible inter-media agenda setting effects. In a political context, it has been found that traditional media such as newspapers or television have a “symbiotic relationship” [16, p. 374] with the Twitter feeds of candidates and political parties for certain issues such as employment and health care during election times [16, 35].

Another research area concerning this topic is network agenda setting. This theory examines agenda setting effects between the media and public agenda from a network perspective. Using Big Data analysis, this theory has been confirmed for the 2012 election, when Mitt Romney was the Republican candidate who competed with Barack Obama. The authors found that the network issue agendas of the candidates’ supporters correlated positively with the network issue agendas of certain media channels, in particular of horizontal media such as talk shows and cable news [36]. Especially young Americans who are part of the Twitter network also search for information on political issues and express their opinions [37].

In summary, Twitter is a useful and promising tool for studying agenda setting, but inter-policy agenda setting has not yet been explored in this context. We therefore test the following hypotheses on Twitter data.

2.3 Hypotheses

Inter-policy agenda setting can take place between parties. Vliegenthart et al. [38] examined the dynamics of the policy agenda in Belgium in a long-term study. They found that the parties influence each other and are more likely to take up the issues of other parties in parliament if they are from the same language community. Moreover, governing parties have more agenda setting power than other parties. Hillary Clinton belongs to the governing party in the US, was part

of it as United States Secretary, and is also supported by the President. We therefore hypothesize that she will lead the agenda of Donald Trump:

H1 The issues mentioned in Hillary Clinton’s tweets will predict the issues mentioned in Donald Trump’s tweets.

Tedesco [39] found inter-candidate agenda setting effects in the candidate and campaign press releases of the Democratic candidates during the primaries in 2004. The author assumes that the agenda of the Democratic candidate John Kerry was set by the shared agenda of the other Democratic candidates. His opponent Howard Dean gained financial support and large media attention early, but he did not lead the other candidates’ agendas. According to the author, Dean was not able to take advantage of the media attention. Furthermore, Vliegenthart et al. [38] find that extreme-right parties also have an agenda-setting power.

In 2016, Donald Trump received an exceptional amount of media attention, which he might be able to take advantage of. He has more Twitter followers than Clinton and makes polarizing statements that other candidates may have no choice but to react to. Thus, we hypothesize:

H2 The issues mentioned in Donald Trump’s tweets will predict the issues mentioned in Hillary Clinton’s tweets.

In summary, there are good reasons to believe that the candidates should influence each other’s agenda. Examining whether this is indeed the case helps understand how Twitter was used by the candidates before the election.

3 Methods

To address the research questions and test the hypotheses, we chose a quantitative research design. A large dataset of relevant tweets was collected. Afterwards we conducted a content analysis to identify the most relevant political topics during the US primaries 2016. In a time series analysis, we focused on these identified topics and examined if any agenda setting effects occurred.

3.1 Dataset

As the present analysis focuses on the two main presidential primary candidates, only tweets and retweets by Hillary Clinton and Donald Trump (@HillaryClinton and @realDonaldTrump) were collected via the `GET statuses/user_timeline` endpoint of the Twitter API. This means we queried the API for all tweets and retweets sent from Donald Trump’s and Hillary Clinton’s accounts. Contrary to other research on Twitter, we did not search for tweets containing hashtags or keywords related to the candidates, as our research focused on the communication between the candidates and not on the communication of other Twitter users about them. Every tweet posted between November 15, 2015 and June 4, 2016 was collected, because the primaries took place within this timespan. Hillary Clinton occasionally tweets in Spanish. These tweets were excluded from further analysis. The cleaned dataset contained 6,099 tweets. Of these, 3,056 were posted by Donald Trump and 3,043 by Hillary Clinton, so we were able to analyze a similar amount of tweets by each candidate.

3.2 Content Analysis

To address the first research question – that is, to examine the communication on Twitter by both candidates during the campaign –, we conducted a content analysis of the tweets and determined the most salient topics in each candidate’s messages. As the present dataset is too large to analyze them manually, the content analysis was conducted in a computer-assisted way.

The computer-assisted qualitative coding program QDA Miner and its text mining component WordStat were used to analyze the most frequent topics of both candidates. WordStat offers a few ready-to-use dictionaries. After testing those dictionaries on a small sample dataset, none of those dictionaries were found to be suitable for this research context. As political topics differ across elections, we used WordStat to develop a suitable dictionary ourselves.

The literature search revealed that Conway et al. [16] also conducted a computer-assisted content analysis to analyze agenda setting during US primaries. They used a dictionary including 21 political topics. These categories were used as a starting point for our own dictionary. First of all, all tweets were entered into QDA Miner and word frequencies were analyzed in WordStat. The most frequent words were classified and put into the dictionary categories based on the work of Conway et al. [16]. As expected, topics during these primaries differed from previous primaries, so not all categories by Conway et al. [16] were used and some new categories were added. As several words have different meanings, we resolved uncertainties by using the Keyword-in-Context tool. This shows all tweets including the word in question, so it is easier to decide into which category a word belongs.

After adding a decent amount of words, we conducted a first content analysis based on our own dictionary. WordStat was configured to use Porter Stemming and a built-in English exclusion list. Porter Stemming removes common English prefixes and suffixes before the categorization process. The exclusion list contained English stop words which provide no further meaning to a text (e.g. and, or, the). The built-in list was manually extended with Twitter-related stop words such as RT (the abbreviation of retweet). During the categorization process, the dictionary recognizes the beginnings and endings of words by identifying space characters. If a tweet contained one or more words included in the dictionary, it was assigned to all matching categories. Results returned a list of leftover words which were not included in the dictionary yet. We classified the most frequent leftover words to make sure that our dictionary contains all words occurring in more than one percent of all tweets.

Our final dictionary includes the following 21 categories: *employment, environment, guns, health care, military and defense, terrorism, slogans, media, family, rights, meetings, thank-you messages, campaign funding, parties and politicians, caucus, foreign politics, education, economics, justice, Trump family and minorities*.

To validate our dictionary, we calculated recall and precision for each category. Therefore, 60 random tweets were coded manually first. Afterwards, the same tweets were coded by WordStat, using the developed dictionary. We calcu-

lated recall and precision values for each category. Scores for both measures can range from 0 to 1.0, where 1.0 would be the ideal result. A recall of 1.0 means that all tweets belonging to a specific category were labelled as belonging to this category by the dictionary, but says nothing about how many other tweets were labelled incorrectly as belonging to this category. A precision score of 1.0 means that every tweet labelled as belonging to a specific category indeed belongs to this category, but says nothing about the number of tweets that also belong to this category but were labelled incorrectly [40]. Most categories reached high values in recall and precision, but there are a few exceptions, for example the category *justice* ($R = 0.50, P = 1$). In sum, the dictionary reached an average recall of 0.84 and an average precision of 0.97 over all categories.

3.3 Time Series Analysis

To address the second research question and study the interrelations between the agendas of the two candidates, we used time series analysis. The content analysis served as a preprocessing step for the time series analysis. The agenda setting hypotheses were tested on political topics which were discussed frequently by both candidates. To identify these topics, the results of the content analysis were used.

During content analysis, the political topics *family*, *employment*, *minorities* and *terrorism* were identified as the ones most frequently discussed by both candidates. Therefore the dataset for time series analysis contained only tweets which were classified into at least one of these categories. For every candidate and topic, a time series was created resulting in eight different time series. All of these contain date and number of tweets related to a specific topic as variables. As Twitter is a very fast-paced medium, the number of tweets related to a specific topic was calculated for every day. The following method for analysing time series data was also adapted from Conway et al. [16], as their research took place in a similar context.

The statistic software SPSS was used to analyze relationships between Donald Trump's and Hillary Clinton's time series. At first, all time series were tested for auto-correlations, which are correlations within a time series. Next, all time series were examined for linear trends by using curve estimation. For every time series with significant linear trends SPSS automatically calculated a de-trended version of the original time series as a new variable. Finally, cross-correlations for every topic were calculated. Every time Donald Trump's time series was entered as the first variable and Hillary Clinton's as the second variable. In case a linear trend was found in the previous step, the de-trended time series was entered instead.

4 Results

In the following section results from content analysis and time series analysis are presented. At the end, we summarize shortly which hypotheses are supported by our results.

4.1 Content Analysis

The topic distributions of Donald Trump’s and Hillary Clinton’s tweets are shown in Table 1. It stands out that both candidates tweeted mostly about their media appearances, parties, and other politicians. Topics regarding political issues, for example, *employment*, *healthcare* or *human rights* were discussed much less often. *Employment* was the most frequently discussed political issue by Donald Trump, but occurred only in 4% of his tweets. This means that all other political issues were covered even less frequently. Hillary Clinton’s topic distribution looks quite similar, but there are some differences. Her most frequently discussed political issue *family* occurred in 16% of her tweets. So both candidates had a different favourite political issue and Hillary Clinton tweeted more often about her favourite issue *family* than Donald Trump tweeted about *employment*. Whereas Donald Trump discussed all political issues rarely, Hillary Clinton has one clear main issue, but tweeted about all other political issues as seldom as Trump. *Minorities* as her second political issue, for example, accounted only for 6% of her tweets.

The main goal of the content analysis was to identify political topics appropriate for the subsequent time series analysis. These topics should occur quite often in both candidates’ tweets, so that enough data for valid results are available. We decided to choose the most frequently discussed political topics from Trump’s topic distribution and checked if they also occur often enough in Clinton’s tweets. As a result, the political topics *employment*, *family*, *terrorism* and *minorities* were chosen for further analysis.

4.2 Time Series Analysis

As described in the method section every time series was tested for auto-correlations and linear trends. In the following time series significant auto-correlations were found: Trump family (lag 1, lag 2), Trump terrorism (lag 1, 2, 3 and 14), Clinton minorities (lag 1) and Clinton family (lag 14). Significant linear trends were found in these time series: Trump minorities ($R^2 = .03, p < .05$), Trump terrorism ($R^2 = .05, p < .01$), Clinton family ($R^2 = .02, p = .05$) and Clinton terrorism ($R^2 = .03, p = .01$).

In the next step, cross-correlation coefficients were calculated for all four topics. Table 2 shows that for the topic *minorities*, only the cross-correlation coefficient for lag -4 was significant. This means that Trump’s tweets about minorities were predicted by Clinton’s tweets about this topic four days earlier. Table 2 also shows that for the topic *terrorism*, cross-correlation coefficients for several lags and leads were significant (lag -3 and -1, lead 2 and 4). These results imply that in contrast to the topic *minorities*, correlations between both candidates’ time series are bi-directional. In other words, Trump’s tweets about terrorism were predicted by Clinton’s tweets about this topic one and three days earlier, but Clinton’s tweets are also predicted by Trump’s tweets two and four days earlier. For the other topics (*family* and *employment*), no significant cross-correlation coefficients were found.

Table 1. Topic distribution of Donald Trump’s and Hillary Clinton’s tweets in descending order of frequency. Categories marked with * were the most frequently discussed political topics and used in further analysis.

		Trump		Clinton		
	Category	No. of cases	% of cases	Category	No. of cases	% of cases
1	Parties and politicians	1783	58.36	Parties and politicians	1442	47.39
2	Media	778	25.47	Family*	488	16.04
3	Slogans	569	18.63	Media	446	14.66
4	Thank-you messages	493	16.14	Slogans	432	14.20
5	Caucus	296	9.69	Meetings	195	6.41
6	Employment*	129	4.22	Minorities*	189	6.21
7	Family*	92	3.01	Employment*	177	5.82
8	Terrorism*	83	2.72	Caucus	138	4.53
9	Trump family	78	2.55	Human rights	129	4.24
10	Minorities*	56	1.83	Healthcare	119	3.91
11	Healthcare	21	0.69	Thank-you messages	90	2.96
12	Military and defense	20	0.65	Environment	87	2.86
13	Foreign politics	13	0.43	Guns	85	2.79
14	Human rights	11	0.36	Terrorism*	68	2.23
15	Justice	8	0.26	Education	52	1.71
16	Campaign funding	7	0.23	Justice	49	1.61
17	Education	7	0.23	Economics	29	0.92
18	Economics	4	0.13	Military and defense	19	0.62
19	Guns	4	0.13	Campaign funding	6	0.20
20	Environment	2	0.07	Foreign politics	5	0.16

Table 2. Cross-correlation results for the topics minorities, terrorism, employment and family

Political topic	Significant lags and leads for Trump with Clinton	Cross-correlation coefficient
Minorities	Lag (-4)	0.20
	Lag (-3)	0.16
Terrorism	Lag (-1)	0.32
	Lead (2)	0.19
	Lead (4)	0.18
Employment	No significant lags or leads	
Family	No significant lags or leads	

In Figs. 1 and 2, visualizations of the *minorities* and *terrorism* time series are shown, as cross-correlation returned significant results for these topics. It stands out that both candidates tweet much less continuously about terrorism. Most of the time numbers of daily tweets are quite low, but four different peaks can be identified during the tracking timespan. Fig. 2 shows that terror attacks took place right before the first three peaks. Since many significant auto-correlations were found in Trump’s *terrorism* time series and terror attacks took place right before the peaks, the significant cross-correlation should be interpreted carefully. It is possible that these external events instead of agenda setting explain the correlations between Trump’s and Clinton’s time series for the topic *terrorism*. For the topic *minorities* no such external events were found, so agenda setting might be a reasonable explanation for the significant cross-correlation.

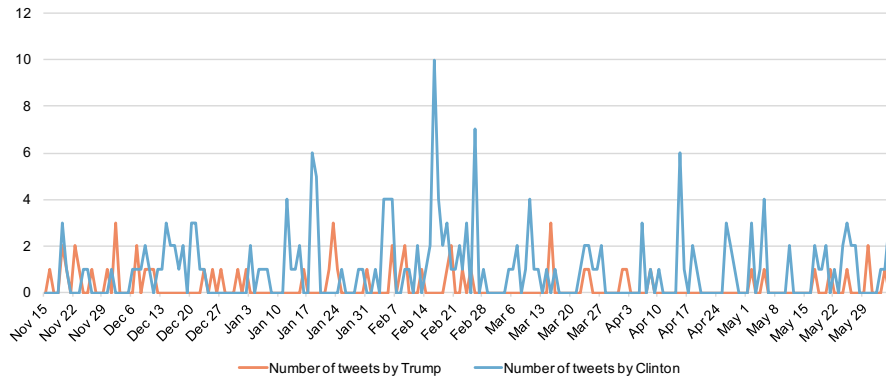


Fig. 1. Visualization of both candidates’ time series for the topic *minorities*.

Table 3 summarizes the results of the hypothesis tests. The findings provide partial support for the first hypothesis, and no support for the second hypothesis.

Table 3. Results of hypothesis tests

Hypothesis	Result
H1 The issues mentioned in Hillary Clinton’s tweets will predict the issues mentioned in Donald Trump’s tweets	Supported for topic <i>minorities</i>
H2 The issues mentioned in Donald Trump’s tweets will predict the issues mentioned in Hillary Clinton’s tweets	Not supported

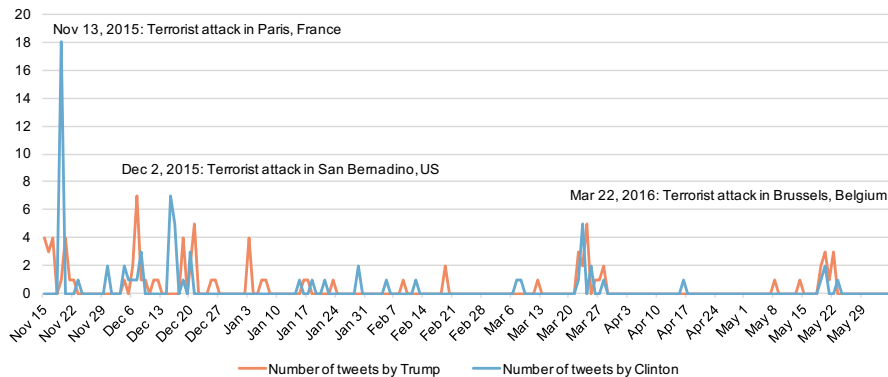


Fig. 2. Visualization of both candidates' time series for the topic *terrorism*.

5 Discussion

This section discusses the results and addresses the research questions. It also addresses the limitations of the study and mentions implications for future research.

5.1 Communication topics

The first goal of this research was to study the nature of communication by the eventual presidential nominees on Twitter. We found that political issues on Twitter are not as frequent as thank-you messages and announcements for upcoming media presences of the candidates. This confirms the finding of Sandoval et al. [11].

This finding also has some practical implications. Twitter serves as a source of political information for many people [37], so politicians could likely benefit from disseminating more political statements on Twitter than they currently do. On the other hand, Twitter only allows messages with up to 140 characters, which may make it difficult to discuss complex topics. Secondly, during his campaign, Donald Trump was known for his plan of building a wall between Mexico and the US to stop crime. He was also frequently mentioned in the media for his plans to institute a law that would make the immigration of Muslims into the US illegal [3]. It can therefore be considered somewhat surprising that the number of tweets from Donald Trump about minorities was very low. There were only 56 tweets regarding this issue in the tracking period. An explanation for this

divergence might be inter-media agenda setting. Perhaps, the statements were so arousing or polarizing that journalists picked up on them and wrote or talked about them much more than Donald Trump did himself.

A comparison of the candidates regarding specific topics reveals that both politicians took them up differently. For example, after the terrorist attack of San Bernadino, the biggest terror attack in the US [41], Donald Trump criticized that it was not reported as a terrorist act (December 4, 2015). Hillary Clinton claimed that the attack could only take place because “Republican Senators blocked a bill to stop suspected terrorists from buying guns” (December 4, 2015). Here, Hillary Clinton uses the terror attack to criticize the Republican Party. Donald Trump also blamed Hillary Clinton indirectly in March, during the Brussels terror attacks: “Hillary Clinton has been working on solving the terrorism problem for years. TIME FOR CHANGE, I WILL SOLVE - AND FAST” (March 24, 2016). During these bombings, Clinton twittered: “These terrorists seek to undermine the democratic values that are the foundation of our way of life. They will never succeed. -H.” (March 22, 2016). All in all, both candidates used terrorist attacks for their purposes. When comparing the issue *family*, it becomes clear that the perception that Hillary Clinton plays the “woman card” [42] may be rooted in the fact that she addresses this topic five times as often as Trump.

5.2 Agenda setting

In addressing the second research question, this paper is the first one to examine inter-policy agenda setting effects on the microblogging service Twitter for candidates during US primary elections. The goal was to answer the question whether agenda setting takes place between the candidates during the US presidential elections. This question can only partially be answered with yes. For the topic *minorities*, Clinton is leading Trump’s agenda. Results for *employment* and *family* were not significant. We conclude that the presence of agenda setting depends on the political issue. With this research, we contribute to the work of Soroka [21], who introduced the notion of inter-policy agenda setting and confirmed existing research by Vliegenthart et al. [38].

For the topic *terrorism*, agenda setting might have taken place in both directions, but significant auto-correlations were present even after removing linear trends, and the cross-correlations observed may therefore be spurious. Fig. 2 shows that attacks took place right before the peaks, which may explain this phenomenon. We therefore refrain from drawing further conclusions from the statistical results.

A closer inspection of the tweets reveals that when Donald Trump takes up the issues of other candidates and politicians, he frequently does so to attack them. For example, Trump twittered on December 7, 2015: “Obama said in his speech that Muslims are our sports heroes. What sport is he talking about, and who? Is Obama profiling?” In this tweet, he takes up Obama’s speech to ask questions, encouraging his community to think about it.

In summary, this study offers some evidence that agenda setting actually takes place on Twitter, but less than could have been expected. In some cases

(e.g. *terrorism*) tweets looked more likely to be prompted by external events. This finding is important because it emphasizes further how little interaction with the political opponent occurred on Twitter in this case. Thereby our research contributes to the small existing body of literature on agenda setting in the context of Twitter.

5.3 Limitations

As any research, ours comes with limitations. Spanish tweets were not considered in this analysis. Expanding the dictionaries with Spanish words would have been very time-consuming. However, since Clinton sometimes tweeted in Spanish, this decision could skew the results on the topic of *minorities*.

Furthermore, when creating a dictionary for content analysis, there are always ambiguities regarding the appropriate category for a particular word, and building a dictionary is a process that involves subjective decisions. We made use of the Keyword-in-Context tool to resolve these uncertainties and evaluated the dictionary by calculating recall and precision for every category. While validation results should be interpreted carefully, they suggest that the dictionary was suitable for our purposes.

We found significant auto-correlations in some time series, which led us to exclude the topic of *terrorism*. Linear trends were controlled for by using detrended versions of the affected time series as described in Conway et al. [16], but more sophisticated methods are available to remove auto-correlations.

Finally, as already mentioned, the results of the US primaries in 2016 were highly unexpected. Almost no one thought that Donald Trump will be the candidate for the Republican Party. This provided a unique research setting, but it is uncertain if this research is replicable for other contexts and for other countries.

5.4 Future Research

We propose further research to examine if the results can be generalized. Additionally, given the highly emotional content of tweets, it seems worthwhile to examine if emotion has an influence on agenda setting on social media, especially on Twitter. For example, the difference between candidates regarding the sentiment of their tweets could be examined in future research. It is also unclear whether sentiment has an influence on agenda setting on Twitter.

While executing our time series analysis, we found auto-correlations in Trump's series for *terrorism*. Possible external events are predicting the time series of Trump. In further research, a more complex model could be developed that removes these auto-correlations or explicitly takes the influence of outside events into account. Another valuable research direction would be the enhancement of automatic classification methods which allow the identification of political topics in election-related tweets even though topics change between elections.

Future research should also include tweets by the public to evaluate how agenda setting takes place between politicians and citizens on twitter. However,

in this regard it has to be considered that Twitter is only used by a small percentage of the whole population and mostly by younger people. Once again, the influence of sentiment should be considered in this context.

6 Conclusions

In his 1996 analysis of how a new technology had reshaped political campaigning in Texas, Jonathan Coopersmith stated that “the spread of modern information technologies has greatly altered the face of politics” [14, p. 37]. The technology he examined was the fax machine. Twenty years later, many of the observations he made are equally true for Twitter: a flood of data is being generated, information can be disseminated rapidly, and there is consequently increased pressure on political campaigns to make use of these new technologies effectively.

But Twitter does not only enable campaigns to spread information rapidly, it also allows researchers an unprecedented glimpse at the daily activities of campaigns. When Wattal et al. [12] laid out their research agenda, they called on researchers to examine how the political system might change as a result of the Internet. They ask, “how might the web be used to support increased mutual understanding and tolerance in political discourse”?

Twitter has indeed become one of the most important social media used by campaigns – but our analysis showed that very little political discourse actually takes place there. The medium is dominated by thank-you messages and simple political slogans. Candidates use it to reach out to their followers, not to engage with the political opposition.

Still, the few political messages present in the data open new avenues for researchers. Previous research on agenda setting had considered the agenda of political actors and institutions in power. Now, a large part of the communication by political campaigns is readily available to researchers in a digitized form. We can analyze the agenda of those who will wield political power even before they do it. Twitter has made it possible to carry out this analysis with less effort and at a larger scale than before.

In this study, we combined content analysis and time series analysis. Through the resulting analysis of day-to-day frequencies of topic mentions, we were able to find little evidence for inter-policy agenda setting during the run-up to the US presidential elections. Instead of fostering discussion and helping mutual understanding, Twitter seems to represent a fractured social space.

References

1. Sabato, L.J., Kondik, K., Skelley, G.: Republicans 2016: What To Do With The Donald? (2015), <http://www.centerforpolitics.org/crystalball/articles/republicans-2016-what-to-do-with-the-donald/>
2. Lee, J.C., Quealy, K.: The 337 People, Places and Things Donald Trump Has Insulted on Twitter: A Complete List (2016),

<https://www.nytimes.com/interactive/2016/01/28/upshot/donald-trump-twitter-insults.html>

3. Sperling, V.: Masculinity, Misogyny, and Presidential Image-making in the U.S. and Russia (2016), <https://global.oup.com/academic/category/social-sciences/politics/2016-election/mmpimur/>
4. Button, M.E.: Trump and the Triumph of Hubris over Democratic Politics (2016), <https://global.oup.com/academic/category/social-sciences/politics/2016-election/tattohodp/>
5. Schwartzman, P., Johnson, J.: It's not chaos. It's Trump's campaign strategy (2015), https://www.washingtonpost.com/politics/its-not-chaos-its-trumps-campaign-strategy/2015/12/09/9005a5be-9d68-11e5-8728-1af6af208198_story.html
6. Cossu, J.V., Dugue, N., Labatut, V.: Detecting Real-World Influence through Twitter. In: ENIC Proceedings. pp. 83–90 (2015)
7. Stieglitz, S., Dang-Xuan, L., Bruns, A., Neuberger, C.: Social Media Analytics – An Interdisciplinary Approach and Its Implications for Information Systems. *Bus. Inf. Syst. Eng.* 56(2), 101–109 (2014)
8. Cazzoli, L., Sharma, R., Treccani, M., Lillo, F.: A Large Scale Study to Understand the Relation between Twitter and Financial Market. In: ENIC Proceedings. pp. 98–105 (2016)
9. Dang-Xuan, L., Stieglitz, S., Wladarsch, J., Neuberger, C.: An Investigation of Influentials and the Role of Sentiment in Political Communication on Twitter During Election Periods. *Inf. Commun. Soc.* 16(5), 795–825 (2013)
10. Larsson, A.O., Moe, H.: Studying political microblogging: Twitter users in the 2010 Swedish election campaign. *New Media Soc.* 14(5), 729–747 (2012)
11. Sandoval, R., Matus, R.T., Rogel, R.N.: Twitter in Mexican Politics: Messages to People or Candidates? In: AMCIS Proceedings. pp. 1–10 (2012)
12. Wattal, S., Schuff, D., Mandviwalla, M., Williams, C.B.: Web 2.0 and Politics: The 2008 US Presidential Election and An E-Politics Research Agenda. *MIS Q.* 34(4), 669–688 (2010)
13. Maldonado, M., Sierra, V.: Can Social Media Predict Voter Intention in Elections? The Case of the 2012 Dominican Republic Presidential Election. In: AMCIS Proceedings (2015)
14. Coopersmith, J.: Texas Politics and the Fax Revolution. *Inf. Syst. Res.* 7(1), 37–51 (1996)
15. Bühler, J., Bick, M.: The impact of social media appearances during election campaigns. In: AMCIS Proceedings. vol. 5, pp. 3406–3416 (2013)
16. Conway, B.A., Kenski, K., Wang, D.: The Rise of Twitter in the Political Campaign: Searching for Intermedia Agenda-Setting Effects in the Presidential Primary. *J. Comput. Mediat. Commun.* 20(4), 363–380 (2015)
17. Gruszczynski, M.W.: Examining the Role of Affective Language in Predicting the Agenda-Setting Effect. In: APSA Annual Meeting (2011)
18. Baran, S.J., Davis, D.K.: *Mass Communication Theory: Foundations, Ferment, and Future*, vol. 6. Wadsworth, Boston (2015)
19. Cohen, B.C.: *The Press and Foreign Policy*. Princeton University Press, Princeton, NJ (1963)
20. Dearing, J.W., Rogers, E.M.: *Communication Concepts 6. Agenda-Setting*. Sage, Thousand Oaks, CA (1996)
21. Soroka, S.N.: Issue Attributes and Agenda-Setting by Media, the Public, and Policymakers in Canada. *Int. J. Public Opin. Res.* 14(3), 264–285 (2002)

22. Krasa, S., Polborn, M.: The binary policy model. *J Econ. Theory* 145(2), 661–688 (2010)
23. Colomer, J.M., Llavador, H.: An agenda-setting model of electoral competition. *SERIEs* 3(1-2), 73–93 (2012)
24. Baumgartner, F.R., Green-Pedersen, C., Jones, B.D.: Comparative Studies of Policy Agendas. *J. Eur. Public Policy* 13(7), 959–974 (2006)
25. Wolfe, M.: Putting on the brakes or pressing on the gas? Media attention and the speed of policymaking. *Policy Stud. J.* 40(1), 109–126 (2012)
26. Peake, J.S.: Presidential Agenda Setting in Foreign Policy. *Polit. Res. Q.* 54(1), 69–86 (2001)
27. Eshbaugh-Soha, M.: Presidential Influence of the News Media: The Case of the Press Conference. *Polit. Commun.* 30(4), 548–564 (2013)
28. Rutledge, P.E., Larsen Price, H.A.: The President as Agenda Setter-in-Chief: The Dynamics of Congressional and Presidential Agenda Setting. *Policy Stud. J.* 42(3), 443–464 (2014)
29. Kiouisis, S., Shields, A.: Intercandidate agenda-setting in presidential elections: Issue and attribute agendas in the 2004 campaign. *Public Relat. Rev.* 34(4), 325–330 (2008)
30. Statista: Number of monthly active Twitter users in the United States from 1st quarter 2010 to 2nd quarter 2016 (in millions) (2016), <https://www.statista.com/statistics/274564/monthly-active-twitter-users-in-the-united-states/>
31. Vargo, C.J.: Twitter as Public Salience: An Agenda-Setting Analysis. In: AEJMC Annual Conference (2011)
32. Meraz, S.: Is There an Elite Hold? Traditional Media to Social Media Agenda Setting Influence in Blog Networks. *J. Comput. Mediat. Commun.* 14(3), 682–707 (2009)
33. Vergeer, M.: Twitter and Political Campaigning. *Sociol. Compass* 9(9), 745–760 (2015)
34. Robertson, S.P., Vatrappu, R.K., Medina, R.: Off the wall political discourse: Facebook use in the 2008 U.S. presidential election. *Inf. Polity* 15(1-2), 11–31 (2010)
35. Groshek, J., Clough Groshek, M.: Agenda Trending: Reciprocity and the Predictive Capacity of Social Networking Sites in Intermedia Agenda Setting across Topics over Time. *Media Commun.* 1(1), 15–27 (2013)
36. Vargo, C.J., Guo, L., McCombs, M., Shaw, D.L.: Network Issue Agendas on Twitter During the 2012 U.S. Presidential Election. *J. Commun.* 64(2), 296–316 (2014)
37. Ancu, M., Cozma, R.: MySpace Politics: Uses and Gratifications of Befriending Candidates. *J. Broadcast. Electron. Media* 53(4), 567–583 (2009)
38. Vliegthart, R., Walgrave, S., Meppelink, C.: Inter-party Agenda-Setting in the Belgian Parliament: The Role of Party Characteristics and Competition. *Polit. Stud.* 59(2), 368–388 (2011)
39. Tedesco, J.C.: Intercandidate Agenda Setting in the 2004 Democratic Presidential Primary. *Am. Behav. Sci.* 49(1), 92–113 (2005)
40. Liu, B., Hu, M., Cheng, J.: Opinion Observer: Analyzing and Comparing Opinions on the Web. In: WWW Proceedings. pp. 342–351 (2005)
41. CNN: San Bernadino Shooting (2016), <http://edition.cnn.com/specials/san-bernardino-shooting>
42. Zezima, K.: Trump: Clinton is playing the 'woman card' (2016), <https://www.washingtonpost.com/news/post-politics/wp/2016/04/26/trump-clinton-is-playing-the-woman-card/>