Political Communication and Influence through Microblogging – An Empirical Analysis of Sentiment in Twitter Messages and Retweet Behavior

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Abstract

Microblogging services such as Twitter are said to have the potential for increasing political participation. Given the feature of "retweeting" as a simple yet powerful mechanism for information diffusion, Twitter is an ideal platform for users to spread not only information in general but also political opinions through their networks as Twitter may also be used to publicly agree with, as well as to reinforce, someone's political opinions or thoughts. Besides their content and intended use, Twitter messages ("tweets") also often convey pertinent information about their author's sentiment. In this paper, we seek to examine whether sentiment occurring in politically relevant tweets has an effect on their retweetability (i.e., how often these tweets will be retweeted). Based on a data set of 64,431 political tweets, we find a positive relationship between the quantity of words indicating affective dimensions, including positive and negative emotions associated with certain political parties or politicians, in a tweet and its retweet rate. Furthermore, we investigate how political discussions take place in the Twitter network during periods of political elections with a focus on the most active and most influential users. Finally, we conclude by discussing the implications of our results.

1. Introduction

Recently, more than 500 million people worldwide were members of the Facebook network [11]. Twitter also counts more than 100 million users in total [19]. Given this tremendous growth of some social media, it is argued that from the perspective of politicians and political parties it is important to actively participate in the political communication via social media, especially during election campaigns. In this regard, U.S. politicians are said to play a leading role. The most prominent example is Barack Obama who successfully employed social media within his last election campaign [38].

In particular, microblogging has been viewed as having the potential for increasing political participation among previously unengaged citizens (e.g., [8]). While social networking sites (SNS) such as Facebook support communication within a pre-defined personal network (e.g., among friends), microblogging platforms enable users to contribute new postings publicly. Furthermore, other users may publicly answer to already published issues as well. In fact, Twitter has become a legitimate and frequently used communication channel in the political arena [36]. Besides being increasingly used for political communication, Twitter is said to be capable of reflecting collective emotive trends and thus might have predictive power with regard to certain events in the political, social and cultural sphere [5]. Furthermore, studies have shown that sentiment of contemporaneous Twitter messages (or "tweets") correlates with voters' political opinion and preferences (e.g., [28; 36]).

Given the unique feature of "retweeting" as a simple yet powerful mechanism for information diffusion, Twitter is an ideal platform for users to spread information. Thus, political opinions might also be disseminated. In general, retweeting behavior is associated with certain values of the original information items. Besides sharing information, users may retweet to entertain a specific audience, to comment on someone's tweet or to publicly agree with someone [6]. However, little is known about how and why certain information spreads more widely than others. In a large-scale study, Suh et al. [33] addressed these questions and identified several factors that significantly impact retweetability of Twitter messages ("tweets"), including URL posting and hashtag inclusion as well as the number of followers and the age of users' accounts.

In this paper, we aim to extend the findings by Suh et al. [33] by investigating potential impacts of sentiment or affective dimensions articulated in tweets on the diffusion of these messages through the network. Besides their content and intended use, tweets

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often convey pertinent information about their author's emotional state or his/her judgement of a certain topic or the intended emotional communication (i.e., the emotional effect the author wishes to have on the reader of the tweet) [5]. At different levels of analysis, previous studies from various disciplines have investigated and confirmed the relevance of sentiment or emotions expressed in online communication (e.g., [5; 28; 10; 31; 36; 18; 22]). However, there are, to our knowledge, no studies that have explicitly examined the potential impact of sentiment on the communication on Twitter, in particular political communication.

The growing relevance of political communication in social media, particularly microblogging, implies a fundamental change in traditional political communication, which has usually been exclusively initiated and managed by political actors as well as journalists [25]. However, as this field is relatively young, more research is needed to better understand the principles of communication on microblogging platforms.

Therefore, in this paper, we first seek to examine how Twitter can be used for political discussions and for affecting political opinion-making processes during election periods by focusing on high-end and most influential users. Second, we investigate whether sentiment occurring in politically relevant tweets has an effect on their retweetability. More specifically, we want to know how the affective dimensions of tweets, including positive and negative emotions associated with certain political parties or politicians, affect the quantity of retweets. For this purpose, we examined communication on Twitter dealing with two specific political elections in Germany in 2011. By tracking relevant tweets, we gained a data set consisting of 64,431 tweets for our analyses.

The remainder of this paper is organized as follows. First, we give a short overview of microblogging with an emphasis on Twitter and point out related work. In the subsequent section, we provide a theoretical background for our research questions and derive hypotheses. Following that, we describe our research methodology and present our empirical results. We conclude by discussing our results, pointing out limitations, and giving potential research outlook.

2. Microblogging and Twitter

Microblogging is a form of blogging in which entries typically consist of short content such as phrases, quick comments, images, or links to videos. Notable services include Twitter, Tumblr, Jaiku, and Google Buzz. As microblogging services have recently gained wide popularity, users have adopted them for sharing news, promoting political views, marketing, and tracking real-time events [6][21][42]. In addition, there have been attempts to adopt microblogging to enterprise environments with example services such as SocialCast, Jive, Yammer, etc. [30].

Of the various microblogging platforms, Twitter is said to be the most popular service. Twitter is a social networking and microblogging service that allows users to send and read 140-character short messages known as "tweets", enabling users to share and discover topics of interest with a network of followers in real-time. Modes of communication on Twitter (e.g., answering or drawing attention to external content) are signified by user-accepted norms, such as annotating their tweets with different characters. To start conversations, the @-sign is used to mark the addressee of a message. For example, posting a message including @username indicates that the message is intended for or somehow relevant to a specific user. Retweets refer to the practice of resending a tweet posted by another user and is one particular case of mentioning. When users find an interesting tweet written by another Twitter user and want to share it with their followers, they can retweet the tweet by copying the message, typically adding a text indicator (e.g. "RT", "via", or "by") followed by the user name of the original author in @username format. When retweeting, users often add more content or slightly modify the original tweet. Tweets can also include so-called hashtags, where the #-character is used in conjunction with a word or phrase in order to connect the tweet to a particular theme. This use of the #-sign allows users to search the "Twittersphere" for specific topics of interest and to follow certain threads of discussion.

3. Related Work

3.1. Twitter Use

Since its creation in 2006, Twitter has gained popularity worldwide. Kwak et al. [23] conducted a large-scale study to analyze the topological characteristics of Twitter and its power as a new medium of information sharing. From Twitter's public timeline, Java et al. [21] examined the topological and geographical properties of Twitter's social network. They identified a number of usage categories such as daily chatter, conversations, sharing information/URLs, and reporting news. Honeycutt and Herring [16] employed a grounded theory approach on their sample and found 12 distinct categories of tweets: about the addressee, announce/advertise, exhort, information for others, information for self, meta-commentary, media use, opinion, other's experience, self-experience, solicit information and others. As studies indicated, one of the most popular usages is for users to inform others and to express themselves. For example, Naaman et al. [26] examined the content of 3,379 tweets by manually coding the messages collected from the public timeline, finding that 80 percent of the 350 users they studied posted messages relating to themselves or their thoughts, as opposed to sharing general news.

3.2. Twitter and Political Communication

Social media play an important role in shaping political debates in the U.S. and around the world (e.g., [4; 3; 34; 12; 1; 36; 28]). Recently, researchers have studied political microblogging (i.e., Twitter) use, with studies focusing on either non-parliamentary or parliamentary uses of the service. As for non-parliamentary uses, the notion of "Twitter revolutions" in totalitarian countries has been introduced, although the exact contents and effects of these uprisings are disputed. For example, Gaffney [13] studied Twitter use during the 2009 Iran elections by tracking the use of the #IranElection hashtag. Although Twitter helped protesters in Iran and around the world in organizing their efforts, the author claimed, "it is difficult to say with any certainty what the role of Twitter was" [13].

A number of studies focusing on different parliamentary uses of Twitter have been published, the majority dealing with the U.S. For example, Golbeck et al. [14] focused on the U.S. Congress and analyzed the contents of over 6,000 tweets from members of Congress. They found that Congress members primarily use Twitter to disperse information, in particular links to news articles about themselves and to their blog posts, and to report on their daily activities. Twitter was rather seen as a vehicle for self-promotion. In a study of over 100,000 messages containing a reference to either a political party or a politician in the context of the 2009 German federal election, Tumasjan et al. [36] showed that Twitter is extensively used for political communication and that the mere number of party mentionings accurately reflects the election result. This suggests that microblogging messages on Twitter seem to validly mirror the political landscape offline and can be used to predict election results to a certain extent.

In a study of 250,000 politically relevant tweets during the six weeks leading up to the 2010 U.S. congressional midterm elections, Conover et al. [9] demonstrated that the network of political retweets exhibits a highly segregated partisan structure, with extremely limited connectivity between left- and right-leaning users. On the other hand, the user-to-user mention network is dominated by a single politically heterogeneous cluster of users in which ideologically-opposed individuals interact at a much higher rate compared to the network of retweets.

3.3. Retweeting Practice and Information Diffusion

As mentioned above, retweeting has become the key mechanism for spreading information on Twitter. There are only few studies, which have explicitly dealt with the practice of retweeting. For example, Nagarajan et al. [27] analyzed over a million tweets referring to three real-world events and the properties of the retweet behavior surrounding the most tweeted content pieces. They found that all tweets categorized as "call for action", "crowd-sourcing" or "collective group identity-making" generated sparse retweet graphs while tweets sharing information (e.g., containing URLs) generated a denser retweet network. In a large-scale study of 74 million tweets, Suh et al. [33] built a predictive retweet model and identified several factors significantly impacting retweetability on Twitter, including URL posting and hashtag inclusion as well as the number of followers and the age of users' accounts.

Regarding diffusion of information on Twitter, Lerman and Ghosh [24] conducted an empirical analysis of user activity on Digg and Twitter. They found that the Twitter network is less dense than Digg's, and that stories spread through the network slower than Digg stories do initially, but they continue to spread at this rate as the story ages and generally penetrate the network farther than Digg stories. Applying survival analysis, Yang and Counts [40] constructed a model to capture the three major properties of information diffusion: speed, scale, and range. They showed that the mentioning rate of the person tweeting is a strong predictor of all aspects of information diffusion on Twitter. Other attributes of the tweets themselves, such as whether they include a link or come at early or late stages of a discussion, also have an influence on the properties of information diffusion.

4. Theoretical Background

Scholars from various disciplines have investigated the role of sentiment in online communication at different levels of analysis. There is a growing body of research examining the relationship between sentiment occurring in short-text messages and other real-world events or phenomena. For example, in a recent study, Bollen et al. [5] found that events in the social, political, cultural and economic sphere do have a significant, immediate and highly specific effect on the various dimensions of public mood displayed in Twitter messages. Their findings suggested that large-scale analyses of mood can provide a “solid platform to model collective emotive trends in terms of their predictive value with regards to existing social as well as economic indicators”. O’Connor et al. [28] attempted to link measures of public opinion derived from polls to sentiment measured from Twitter messages. They found that sentiment word frequencies in contemporaneous Twitter messages do correlate with several public opinion time series such as surveys on consumer confidence and political opinion in the 2008 to 2009 period.

Other works, such as studies by Diakopoulos and Shamma [10], and Shamma et al. [31] sought to characterize performances of political election debates by aggregated Twitter sentiment. They developed an analytical methodology and visual representations that could help to better understand the temporal dynamics of sentiment in reaction to the debate video. They demonstrated visuals and metrics that can be used to detect sentiment pulse, anomalies in that pulse, and indications of controversial topics that can be used to inform the design of visual analytic systems for social media events. In a study of political tweets around the 2009 German federal election, Tumasjan et al. [36] showed that tweet sentiment (e.g., positive and negative emotions associated with a politician) corresponds closely to voters’ political preferences. In addition, party sentiment profiles can reflect the similarity of political positions between parties.

4.1. Impact of Sentiment on Individual Communication

At the level of individual communication, previous studies have dealt with the role of sentiment in the communication in newsgroups, discussion forums or in other contexts. The main results from these studies indicated that affective dimensions of messages (both positive and negative emotions) can trigger more attention, feedback or participation (e.g., [32; 18; 22]). Further, studies have shown that emotional states articulated in messages might spread through different kinds of networks (e.g., [15; 18]). Hence, at this point it would be interesting to ask whether the diffusion of emotions also applies to the communication in social media, in particular Twitter, i.e., to investigate whether, and if so how, sentiment of tweets might disseminate through the Twitter network. Given the nature of political polarization which has been shown to also prevail in Twitter communication [9], sentiment associated with certain political topics, political parties or politicians might play an even more important role, particularly in times of elections. In particular, the dissemination of such sentiment might have an impact on the political opinion-making process.

This motivates us to address the following research questions:

RQ1: How does political discussion take place in the Twitter network during periods of political elections? Who are the most active and the most influential users and how do they affect the political opinion-making process?

RQ2: Do affective dimensions of political Twitter messages associated with political parties or politicians have an impact on how often these messages will be retweeted (i.e., retweetability)?

Previous works have laid some theoretical foundations regarding RQ2. Results from a study of online interactions [22] suggested that negative affect of messages can actually trigger participation. This, however, seems to apply to negative affect in terms of anger rather than sadness or fear. Meanwhile, the same study found that positive affect in messages encourages continued participation in newsgroups by creating a sense of community among users. These results were confirmed in a large-scale study of online communities [18] showing that people who use affective language in their messages receive more feedback than those who do not. This applies to both positive and negative emotions. Further, Smith and Perry [32] showed that positive as well as negative framing of a message could create attention and cognitive involvement, in particular when the framing is unexpected for the recipient of the message.

Beyond triggering more attention or feedback, affects articulated in a message might diffuse through networks. Human populations are arranged in social networks that determine interactions and influence not only the spread of behaviors and ideas, but also emotions. Hill et al. [15] showed that, over long periods of time, emotional states spread across social networks in the same way as contagious diseases do. In various contexts, it has been shown that both positive and negative moods can be “infectious”, for example during workplace interactions [2], in negotiations [37], and among roommates [17]. Furthermore, Huffaker [18] showed that in verbal interaction, communication partners sync their wording, which would indicate that messages containing positive (negative) emotions and words are likely to receive verbal responses, which also express positive (negative) emotions. Additionally, Huffaker [18] provided evidence for the concept of language diffusion in online communities: the more often people used words that express affect, the more of the words they used were repeated in subsequent replies. All of these findings lead us to conjecture a positive relationship between sentiment articulated in tweets and their likelihood to spread through the Twitter network. Therefore, in political context we derive the following hypothesis:

H1: The more words indicating affective processes a political Twitter message contains, the more often it will be retweeted.

5. Methodology

5.1. Data

We examined political tweets, which were published on Twitter's public message board for a period of one week from March 21 to 27, 2011, prior to the two *Landtag* (state parliament) elections in the populous states *Baden-Württemberg* and *Rheinland-Pfalz* in Germany. Both elections took place on March 27, 2011. We systematically collected all tweets that contained the names of either the five most important German parties (*CDU, SPD, FDP, B90/Die Grünen,* and *Die Linke*) or the front-runners of these parties in both elections, yielding a total number of about 108,000 tweets. We consolidated our data set by ruling out redundant or irrelevant tweets (e.g., advertising tweets) as well as tweets in other languages than German. More importantly, to avoid confusion, tweets that contained multiple party or candidate mentionings were also excluded from the analysis. As a result, we obtained a final sample of 64,431 tweets in total for our analyses.

5.2. Tweet Sentiment

We used the Linguistic Inquiry and Word Count (LIWC) software [29] to objectively and systematically analyze tweets for various linguistic traits, in particular emotional components of text samples using a psychometrically validated internal dictionary. LIWC is a text-analysis software program that places words from a text file into categories based on a series of built-in dictionaries. These dictionaries have over 4,500 words and word stems containing a total of 80 categories into which words may fit. These categories include descriptive dimensions (e.g., total number of words in text), linguistic dimensions (e.g., words in text that are pronouns or verbs), dimensions of psychological constructs (e.g., affect words, cognition words), dimensions of personal concerns (e.g., leisure, work), paralinguistic dimensions (e.g., fillers, assent), and punctuation. LIWC has been widely used for academic purposes in psychology and linguistics but also for topics related to political science and communication studies (e.g., [41; 18]. Further, LIWC-based analyses have also been conducted to examine shorter text samples such as instant message conversations or Twitter messages (e.g., [36]; for a comprehensive overview of related studies, see [35]).

For our analysis, we used the LIWC category "affective processes", including the subcategories "positive emotions" and "negative emotions" to profile sentiment in political tweets. These categories have either been successfully used in previous studies of political text samples or seemed best suited to profile messages in the political domain by covering emotions. We concatenated all tweets published over the relevant time frame into one text sample to be evaluated by LIWC. Since our sample consists of only German-language tweets, we processed our data by using the LIWC German dictionary. The accuracy and robustness of LIWC analysis for German-language text samples have been positively assessed by other studies such as Wolf et al. [39]. However, as our analysis deals with Twitter, where the use of short forms, acronyms and emoticons is prevalent, we performed the following steps to additionally ensure the validity of the measurement of sentiment. First, we added to the LIWC standard dictionaries a custom list of short forms and acronyms that might indicate sentiment as well as another list of emoticons. Second, we addressed the issue of potential ambiguity when classifying tweets according to the prevailing sentiment. For example, a tweet might contain both positive- and negative-emotion words, or a positive message might be retweeted but a negative tone might be added to it. In such cases, two independent coders were employed to manually identify the overall sentiment. Inter-coder reliability constituted 0.95 (p-value < 0.000) suggesting a high level of agreement between the coders.

5.3. Analysis Method

To examine whether articulated sentiment in political tweets, in particular those directly associated with a certain political party or politician, has an effect on their retweetability, we built a predictive retweet model focusing on tweet sentiment as a factor that might impact the retweetability. Following Suh et al. [33], we included further factors (as control variables) representing content and contextual features such as the inclusion of hashtags or URLs, users' number of followers as well as age of users' accounts. This led us to construct the following variables for each tweet:

- The number of times the tweet has been retweeted: RT
- LIWC categories:
  - Number of words indicating affective processes in the tweet: AFFECT
  - Number of words indicating positive emotions in the tweet: POSEMO (as subcategory of affective processes)
  - Number of words indicating negative emotions in the tweet: NEGEMO (as subcategory of affective processes)

Studies have shown that there are a number of other factors that also have an impact on retweet behaviour on Twitter such as whether a tweet contains hashtags, URLs or users' number of followers (e.g., [33]). Therefore, we also include the following variables as controls:

- Dummy (binary) variable for whether or not a hashtag was included in the tweet: HASH
- Dummy (binary) variable for whether or not a URL was included in the tweet: URL
- Users' number of followers: FOLLOWER
- Age of users' accounts (in days): ACCOUNTAGE

We applied regression techniques to examine whether tweet sentiment has an effect on how often a tweet has been retweeted. As the dependent variable RT represents true-event count data, i.e., non-negative and integer-based, we employed a Poisson regression model [7]. Poisson regression relies on a log-transformation of the dependent variables and requires an antilog-transformation of the coefficients of each predictor in the regression model to interpret the odds ratio, which is used to assess the effect size. The resulting regression models are as follows:

$$(1)\ \log(E(RT|*)) = \beta_0 + \beta_1 X + \beta_2 HASH + \beta_3 URL + \beta_4 FOLLOWER + \beta_5 ACCOUNTAGE + \varepsilon,$$

where E(RT|*) is the conditional expectation of RT, and X denotes each of the sentiment-related variables such as AFFECT, POSEMO, and NEGEMO.

6. Empirical Results

6.1. Twitter Use for Political Communication

Table 1 shows the distribution of different formats of communication on Twitter for our sample. About 16 percent of all tweets in the total sample contain an @-sign, which is in line with previous research that has also suggested that the vast majority of @-signs are used to direct a tweet to a specific addressee [16]. Note that retweets which also contain an @-sign are excluded from this statistic. A more conservative measure of direct communication is direct messages from one user to another starting with an @-sign. About eight percent of the messages in our sample are direct messages, indicating that people not only use Twitter to post their opinions but also engage in interactive discussions. The share of retweets is relatively high with roughly 33 percent. In addition, more than half of the tweets contain a link to a website. These numbers indicate that people tend to share political information (e.g., political news) with their network of followers. About 23 percent of all tweets are so-called singletons, which represent ordinary tweets without an @-sign [23].

Table 1. Formats of communication

Format	**# Tweets (%)**
Mention	7,174 (16.66%)
Direct Message	5,148 (8.00%)
Retweet	21,350 (33.14%)
URL	33,850 (52.54%)
Singleton	14,537 (22.56%)
Total	*64,431*
Note that the numbers might not add up to exactly 100% as a tweet can be of different formats at the same time (e.g., a retweet can also contain a URL).	

Regarding RQ1, the categorization of users according to their Twitter activity is illustrated in Table 2. It shows that political discussion on Twitter is led by a few highly active users ("very heavy" users) who represent only about one percent of all users but account for almost 30 percent of all posted tweets. This is consistent with findings by Jansen and Koop [20] and Tumasjan et al. [36] who also found a large inequality of participation in political communication on Twitter.

Descriptive statistics for the total sample are presented in Table 3. On average, one tweet in our sample was retweeted 0.43 times. The average number of words per tweet reflecting affective dimensions is 0.52 while those indicating positive and negative emotions are 0.19 and 0.33, respectively. For the purpose of comparison, a tweet contains 140 characters at the most, which is equivalent to roughly 20 words. In our sample, a user has 403 followers on average and the age of his or her account is roughly more than one-and-a-half years (576 days).

Table 2. Distribution of user activity

User group	# Users (%)	# Tweets (%)
One-time (1)	8,155 (55.70%)	8,155 (12.66%)
Light (2-5)	4,443 (30.35%)	12,512 (19.36%)
Medium (6-20)	1,554 (10.61%)	15,363 (23.84%)
Heavy (21-50)	340 (2.32%)	10,143 (15.74%)
Very heavy (50+)	149 (1.02%)	18,258 (28.34%)
Total	*14,641 (100%)*	*64,431 (100%)*

Table 3. Descriptive statistics

Variable	Mean	SD
RT	0.43	2.07
AFFECT	0.52	0.77
POSEMO	0.19	0.46
NEGEMO	0.33	0.61
FOLLOWER	403	221
ACCOUNTAGE	576	341

Table 4 outlines the ten most active Twitter users in our sample led by “landtagswahl”, a retweeter of political news, particularly those associated with state parliament elections in Germany. Interestingly, most of the top-10 accounts belong to users who were identified as leftists or activists according to profile descriptions or contents of their postings. For example, “AntiStuttgart21” is an account that mobilizes people to oppose a highly controversial large infrastructure project called “Stuttgart 21”, initiated by the state government in Baden-Württemberg, to rebuild the main train station in the city of Stuttgart. This corroborates the general impression that political discussion in Germany tends to be left-leaning or more dominated by government-critical actors.

Table 4. Top 10 most active accounts

Username	Background	# Tweets
landtagswahl	political retweeter	637
KRABAT44	private person/leftist	610
_hdb	private person/leftist	465
AntiStuttgart21	private person/activist	404
DK2GA	private person	404
wahlenrt	political retweeter	377
p0litix	blogger	372
regimekritiker	private person/leftist	359
Klangerzeuger	blogger/activist	329
dabohne	private person	326

Looking at the most retweeted users in our sample (see Table 5) also reveals that the most influential users are leftists, activists or bloggers whose postings tend to be spread more in the network. As a preliminary step, for each user we calculated the average quantity of words indicating linguistic dimensions, including affective processes and the subcategories positive and negative emotions. We found that AFFECT (0.68) as well as POSEMO (0.29) and NEGEMO (0.39) are, on average, significantly higher than the total-sample means (see Table 3). This implies that besides other factors, linguistic properties reflecting sentiment in Twitter messages might indeed have a significant impact on the influence of users, i.e., the retweetability of their messages. In the next subsection, we will empirically verify this potential relationship by conducting regression analysis for our entire data sample.

Table 5. Top 10 most retweeted accounts

Username	Back-ground	# Retwets	AFFECT (avg.)	POSEMO (avg.)	NEGEMO (avg.)
p0litix	blogger	384	0.69	0.30	0.40
_hdb	leftist	373	0.68	0.29	0.39
KRABAT44	leftist	223	0.68	0.28	0.40
Backnang	blogger	178	0.82	0.37	0.45
piratenpartei	polit. party	168	0.50	0.20	0.30
Mutbuerger	activist	164	0.64	0.26	0.38
giwit1	leftist	125	1.04	0.36	0.64
DirekteAktion	blogger	118	0.53	0.25	0.28
GLiAdM	news poster	118	0.63	0.29	0.34
die_linke_bw	polit. party	110	0.60	0.39	0.30
		Mean	*0.68*	*0.29*	*0.39*

6.2. Regression Analysis

In H1, we hypothesize that the more words indicating affective processes a Twitter message contains, the more often it will be retweeted. Results of the Poisson regression (see Table 6, Model (1)) show that messages featuring more words associated with affective processes indeed tend to trigger more retweets (H1 supported). The coefficient of AFFECT (b = 0.05) is positive and statistically significant at the five-percent level ($p < 0.05$). The magnitude of the effects of the independent variables on the dependent one can be inferred from the coefficients. As Poisson regression was applied, the interpretation requires an antilog (i.e., exponential) transformation of the coefficients to interpret the odds ratio. For example, the coefficient of AFFECT of 0.05 means that a one-unit change in occurrence of affective-processes words will, on average, trigger about one more retweet (exp(0.05)=1.05).

As a robustness check, we also take a look at the potential effects of positive and negative emotions as subcategories of affective processes. We expect a positive relationship between the quantity of positive- and negative-emotion words in a tweet and its retweetability, respectively. In fact, we also find support for our predictions as the coefficients of POSEMO and NEGEMO are each positive and statistically significant (b = 0.04, $p < 0.10$, see Table 6, Model (2); b = 0.06, $p < 0.05$, see Table 6, Model (3)). This implies that tweets containing more positive-emotion or negative-emotion words also tend to induce more retweets.

Comparing the estimates of POSEMO and NEGEMO reveals that the estimate of NEGEMO has a slightly larger effect size, i.e., tweets with negative sentiment tend to induce slightly more retweets on average. In all three models, control variables (HASH, URL, FOLLOWER and ACCOUNTAGE) are each significantly positively related to the quantity of retweets, which is in line with findings from the literature (e.g., [33]). It should be noted that the effect sizes of sentiment-related variables are relatively small compared to those indicating content features such as hashtag inclusion or URL posting. This indicates that although sentiment might be a factor behind retweetability, hashtags and links to further information remain the main drivers of the dissemination of tweets. Overall, all p-values corresponding to $\chi 2$-statistics are below 0.01, implying that our model and corresponding specifications are well-fitted.

Table 6. Poisson regression output

	Dependent Variable: RT		
Independent Variable	**(1)**	**(2)**	**(3)**
AFFECT	0.05**		
POSEMO		0.04*	
NEGEMO			0.06**
HASH	0.83***	0.82***	0.82***
URL	0.27*	0.26*	0.26*
FOLLOWER	$5x10^{-4}$***	$4x10^{-4}$***	$4x10^{-4}$***
ACCOUNTAGE	$9x10^{-4}$***	$9x10^{-4}$***	$9x10^{-4}$***
$p > \chi^2$	0.001	0.001	0.001
Pseudo-R^2	0.22	0.21	0.21

, ** and * indicate significance level at 10%, 5% and 1%, respectively, with robust standard errors. Note that this data set includes 43,081 observations of tweets (where retweets are excluded) which contain either the name of a politician or that of a party.*

7. Conclusion

Given the growing relevance of social media, in particular Twitter, in political communication, we have addressed two research questions in this paper. In RQ1, we asked how political discussion takes place on Twitter and if there are actors who are particularly influential. As we have shown, an interactive and intensive discussion on Twitter related to the investigated elections could be identified. The large shares of retweets and direct messages within the discussion support this conclusion. Furthermore, we found out that only a few actors published the major share of all tweets in our sample. In addition, those actors received a high number of retweets and therefore seem to be strongly influential for the whole communication process we observed.

Regarding RQ2, we asked whether affective dimensions of politically relevant Twitter messages have an impact on the quantity of retweets that might be triggered (i.e., retweetability). To address this research question, we investigated the relationship between sentiment in political Twitter messages associated with certain political parties or politicians and their retweetability. We found that tweets containing words that reflect affective processes tend to be retweeted more often than those, which do not contain such words. More specifically, both positive and negative emotions articulated in tweets make them more likely to spread through the Twitter network. This way, not only information but also sentiment in political context could be disseminated, which might influence the political opinion-making process.

In our study, leftists seemed to stimulate the discussion by being actors who are highly retweeted. This was also in line with the election results. As an implication, it is important for politicians and political parties to identify the most influential users and follow the discussions, including sentiment occurring among their peers, particularly during periods of election campaigns. To attain this, political parties and politicians might follow the approach of social media intelligence, which has been widely used in the corporate context to systematically monitor and analyze user-generated contents in social media for specific purposes.

A limitation is that our study relies on a data sample, which is restricted to regional political events raising issues of generalizability (e.g., are our findings also applicable to other political events in other countries?). However, given that Twitter is widely used for political communication around the world [9] - not only in developed democratic countries but also in countries under less democratic regimes with Iran, Egypt, Syria etc. as recent examples - the problem of generalizability might not be that severe. Nevertheless, as future work we aim at extending our study to a larger scale (e.g., longer time periods of data collection, other countries and languages) and more general contexts, i.e., we will not limit our investigation only to political events such as elections.

8. References

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