5-15-2012

IMPACT AND DIFFUSION OF SENTIMENT IN PUBLIC COMMUNICATION ON FACEBOOK

Stefan Stieglitz
University of Münster

Linh Dang-Xuan
University of Münster

IMPACT AND DIFFUSION OF SENTIMENT IN PUBLIC COMMUNICATION ON FACEBOOK

Stieglitz, Stefan, University of Münster, Leonardo-Campus 11, 48149 Münster, Germany, stefan.stieglitz@uni-muenster.de

Dang-Xuan, Linh, University of Münster, Leonardo-Campus 11, 48149 Münster, Germany, linh.dang-xuan@uni-muenster.de

Abstract

In recent years, political parties and politicians have begun to use public Facebook "pages" not only for the purpose of self-presentation but also to aim at entering into direct dialogues with citizens and enabling political discussions. Not only the owner of the page but also any people who are politically interested can create politically relevant postings on the "Wall" of the page. These "Wall posts" often exhibit sentiment associated with certain political topics, political parties or politicians. In this paper, we seek to examine whether sentiment occurring in Wall posts on public political Facebook pages has an effect on feedback in terms of the quantity of triggered comments. Based on a data set of 5,626 Wall posts from Facebook pages of German political parties and politicians, we find different significant relationships between the quantity of words indicating positive and negative emotions in a Wall post and the number of its corresponding comments. Furthermore, our results show that positive as well as negative emotions might diffuse in the subsequent comments.

Keywords: social media, Facebook, sentiment, political discussion.

1 Introduction

Recently, more than 800 million people worldwide were members of the Facebook network (Facebook, 2011). Twitter also counts more than 200 million accounts in total (HuffPost Tech, 2011). This mainstream adoption of social-media applications has changed the physics of information diffusion. Until a few years ago, the major barrier for someone who wanted a piece of information to spread through a community was the cost of the technical infrastructure required to reach a large number of people. Today, with widespread access to the Internet, this bottleneck has largely been removed. In this context, personal publishing modalities such as social network sites (SNS), microblogging and weblogs have become prevalent (Kaplan and Haenlein, 2010). The growing relevance of communication in social media implies a fundamental change in traditional public communication, which has usually been exclusively initiated and managed by specific actors, e.g., politicians, companies as well as journalists (Chadwick, 2006).

This phenomenon is currently observed by numerous disciplines such as sociology, information communication studies, information systems, political science, and linguistics. Among other fields of interest, it is a common goal to better understand modes of communication such as agenda-setting or opinion-making in social media.

In recent years, political parties and politicians have used public Facebook pages not only for the purpose of self-presentation but also to aim at entering into direct dialogues with citizens and enabling political discussions. Not only the owner of the public page but also any people who are politically interested can create politically relevant postings on the Wall of the page ("Wall posts"). These posts often exhibit sentiment (moods) associated with certain political topics, political parties or politicians.

In this study, we seek to find out (a) whether politically relevant contributions or postings containing affective dimensions would receive more feedback in terms of comments, and (b) whether emotional states or sentiment might spread or diffuse in social media-based discussions. To address these questions, we focus on discussions that take place on public Facebook pages of large political parties and prominent politicians. Facebook seems to be suitable for our analysis because of its very large number of users and that, in contrast to Twitter, no limitations exist regarding the length of posts. Furthermore, it can be assumed that serious political discussions and interaction could take place on public Facebook pages as these are quite comparable to regular discussion forums. In addition, given the controversial nature of politics, we are able to capture postings or discussions, which are characterized by controversy and emotionality.

The remainder of this paper is organized as follows. In the next section, we provide an overview of related work with a focus on Facebook and political discussions. We then discuss some theoretical foundations and present our research questions and hypotheses. Section 4 outlines our methodology regarding sentiment and regression analyses. In section 5, we present and discuss our empirical results. Finally, the paper ends with a conclusion and an outlook for further research.

2 Related Work

Social media play an important role in shaping political debates in the U.S. and around the world (e.g., Benkler, 2006; Bennett, 2003; Farrel and Drezner, 2008; Sunstein, 2002; Tumasjan et al., 2010). Kaplan and Haenlein (2010) define social media as "a group of internet-based applications that build on the ideological and technological foundations of Web 2.0 that allow the creation and exchange of user-generated content (UGC)". The potentials of social media such as SNS, blogs, microblogging and wikis appear to be most promising in political context as social media can be an enabler for more participation and democracy. Creighton (2005) defines public participation as the process by which public concerns, needs and values are incorporated into governmental and corporate decision making.

The so-called “e-participation” focuses not only on this process but also on using the Internet as an additional or exclusive instrument to create dialogues between the elected and the electorate. Related to this, Karpf (2009) introduces the notion of “Politics 2.0,” which can be understood as the harnessing of the Internet’s lowered transaction costs and its condition of information abundance, toward the goal of building more participatory, interactive political institutions.

There is a growing body of research focusing on the role of Web 2.0 technologies in political election campaigns. The recent U.S. presidential campaign in 2008 has shown that Web 2.0 has become an important tool for political communication and persuasion (Wattal et al., 2010). It became obvious, that particularly SNS could be successfully adapted to contact and discuss with voters as well as to disseminate important information to them. Especially young people were inspired to political topics by using social media as the communication platform (Chen, 2009; Kushin and Kitchener, 2009). Wattal et al. (2010) investigate the contingent impact of related Web 2.0 technologies on the campaign process. Their results show that in particular the blogosphere can influence the campaign process and the election outcomes. They also argue that Information Systems (IS) as a discipline has an important role to play in understanding “e-politics.”

Analyzing publicly available content on SNS such as Facebook has become an increasingly popular method for studying socio-political issues. Such public-contributed content, primarily available as Wall posts and corresponding comments on Facebook pages or Facebook groups, let people express their opinions and sentiments on a given topic, news or persons, while allowing social and political scientists to conduct analyses of political discourse.

Recently, previous studies have specifically focused on SNS and their use in the political context. Williams and Gulati (2007, 2009) investigate the extent of Facebook use by Congressional candidates during election campaigns. They find that the number of Facebook supporters can be considered a valid indicator of electoral success. In the context of the 2006 Dutch elections, Utz (2009) shows that SNS provide an opportunity to reach individuals less interested in politics. Thereby, viewing a candidate’s profile further strengthens existing attitudes. On the other hand, politicians who react on the comments of users are perceived more favourable. Kushin and Kitchener (2009) explore the use of Facebook for online political discussion. Their results indicate that Facebook is a legitimate location for discussion of political issues and, to some extent, the discussion appears to have succeeded in overcoming polarization of online discussion that has pervaded online political discussion in the past.

3 Theoretical Foundation

Previous studies have dealt with the role of sentiment in online communication. It has been shown that affective information could be effectively transferred through computer-mediated communication (Harris and Paradice, 2007). Results from previous studies of social media, discussion forums, online news portals or in other contexts indicate that affective dimensions of messages (both positive and negative emotions) could trigger more attention, cognitive involvement (e.g., Smith and Petty, 1996), feedback (e.g., Huffaker, 2010; Dang-Xuan and Stieglitz, 2012), participation (e.g., Joyce and Kraut, 2006), and social transmission and sharing behavior (e.g., Berger and Milkman 2012, Stieglitz and Dang-Xuan, 2012). Further, studies have shown that not only behaviors and ideas but also emotions might spread through different kinds of social networks in various contexts (e.g., Bono and Ilies, 2006; Huffaker, 2010; Dang-Xuan and Stieglitz, 2012), which is referred to as emotional contagion (Hatfield et al., 1994). However, until now little is understood about whether the diffusion of emotions as well as the generation of feedback or participation by emotions also applies to the communication on Facebook. Given the nature of political controversy, sentiment associated with certain political topics, political parties or politicians might play an important role in political communication. In particular, the dissemination of such sentiment might have an impact on political opinion-making processes. To our knowledge, however, there are no studies that have explicitly examined the potential impact of sentiment on the political communication on Facebook. This motivates us to address the following research questions:

RQ1: Is there a relationship between affective dimensions of Wall posts on public Facebook pages of political parties or politicians and the quantity of feedback in terms of triggered comments?

RQ2: Does diffusion of sentiment take place in political discussions on public Facebook pages?

3.1 Affective Dimensions of Wall Posts and Feedback

Previous works have laid some theoretical foundations regarding *RQ1*. For example, Smith and Petty (1996) demonstrate that positive as well as negative framing of a message could create attention and cognitive involvement, particularly when the framing is unexpected for the recipient of the message. In a large-scale study of discussion forums, Huffaker (2010) shows 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. Similarly, in a study of political weblogs, Dang-Xuan and Stieglitz (2012) find that blog entries with either more positive or more negative overall sentiment tend to receive significantly more comments compared to sentiment-neutral or mixed-sentiment entries. A study of newsgroups by Joyce and Kraut (2006) also reveals that positive affect in messages reinforces a sense of community and encourages continued participation, whereas negative affect can result in feedback through hostile and insulting interactions. Drawing on these findings from prior research, we derive the following hypotheses:

H1a: The more words indicating positive emotions a Wall post on a Facebook page of a political party or politician contains, the more comments it will trigger.

H1b: The more words indicating negative emotions a Wall post on a Facebook page of a political party or politician contains, the more comments it will trigger.

3.2 Sentiment Diffusion

Studies have shown that not only behaviors and ideas but also emotions might spread through different kinds of social networks in various contexts, which is related to the theory of emotional contagion (Hatfield et al., 1994) - a subfield of the social contagion theory (Levy and Nail, 1993). For example, it has been shown that both positive and negative moods can be “infectious” during workplace interactions (e.g., Barsade, 2002), in negotiations (e.g., van Kleef et al., 2004), or in leadership situations (e.g., Bono and Ilies, 2006). Regarding online communication, Huffaker (2010) provides evidence for the concept of sentiment diffusion in discussion forums in the way that messages containing positive (negative) emotions and words are likely to receive verbal responses, which also express positive (negative) emotions. Similarly, articulated sentiment (positive and negative) in weblog postings might also diffuse in the corresponding subsequent comments (e.g., Dang-Xuan and Stieglitz, 2012). Furthermore, studies have also found out that emotionally-charged content is more likely to be shared by online users (e.g., Berger and Milkman 2012, Stieglitz and Dang-Xuan, 2012). All of these findings lead us to conjecture a diffusion of sentiment in political discussions on public Facebook pages. More specifically, we derive the following hypotheses:

H2a: The more words indicating positive emotions a Wall post on a Facebook page of a political party or politician contains, the more positive-emotions words will also occur in the subsequent comments.

H2b: The more words indicating negative emotions a Wall post on a Facebook page of a political party or politician contains, the more negative-emotions words will also occur in the subsequent comments.

4 Methodology

4.1 Data Collection

We developed a Java-based crawler, which uses a Facebook API ("Graph API") to quickly and efficiently collect data from nine different public Facebook pages. For a six-month period from March 21 to September 20, 2011, we tracked all Wall posts and corresponding comments from the public Facebook pages of the seven most important German parties (*CDU, CSU, SPD, FDP, B90/Die Grünen, Die Linke,* and *Piratenpartei*) as well as the German chancellor *Angela Merkel* and the German president *Christian Wulff*.

In total, 5,626 Wall posts from 1,789 users including 36,397 corresponding comments by 10,438 users were obtained. The quantities of Wall posts published on each page in six months are quite equal averaging around 625. Note that we excluded all Wall postings featuring only photographs or videos without any textual content from the analysis. Also, we dropped a number of mixed-emotional posts in order to avoid any potential ambiguity when classifying sentiment. We will address this issue in more detail in the following subsection.

4.2 Analysis Methods

4.2.1 Sentiment Analysis

We used the German version of the Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al., 2006) to objectively and systematically analyze Wall posts 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., Huffaker, 2010; Yu et al., 2008). Its lexicon was designed to analyze diverse genres of text such as emails, speeches, poems or transcribed daily speech. Further, LIWC-based analyses have also been conducted to examine shorter text samples such as instant or Twitter messages (e.g., Golder and Macy, 2011; Tumasjan et al., 2010; for a comprehensive overview of related studies, see Tausczik and Pennebaker, 2010).

In our study, we used the LIWC categories "positive emotions" and "negative emotions" to profile sentiment in Wall posts. While "positive emotions" contains sub-categories such as "positive feelings" and "optimism," "negative emotions" is, among others, related to the sub-categories "anxiety," "anger" and "sadness." These (sub-)categories were created using emotion rating scales and thesauruses and validated by independent judges. Moreover, 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. Since our sample consists of only German-language postings, 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. (2008). However, as our analysis deals with Wall posts, where the use of short forms, acronyms and emoticons is not unusual, 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 in case that a post might contain both positive- and negative-emotion words. Also, there is another problem related to the negation of adjectives (e.g., *"I am **not** that happy!")*. In such cases, two independent coders were employed to manually identify the overall sentiment. Inter-coder reliability (Cohen's *kappa* coefficient) constituted 0.95 ($p < 0.00$) suggesting a high level of agreement between the coders (Landis and Koch, 1977). However, there still might be real mixed-emotional posts, i.e., posts that contain both positive and negative content. For example, a political post of that nature might be like this: *"We love helping people out but hate spending money."* We decided to drop such mixed-emotional posts in order to avoid any potential ambiguity.

To get a feel for Wall posts featuring emotions associated with political topics, political parties or politicians, we provide the following illustrative examples, which were translated from German into English. Words that account for the classification of positive and negative emotions are highlighted and additionally indicated by the succeeding signs "+" and "-", respectively.

- Positive emotions:
  - ***Happy*** **(+)** *5th birthday, Pirate Party! Stay on target and full speed ahead!*
  - *The election today is a* **victory** **(+)** *for freedom!* ***Nice!*** **(+)** *Hurraaaaaaaa! **;-)*** **(+)**
- Negative emotions:
  - *I am somehow* ***disappointed*** **(-)** *that this party does not have the guts to meet challenges and answer tough questions.*
  - *You guys just* ***screwed*** **(-)** *it up!*

4.2.2 Regression Analysis

To test *H1a* and *H1b*, we constructed the following variables:

- number of comments: *COMMENTS*
- number of LIWC words indicating positive emotions occurring in the Wall post: *POSEMO*
- number of LIWC words indicating negative emotions occurring in the Wall post: *NEGEMO*

Further, we included word count of a Wall post as a control variable. Previous research has shown that frequent or longer messages should generate more conversation (e.g., Huffaker, 2010). Similarly, research shows that language assertiveness or powerful language affects the perception of the source (Huffaker, 2010). Powerful language is defined by its lack of powerless cues such as the use of hedges (e.g., *"sort of"*, *"maybe"*), tag questions (*"isn't it?"*), hesitations (e.g., *"um"*) or fragmented sentences. Most findings suggest that powerful language is more persuasive or influential than powerless language (Huffaker, 2010), i.e., language assertiveness has a positive effect on triggering replies. Hence, we introduced an LIWC measure of language assertiveness/certainty (category "certainty") as another control variable.

We also included an indicator for whether or not a URL was included in the Wall post. It has been shown that the inclusion of hyperlinks might have an impact on feedback. For example, Twitter messages with URL are significantly more retweeted (Suh et al., 2010). In addition, another dummy variable is used to indicate whether the Wall post was contributed by the owner of the page herself. Due to the nature of being the owner of the page, such postings are expected to receive significantly more comments than Wall posts by other users. Finally, we controlled for posting activity of individual authors as posting frequency might spark more dialogs and discussions (Huffaker, 2010):

- word count: *WC*
- number of LIWC words indicating language assertiveness/certainty: *ASSERT*
- indicator (binary variable) for whether or not a URL was included in the post: *URL*
- indicator (binary variable) for whether or not the author of the post is also the owner of the page: *OWNER*
- total number of posts and comments the author of the post have contributed: *ACTIVE*

To test *H2a* and *H2b*, we included LIWC measures of affective dimensions (positive and negative emotions) with regard to corresponding comments of each Wall post. Since each post can trigger multiple comments, we calculated the average numbers of LIWC words for each category over all comments. Note that since not every Wall post has received a positive number of comments (i.e., no comments to be processed by LIWC at all), the sample is reduced to 3,234 Wall posts each of which has triggered at least one comment. The resulting variables are:

- average number of LIWC words indicating positive emotions occurring in the corresponding comments: *COMPOSEMO*
- average number of LIWC words indicating negative emotions occurring in the corresponding comments: *COMNEGEMO*

We seek to investigate the relationships between sentiment occurring in Wall posts and the quantity of triggered feedback as well as the diffusion of such sentiment through the corresponding comments. Therefore, we applied regression techniques to test our hypotheses. In *H1*, we hypothesize a positive correlation between the affective dimensions of Wall posts in terms of (a) positive and (b) negative emotions, respectively, and the number of comments triggered. As the dependent variable *COMMENTS* represents true-event count data, i.e., non-negative and integer-based, the Poisson regression model, at the first glance, is recommended for this particular data distribution (Cameron and Trivedi, 1998). However, as the standard deviation (and hence the variance) of the dependent variable (*COMMENTS*) is larger than its mean (see Table 1), the analysis needs to be adjusted for over-dispersion (Cameron and Trivedi, 1998). Therefore, we applied the negative binomial regression model assuming the dependent variable to follow the negative binomial distribution. Negative binomial regression relies on a log-transformation of the conditional expectation of the dependent variable and requires an antilog (i.e., exponential) transformation of the estimated coefficients for the assessment and interpretation of the effect sizes. The resulting regression model is as follows:

$$(1)\ log(E(COMMENTS|*)) = \beta_0 + \beta_1 X + \beta_2 ASSERT + \beta_3 log(WC) + \beta_4 URL + \beta_5 OWNER + \beta_6 log(ACTIVE) + \varepsilon,$$

where $E(COMMENTS|*)$ is the conditional expectation of *COMMENTS*, and *X* denotes each of the sentiment-related variables such as *POSEMO* and *NEGEMO*. Note that we log-transformed WC (word count) and *ACTIVE* (total number of posts and comments the author of the post have contributed) to make our results depend less on outliers.

In *H2*, we expect that the more words indicating (a) positive and (b) negative emotions, respectively, a Wall post contains, the more positive-emotions and negative-emotions words, respectively, will also occur in subsequent comments. Since the dependent variables *COMPOSEMO* and *COMNEGEMO* are average quantities of words indicating sentiment occurring in corresponding comments and thus not true count data, we applied regression analysis using Ordinary Least Square (OLS) estimation to test *H2a* and *H2b*. To account for potential non-normality of the dependent variables, we log-transformed the dependent variables before employing OLS regression. The regression model is as follows:

$$(2)\ log(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 ASSERT + \beta_4 log(WC) + \beta_5 URL + \beta_6 OWNER + \beta_7 log(ACTIVE) + \varepsilon,$$

where *Y* denotes *COMPOSEMO* and *COMNEGEMO*, X_1 *POSEMO* and *NEGEMO*, and X_2 each of the variables for counter-valence emotions *NEGEMO* and *POSEMO*, respectively. Otherwise, all other variables on the right-hand side of the equation remain the same as in equation (1).

5 Empirical Results and Discussion

Descriptive statistics for each variable of interest are shown in Table 1. On average, a Wall post received about six comments. However, the standard deviation is high with 12.80 and about 32% of all Wall posts did not get any feedback at all. Users, who are not the owners of the pages, contributed the majority of those posts. About one half of all posts (51%) were contributed by owners of the pages themselves. Each user has contributed, on average, about seven Wall posts during the sample period.

The average numbers of words reflecting positive and negative emotions in a Wall post are 0.73 and 0.30, respectively, whereas each comment, on average, contains 0.87 words indicating positive and 0.45 words indicating negative emotions, respectively. These figures show a significant difference between positive and negative affect occurring in Wall posts with about twice as many positive-emotions words as negative-emotions ones on average. This indicates that Wall posts might to a large extent be contributed by page owners or "fans", who, by definition, tend to be more well-disposed towards the owner of the page (i.e., political party or politician), which might result in more positive affect associated with the corresponding party or politician. As another linguistic measure, the average number of words reflecting language assertiveness is 0.27. Furthermore, one out of four posts contain a URL while each post has an average length of 22 words. Finally, results of correlation analysis of all relevant measures suggested no multicollinearity concerns for the following regression analyses.

Variable	**Mean**	**SD**
Dependent Variables		
COMMENTS	6.47	12.80
COMPOSEMO	0.87	0.82
COMNEGEMO	0.45	0.62
Independent Variables		
POSEMO	0.73	1.15
NEGEMO	0.30	0.75
WC	22.40	24.41
ASSERT	0.27	0.67
URL	0.25	0.44
OWNER	0.51	0.50
ACTIVE	7.15	44.61

Table 1. Descriptive Statistics

5.1 Affective Dimensions of Wall Posts and Feedback

In *H1*, we hypothesize a positive correlation between the quantities of words reflecting affective dimensions of Wall posts in terms of (a) positive and (b) negative emotions, respectively, and the number of comments triggered. Results of the negative binomial regression (see Table 2) indicate that Wall posts featuring more words associated with negative emotions indeed tend to trigger *more* comments (***H1b*** **supported**), as the coefficient of *NEGEMO* is positive (b = 0.15, $p < 0.05$) and statistically significant at five-percent level (see *Negative-Affect Model*). However, we find **no support for *H1a*** by our analysis. Rather, against our expectation, the coefficient of *POSEMO* is even significantly negative (b = -0.06, $p < 0.01$) suggesting that posts containing more positive-emotions words tend to receive *less* feedback in terms of comments (see *Positive-Affect Model*). One possible explanation for this finding is that posts which articulate a positive sentiment might receive more 'likes' (another kind of giving feedback on Facebook) where people might opt to simply 'like' those posts, rather than making the effort to codify a verbal response. In that sense, 'likes' would, to a certain extent, absorb comments in response to posts which articulate a positive sentiment. Another possible reason is that people might tend to participate more in discussions about politically relevant problems, issues or concerns along with negative affect associated with political parties or politicians.

In each model, control variables such as word count, URL inclusion and owner indicator are each significantly correlated with the number of comments triggered. First, lengthier posts (i.e., higher word count) tend to receive more comments. Also, postings by the owners of the pages themselves triggered much more comments than those by other users on average. However, the negative sign of the coefficient of *URL* suggests that posts with a URL tend to induce fewer comments.

	Dependent Variable: *COMMENTS*			
	Positive-Affect Model		**Negative-Affect Model**	
Independent Variables	***b***	**exp(*b*)**	***b***	**exp(*b*)**
POSEMO	-0.06*** (0.02)	0.94		
NEGEMO			0.15** (0.03)	1.16
ASSERT	0.05 (0.03)	1.05	-0.01 (0.03)	0.99
WC (log)	0.27*** (0.03)	1.31	0.23*** (0.03)	1.26
URL	-0.54*** (0.05)	0.58	-0.55*** (0.05)	0.58
OWNER	2.77*** (0.08)	15.96	2.80*** (0.08)	16.44
ACTIVE (log)	0.02 (0.02)	1.02	0.02 (0.02)	1.02
Intercept	-1.06*** (0.08)	0.35	-1.01*** (0.08)	0.36
$p > \chi^2$	0.0000		0.0000	
Pseudo-R^2	0.21		0.21	

Note that *b* denotes the estimated coefficients, estimated standard errors are in parentheses, and exp(*b*) represents the exponential transformation of the corresponding estimated coefficients. Furthermore, *, ** and *** indicate significance level at 10%, 5% and 1%, respectively. The data set includes 5,626 observations (i.e., Wall posts).
As negative binomial regression was applied, the interpretation of the estimated coefficients requires an antilog (i.e., exponential) transformation of these coefficients. For example, the coefficient of POSEMO (NEGEMO) of -0.06 (0.15) means that a one-unit change in occurrence of positive (negative) emotions words will, on average, trigger about 6% (16%) less (more) comments while holding all other variables in the model constant, since exp(-0.06) = 0.94; exp(0.15) = 1.16.

Table 2. Negative Binomial Regression Output

5.2 Sentiment Diffusion

Results of the OLS regression predicting the average quantities of words reflecting different sentiments in comments to Wall posts are shown in Table 3. *H2a* predicts that the more words indicating positive emotions a Wall post contains, the more positive-emotions words will also occur in subsequent comments. We find **support for *H2a*** as the coefficient of *POSEMO* is positive and significant at one-percent level (b = 0.04, $p < 0.01$, see *COMPOSEMO* model) implying that Wall posts which articulate positive emotions tend to trigger comments that feature positive-emotions words as well. We also include *NEGEMO* to examine the effect of counter-valence emotion as our previously discussed theoretical background would also imply that *NEGEMO* should be a negative predictor of *COMPOSEMO*. Indeed, the coefficient of *NEGEMO* is negative and significant (b = -0.02, $p < 0.1$). Among control variables, word count, URL inclusion and poster's activity are correlated with the average quantities of words reflecting positive emotions in comments to Wall posts.

According to *H2b*, we conjecture that the more words indicating negative emotions a Wall post contains, the more negative-emotions words will also occur in subsequent comments. ***H2b* is supported** by our data as the coefficient of *NEGEMO* is positive and significant at one-percent level (b = 0.17, $p < 0.01$, see *COMNEGEMO* model). This suggests that Wall posts which exhibit negative emotions tend to trigger comments that feature negative-emotions words as well. We again examine the effect of counter-valence emotion by including *POSEMO* while expecting that *POSEMO* should be a negative predictor of *COMNEGEMO*. The coefficient of *POSEMO* indeed turns out to be negative and significant (b = -0.04, $p < 0.1$). This finding, along with the result from the *COMPOSEMO* model discussed above (*NEGEMO* is found to be a negative predictor of *COMPOSEMO*), suggests a diffusion of sentiment in a valence-consistent way. This means that Wall posts containing positive (negative) emotions are likely to receive comments which also express positive (negative) emotions. Almost no control variables have a significant impact on the dependent variables, except *OWNER* and *ACTIVE*. Results imply that page owners' postings tend to trigger comments that feature less negative sentiment (b = -0.24, $p < 0.01$).

	Dependent Variables	
	COMPOSEMO	***COMNEGEMO***
Independent Variables	***b***	***b***
POSEMO	0.04*** (0.01)	-0.04* (0.02)
NEGEMO	-0.02* (0.02)	0.17*** (0.03)
ASSERT	0.01 (0.02)	-0.03 (0.03)
WC (log)	0.07*** (0.02)	0.03 (0.03)
URL	-0.08** (0.03)	0.06 (0.04)
OWNER	0.04 (0.06)	-0.24*** (0.08)
ACTIVE	-0.03** (0.01)	-0.04** (0.02)
Intercept	-0.24*** (0.07)	-0.47*** (0.09)
$p > F$	0.0000	0.0000
Adjusted R^2	0.12	0.12
Note that *b* denotes the estimated coefficients, estimated robust standard errors are in parentheses. Furthermore, *, ** and *** indicate significance level at 10%, 5% and 1%, respectively. The data set includes 3,234 observations (i.e., Wall posts).		

Table 3. OLS Regression Output

To illustrate how people may follow the emotion of the original post, we provide the following (translated) example of a Wall post and three corresponding comments associated with negative affect:

- *Liberalism is burned at the stake in Germany. It is* ***sad*** **(-)** *that the FDP set itself on fire!*
  - *So* ***bitter!*** **(-)** *What made me* ***upset*** **(-)** *is that the neo-Nazis are now twice as strong as the FDP in Mecklenburg-Vorpommern. It's time to ask why so?*
  - *However, it is even more urgent to ask how the established parties can accept the fact that only half of the people go to the polls and just do nothing about that. It's* ***frightening!*** **(-)** *It's a declaration of* ***bankruptcy*** **(-)** *of democracy!*
  - *What a* ***shame*** **(-)** *to be outpaced by those Nazis!*

6 Conclusion

In recent years, political parties and politicians have used public Facebook pages not only for the purpose of self-presentation but also to aim at entering into direct dialogues with citizens and enabling political discussions. Our study showed that political discussions could indeed take place on Facebook pages, particularly when the owners of the pages (i.e., political parties or politicians themselves) make a posting containing a certain topic on the Wall of their own pages. Their postings tend to trigger much more feedback in terms of comments from their audience (e.g., "fans" or other Facebook users) than those posted by other users.

The main contribution of our paper is to examine the role of sentiment in political communication on Facebook as a social media platform. To our knowledge, we are the first to do so. We were able to confirm the impact of emotions on how political discussions take place on Facebook. More specifically, in *RQ1*, we asked whether sentiment occurring in Wall posts on public Facebook pages of political parties or politicians is associated with the feedback which might be triggered. To address this research question, we investigated the relationship between affective dimensions in terms of positive as well as negative emotions and the quantity of feedback in terms of comments. We found that while negative emotions articulated in Wall posts make them more likely to receive more comments, the opposite is true for posts featuring positive emotions. This finding suggests that, on public political Facebook pages, people might tend to participate more in discussions about politically relevant problems, issues or concerns along with negative affect associated with political parties or politicians.

We took a further step in *RQ2* and wanted to know whether sentiment articulated in Wall posts are likely to be picked up by the subsequent feedback. Our results indicated that positive as well as negative emotions might diffuse in the following discussion. This way, not only information but also sentiment in political context could be disseminated, which, to a certain extent, might influence political opinion-making processes. Therefore, our work implies that it is important for politicians and political parties to identify influential users and follow the discussions including sentiment occurring within their peers, particularly during periods of election campaigns. For that, political parties and politicians might follow the approach of social media monitoring, which has more widely been used in the corporate context.

It is a limitation of our study that political Facebook pages such as those we have analyzed in this study might be exposed to potential "curation" of content where posts or comments that have contrasting views to those of the page owner may be removed. The practice of such censorship might have an impact on our results. However, we believe that politicians or political parties are aware of potential bad reputation or image damage, which might be caused by such actions. As a consequence, content curation would rather be unlikely to happen, except in case of so-called "vandalism" postings. Another limitation is that we do not have more data on user level such as user demographics or user's number of Facebook friends. Furthermore, our study relies on a data sample, which is restricted to Facebook pages of German political parties and politicians. 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 communication.

References

Barsade, S.G. (2002). The ripple effect: emotional contagion and its influence on group behavior. Administrative Science Quarterly, 47, 644-675.

Benkler, Y. (2006). The Wealth of Networks: How Social Production Transforms Markets and Freedom. Yale University Press.

Bennett, L. (2003). New media power: The Internet and global activism. In N. Couldry and J. Curran (Eds.), Contesting media power: Alternative media in a networked world, Rowman & Littlefield.

Berger, J. and Milkman, K. (2012). What Makes Online Content Viral?. Journal of Marketing Research, forthcoming.

Bono, J.E. and Ilies, R. (2006). Charisma, positive emotions and mood contagion. Leadership Quarterly, 17, 317-334.

Cameron, A. and P. Trivedi (1998). Regression analysis of count data. Cambridge University Press.

Chadwick, A. (2006). Internet Politics: States, Citizens, and New Communications Technologies. Oxford University Press, New York.

Chen, H. (2009). AI, E-government, and Politics 2.0. IEEE Intelligent Systems, 24 (5), 64-67.

Creighton, J.L. (2005). The Public Participation Handbook: Making Better Decisions Through Citizen Involvement. Jossey-Bass, San Francisco.

Dang-Xuan, L. and S. Stieglitz (2012). Impact and Diffusion of Sentiment in Political Communication - An Empirical Analysis of Political Weblogs. In Proceedings of ICWSM-12.

Facebook (2011). Facebook Official Statistics. http://www.facebook.com/press/info.php?statistics.

Farrell, H. and Drezner, D. (2008). The power and politics of blogs. Public Choice, 134 (1), 15-30.

Golder, S.A. and Macy, M.W. (2011). Diurnal and Seasonal Mood Vary with Work, Sleep, and Daylength Across Diverse Cultures. Science, 333 (6051), 1878-1881.
Harris, R.B. and Paradice, D. (2007). An investigation of the computer-mediated communication of emotion. Journal of Applied Sciences Research, 3, 2081-2090.
Hatfield, E., Cacioppo, J. and R.L. Rapson (1994). Emotional contagion. Cambridge University Press.
Huffaker, D. (2010). Dimensions of Leadership and Social Influence in Online Communities. Human Communication Research, 36 (4), 593-617.
HuffPost Tech (2011). Twitter: We Now Have Over 200 Million Accounts (UPDATE) http://www.huffingtonpost.com/2011/04/28/twitter-number-of-users_n_855177.html.
Joyce, E. and Kraut, R. (2006). Predicting continued participation in newsgroups. Journal of Computer-mediated Communication, 11 (3), 723-747.
Karpf, D. (2009). Blogosphere Research: A Mixed-Methods Approach to Rapidly Changing Systems. IEEE Intelligent Systems, 24 (5), 67-70.
Kaplan, A.M. and Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. Business Horizons, 53 (1), 59-68.
Kushin, M. and Kitchener, K. (2009). Getting political on social network sites: Exploring online political discourse on Facebook. First Monday, 14 (11).
Landis, J.R. and Koch, G.G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33, 159-174.
Levy, D.A. and Nail, P.R. (1993). Contagion: A Theoretical and Empirical Review and Reconceptualization. Genetic, Social and General Psychology Monographs, 119 (2), 235-284.
Pennebaker, J.W., Booth, R.J. and M.E. Francis (2006). Linguistic inquiry and word count: LIWC. Erlbaum, Austin, TX, USA.
Smith, S.M. and Petty, R.E. (1996). Message framing and persuasion: A message processing analysis. Personality and Social Psychology Bulletin, 22 (3), 257-268.
Stieglitz, S. and L. Dang-Xuan (2012). Political Communication and Influence through Microblogging - An Empirical Analysis of Sentiment in Twitter Messages and Retweet Behavior. In Proceedings of HICSS-45, 3500-3509.
Suh, B., Hong, L., Pirolli, P., and E. Chi (2010). Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network. In Proceedings of IEEE SocialCom 2011.
Sunstein, C. (2002). The law of group polarization. Journal of Political Philosophy, 10 (2), 175-195.
Tausczik, Y.R., and Pennebaker, J.W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. Journal of Language and Social Psychology, 29, 24-54.
Tumasjan, A., Sprenger, T., Sandner, P. and Welpe, L. (2010). Election forecasts with Twitter: how 140 characters reflect the political landscape. Social Science Computer Review, Advance online.
Utz, S. (2009). The (Potential) Benefits of Campaigning via Social Network Sites. Journal of Computer-mediated Communication, 14, 221-243.
van Kleef, G.A., De Dreu, C.K.W. and Manstead, A. (2004). The interpersonal effects of anger and happiness in negotiations. Journal of Personality and Social Psychology, 86, 57-76.
Wattal, S., Schuff, D., Mandviwalla, M. and Williams, C. (2010). Web 2.0 and Politics: The 2008 U.S. Presidential Election and an E-Politics research agenda. MIS Quarterly, 34 (4).
Williams, C. and G. Gulati (2007). Social networks in political campaigns: Facebook and the 2006 Midterm elections. Presented at the Annual Meeting of the American Political Science Association 2007.
Williams, C. and G. Gulati (2009). Facebook grows up: An empirical assessment of its role in the 2008 congressional elections. Presented at the Annual Meeting of the Midwest Political Science Association 2009.
Wolf, M., Horn, A., Mehl, M., Haug, S., Pennebaker, J.W. and Kordy, H. (2008). Computergestützte quantitative Textanalyse: Äquivalenz und Robustheit der deutschen Version des Linguistic Inquiry and Word Count. Diagnostica, 2, 85-98.
Yu, B., Kaufmann, S. and D. Diermeier (2008). Exploring the characteristics of opinion expressions for political opinion classification. In Proceedings of dg.o 2008, 82-91.