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Communication power struggles on social media: A case study of the 2011–12 Russian protests

Viktoria Spaiser , Thomas Chadeaux , Karsten Donnay , Fabian Russmann, and Dirk Helbing 

ABSTRACT

In 2011–2012 Russia experienced a wave of mass protests surrounding the Duma and presidential elections. The protests, however, faded shortly after the second election. We study the Russian political discourse on Twitter during this period and the main actors involved: the pro-government camp, the opposition, and the general public. We analyze around 700,000 Twitter messages and investigate the social networks of the most active Twitter users. Our analysis shows that pro-government users employed a variety of communication strategies to shift the political discourse and marginalize oppositional voices on Twitter. This demonstrates how authorities can disempower regime critics and successfully manipulate public opinion on social media.

KEYWORDS

Communication power; natural language processing; political discourse; protest; Russia; social media; Twitter


Social media has played an increasing role in domestic and international politics, in particular in the context of social movements, demonstrations, and protests (Howard & Parks, 2012). The Arab Spring, for example, is often referred to as the “Twitter Revolution,” in that social media contributed to the political debate and the dissemination of the movements’ message across the world, and helped participants coordinate and share information (Cottle, 2011; Howard et al., 2011; Lotan et al., 2011; Tufekci & Wilson, 2012). What sets these new media apart from more traditional media is that they enable private citizens to communicate on a large scale and in real time and may therefore especially benefit oppositional actors without strong institutional support and backing by traditional media outlets (Diamond, 2010; Lynch, 2011; Shirky, 2011). In autocracies in particular, social media is often perceived as a means by which the disenfranchised can express their discontent, given that they are considered to be one of the few uncensored public spaces in which reliable information sharing and free political communication can take place. In other words, social media is often perceived as liberative.

Yet much less attention has been paid to the idea that social media may also be used as an

instrument of oppression. As a tool that allows actors to widely disseminate information, it may not be that different from traditional media such as TV or radio, which have long been recognized as potential instruments of control and coercion (Enikolopov, Petrova, & Zhuravskaya, 2011; Herman, 1985; Silitski, 2005; Thompson, 2007). Governments—not only opposition movements—can use these technologies to their advantage to spread their message, influence audiences, and change the perception of those who might be tempted to challenge their legitimacy. Indeed, oppositional challenges not only need to emerge, but also to remain strong and united over time. Social media can help in achieving that goal, as the Arab Spring made clear (Cottle, 2011; Howard et al., 2011; Lotan et al., 2011; Tufekci & Wilson, 2012). But at the same time, social media can also be used by the governing elite against the opposition, through defamation, discrediting, and counter-mobilization. In this study, we focus on political communication strategies that Russian pro-government and oppositional groups used to advance their causes, mobilize their supporters, and discredit their opponents on Twitter. We in particular investigate whether and how the pro-government camp employed a variety of communication

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strategies to shift the political discourse, marginalize oppositional voices, and successfully manipulate public opinion on Twitter.

Social media, and Twitter in particular, played a prominent role during the two Russian elections—the Duma (lower legislative house of the Russian Federation parliament) elections of December 4, 2011, and the presidential elections of March 4, 2012—as well as the protests that took place during that period (Greene, 2013). People tweeted election results from their local polling stations; posted links to videos and pictures documenting electoral fraud and arrests of prominent oppositional figures such as Alexey Navalny (see Supplementary Information S4 for explanations of terms and names); and linked information about upcoming and past protest events. Twitter was particularly important because many prominent oppositional Web sites were taken down or hacked during and after the elections of December 2011 (Roberts & Etling, 2011). This left Twitter as one of the few platforms that was not targeted by Distributed Denial of Service attacks, although oppositional hashtags were flooded with pro-regime spam (Kelly et al., 2012; Krebs, 2011).

Twitter is certainly just a part of a larger media system that intersects with the wider political system (Chadwick, 2013). Indeed, it would go beyond the scope of this paper to try to take into account the full Russian media ecology (see Becker, 2004; Lipman, 2005; and Arutunyan, 2009 for further information on the Russian media system). Yet, analyzing Twitter communication as an important part of the larger media system is not only relevant for understanding political discourse in social media but also provides insights for the broader Russian political communication context. Digital social spheres, such as the “Twittersphere,” mirror real-world events and traditional media discourses, and hence can serve as a basis for studying the communication and interaction mechanisms between different political fractions and the wider media discourse—especially when information would otherwise be unavailable.

For social science research the popularity of social media for political communication and discourse is extremely useful, as it creates new

opportunities to analyze real-time social network and political opinion formation on a large scale (Conover et al., 2011b; Tumasjan, Sprenger, Sander, & Welpe, 2010). Here, we examine the discourse in the Russian Twittersphere during the two Russian elections and mass protests in 2011–2012 by analyzing nearly 700,000 public tweets. The fine-grained data on political discourse and affiliations over time collected from Twitter provide a unique and powerful case study for political communication on social media channels. The vast amount of text provided by Twitter was analyzed with a new mixed-method approach for dynamic discourse analysis, combining methods of statistical natural language processing with context- and theory-based interpretation and social network analysis. We rely on n-grams to systematically analyze communication strategies used by both the pro-government and oppositional camp. Using a sentiment-based classification procedure we then identify pro-Putin and oppositional Twitter users/tweets. This allows us to study both the social networks of the political camps on Twitter and to follow the evolution of the political discourse within each camp over time to uncover their respective communication strategies.

Our analysis shows that an active pro-Putin campaign between the two elections decisively contributed to changing the momentum of the discourse on Twitter with the initially large and strong political opposition rapidly losing control of the discourse by the time of the March 2012 presidential elections. Our results thus cast doubt on the assertion that traditional powers are necessarily disadvantaged in an increasingly networked and digitalized society. As governments use these new technologies as means for mobilization of their supporters and repression of oppositional voices, the balance of power on social media need not necessarily favor the opposition. In fact, our results suggest that the pro-Putin camp was very successful in regaining control over a means of communication that initially seemed particularly favorable to the opposition. These results confirm recent, more critical analyses of social media in autocratic regimes, which show that autocratic governments have increasingly adopted strategies of proactively subverting and

co-opting social media for pro-regime purposes (Gunitsky, 2015; Rød & Weidmann, 2015).

Mobilization, perceptions and the success of political movements

Mass collective actions such as protests or rebellions take place when the discontented population sees a window of opportunity. Activism typically originates from a small number of radicals, then extends to a wider circle of motivated individuals, before spreading through the rest of the population (Tilly, 1978). The process can be understood as a series of crossed thresholds. First the radicals mobilize. So-far inactive individuals with a higher threshold for mobilization observe them and also mobilize as a result. In turn, their mobilization reaches a threshold sufficient to engage others who are motivated by the size of the existing movement, and so on and so forth. Models by Granovetter (1978) and Schelling (1978) formalized this intuition, later extended by Kuran (1989), Gould (1993), Lohmann (1994), and Siegel (2009). Individual radical instigators sometimes succeed in starting a “prairie fire” (Kuran, 1989), which progressively leads others with more conservative risk preferences to follow suit.

Whether a cascade occurs, therefore, critically depends on beliefs about the probability of success, and hence about existing levels of mobilization. Without knowledge that the radicals have mobilized, the wider circle would not mobilize by itself. And the general population needs to be informed that a wide number of individuals have already joined. This sequence is critical and explains why demonstration leaders often overstate their numbers, whereas governments seek to downplay them. Crossing certain mobilization thresholds—and making it clear that these thresholds have been crossed—is essential to further recruitment and hence to the ultimate success of the movement.

Affecting the perception of the turnout level is therefore essential. Information on the mobilization level is usually gathered from the media. Yet, in authoritarian regimes such as Russia, where the media is highly controlled by the government (Arutunyan, 2009; Becker, 2004; Lipman, 2005), people have learned not to rely on that

information. A growing alternative source of information is social media. People in social media belong to a network and learn about the popularity of the movement from the network nodes they are connected to: friends, colleagues, peers, persons of interest, and public figures but also institutions and established and alternative media who have social media accounts.

Because the perception of a political movement’s success is key for a sustained and expanding mobilization, the government’s and opposition’s ability to shape that perception on social media such as Twitter can be of great importance in determining the course of events. Here we show that both sides strategically used different political communication strategies on Twitter. Our analysis suggests that, in particular, the Russian government successfully used Twitter to affect perceptions of the oppositional movement’s success and legitimacy.

Effectively challenging an opposition movement is a critical prerequisite to preventing any revolutionary spark from starting a “prairie fire,” or at least to prevent any further expansion and/or consolidation of the movement. By shifting the perceived balance of popular support and legitimacy toward the government and away from the opposition movement, the central government can shape the perception of success and legitimacy, and hence affect mobilization levels. Indeed, if the balance of power and popular support is seen to be favoring the government, then only those with a relatively high level of political conviction and commitment will mobilize. In turn, this can start a downward cascade until only the most radical elements are mobilized. In short, affecting the *perception* of the movement’s success can lead to an endogenously generated effect. In that sense, new media can enhance state capacity.

How mass communication technology (TV, radio, newspaper, Internet) can strengthen the state’s capacity to disseminate political messages and as a result prevent large-scale oppositional mobilization has been shown by Warren (2014) and Weidmann, Benitez-Baleato, Hunziker, Glatz, and Dimitropoulos (2016). Whoever controls the media and more generally the diffusion of information also influences opinions and contributes to setting political agendas. Our paper contributes to this line of work in two

ways. First, we focus on social media (e.g., Twitter) and analyze to what extent they may contribute to strengthening the state's ability to affect public perceptions. New Internet-based media have significantly affected traditional communication mechanisms (Bennett & Segerberg, 2013; Chadwick, 2013). In particular, social media such as Facebook and Twitter have the ability to quickly distribute information, enabling communication on a large scale and in real time, potentially sparking information cascades and the diffusing and scaling up of local protests. Therefore, social media increasingly become platforms and channels for both government and opposition campaigns (Lynch, 2011; Rød & Weidmann, 2015). Our data—who “tweets” what and when—allow us to study the actions and reactions of all parties over time and in response to one another, with great accuracy. This enables us to track attempts to affect popular perceptions and their relative success.

Second, Warren (2014) argues that his findings about the centralized systems of mass communication may not apply to “the Internet, cell phones, and other forms of ‘social’ media, which instead facilitate decentralized horizontal connections between individuals” (Warren, 2014, p. 136). Though this proposition has been challenged very recently by Weidmann et al. (2016), much of the interest in policymaking circles and in academia has been in the potentially liberating effect of these new forms of decentralized communication. In contrast, our analysis illustrates the ability of governments to harness these technologies. While embracing decentralization they at the same time attempt, at least to some extent, to centralize those new media activities supporting the state.

In particular, the government may manipulate social media in a number of ways to influence the perception of an oppositional movement's dynamics and probability of success, which are critical for the movement's evolution, promoting downward spirals in mobilizations. Castells (2007, 2009) distinguishes four main ways in which Internet communication can act on people's minds and thus be used as a strategic tool in struggles for power. First, the Internet facilitates the manipulation of emotions and perceptions (*framing*) (Kramer, Guillory, & Hancock, 2014).

This can include diminishing and discrediting but also exaggerating, enthusing, and claiming broad public support. Indeed, the spread of manipulative information was probably never as rapid and easy as in the age of the Internet (Castells, 2009; Slove, 2007).

Second, the Internet facilitates propaganda campaigns, affecting the way in which individuals evaluate political concepts and ideas but also political figures (*priming*). This can include priming the criteria, agendas and images on which citizens base their political decisions, for instance in elections (Domke, 2001; Druckman, 2004; Roskos-Ewoldsen, Klinger, & Roskos-Ewoldsen, 2011).

Third, social media change the set of people who can contribute to setting the political agenda (*agenda-setting*) and the terms of the debate. This may range from publishing certain information that would otherwise not be revealed or offering counterarguments to the official depiction of certain political events. Social media such as Twitter enable even marginalized political actors to define agendas (Benkler, 2006; Drezner & Farrell, 2004).

Finally, censorship (*indexing*) limits the range of political opinions and agendas (Castells, 2009). Censorship may go as far as cutting all access to communication networks, as witnessed for instance in Egypt (Williams, 2011). Hacking opponents' Web sites and disrupting their communication channels is an even more common means of censorship and was used in Russia during the protest events in the wake of the elections (Roberts & Etling, 2011). Online surveillance may also result in self-censorship, as people lose control over who has access to their online communication or to their private data collected on the Internet (Bitso, Fourie, & Bothma, 2012; Castells, 2009).

Data

Our analysis is based on data from the Twitter Streaming API collected between November 17, 2011, and March 12, 2012.¹ This encompasses two Russian elections: the Duma election of December 4, 2011, and the presidential election of March 4, 2012. The collected tweets were filtered, first for Russian language, and second for political content by using various Russian keywords that broadly refer to political issues, such

as “news,” “protest,” “politics,” or “elections” (see full list of keywords in Supplementary Information S1.2). The subset of Twitter data used in our analysis then comprised 690,297 Russian language tweets with political content.

With the rising attention that social media have received in social and political research as noted in the previous section, social media data and in particular Twitter data has been increasingly used to understand various social and political phenomena (Golder & Macy, 2011; Miller, 2011; Tonkin, Pfeiffer, & Tourte, 2012). Twitter data was for instance used to understand and predict election outcomes (Larsson & Moe, 2011; Tumasjan et al., 2010; Wu, Wong, Deng, & Chang, 2011), political alignment (Conover, Gonçalves, Ratkiewicz, Flammini, & Menczer, 2011a; Hanna, Sayre, Bode, Yang, & Shah, 2011) or shed light on the communication and recruitment strategies of political groups (Conover et al., 2011b; Gaffney, 2010; González-Bailón, Borge-Holthoefer, Rivero, & Moreno, 2011; Ratkiewicz et al., 2011; Yardi & Boyd, 2010).

There is, however, little topic- or region-specific research on the Russian Twittersphere, even though by 2011 Twitter had become an increasingly important means of public communication in Russia (Kelly et al., 2012).² From only about 1,000 Russian Twitter users in 2007, their numbers had soared to over 3.8 million in April 2012 (Oates, 2013).³ Although other popular Russian social media such as Vkontakte (Russian version of Facebook) existed in our period of analysis, they did not exhibit the same publicness in debates and are therefore less suitable for studying public debates.

Any analysis of Twitter data faces a number of well-known difficulties (Ruths & Pfeffer, 2014). First, the sample only includes public tweets from public Twitter accounts. This does not pose a problem in the context of our study, though, because we are interested in the use of Twitter as an instrument of communication in the public sphere. Potentially more problematic is the fact that Twitter has implemented a quality filter that filters out a small amount of tweets if they are considered to be spam or of too low quality. Unfortunately, neither the frequency of this filtering nor its exact criteria are entirely transparent

(see also Supplementary Information S1.1). Despite this filtering practice, inspection of our extracted data revealed that at least 18% of the tweets were ‘spam,’ such as automatically generated advertisements. To minimize biases in our results, we applied an additional filter to detect and remove messages using keywords related to advertisements and spam (see Supplementary Information S1.2). Note that the filtered data—now comprising 601,138 tweets—still contains some spam and advertisements that were not picked up by the filtering algorithm, but with a significantly reduced prevalence (about 5%–7%).

Finally, discourse analysis faces specific difficulties when working with Twitter data. Tweets are short and thus contain only limited information. In fact, because they are limited to 140 characters, users tend to convey only part of the information directly—on average, 19% of all tweets contain links to Web pages with further information (Zarella, 2009). Despite these limitations, the short Twitter messages still allow for political discourse. And how this discourse is framed or what the actors’ overall agendas and aspirations are develops alongside the broader societal discourse. Moreover, even though Twitter users are generally not a representative sample of the overall population, almost all political groups were represented (with their respective supporters) in the Russian Twittersphere in our period of analysis.⁴

Not surprisingly, the amount of political tweets per day in our sample varies strongly—between 2,204 tweets on November 18, 2011, and 12,428 tweets on the day of the presidential election, March 4, 2012 (Median = 5,031; Mean = 5,118, *SD* = 1,504). In fact, the two elections are responsible for the two major peaks in the number of daily political tweets in the time period analyzed. But the relative activity of different factions on Twitter remains comparably stable over time throughout our period of analysis (see Supplementary Information Figure S5). To relate the analysis of tweets to the time line of the protest movement, we also collected detailed information on the election and protest events for the period of time represented in the sample. Data on political events were retrieved from various online sources⁵ and compiled in a political events data set, with information on political event type (e.g., rally,

political action), time, place, involved political groups, size (e.g., number of demonstrators), and repression extent if any (e.g., number of arrests).

Methodology

Twitter data have to date only rarely been used for discourse analysis,⁶ despite Twitter's potentially rich and authentic coverage of the political discourse. In fact, only few studies have analyzed Twitter data beyond word counts or binary sentiment analysis. A notable exception is Wu et al. (2011), who uses a semantic network approach applied to political discourse to understand its social impact on the formation of political attitudes. Sentiment analyses are often criticized for failing to account for the complexity and contextuality of human communication, which would require, for example, taking into account the ambiguity of sentiment terms (Weichselbraun, Gindl, & Scharl, 2010; Wilson, Wiebe, & Hoffmann, 2009). Moreover, Twitter users often communicate their messages through irony, sarcasm, or symbols—communication means that are hard to detect by automated text processing.

In this study, we used two main text-mining techniques: word counts and their temporal evolution (see Supplementary Information Figure S3 and S4), and dynamic “meme” or n-gram analyses based on bi- and trigram collocation (see Supplementary Information S2.1 and Figure S2). We detected collocations of words using the association and scoring function student's *t* test (Manning & Schuetze, 1999; Perkins, 2010). The student's *t* test assesses whether two or three words co-occur more frequently than by chance. The null hypothesis is the absence of association between the two or three words beyond coincidental co-occurrence, that is, that the words are independent, and *p* is the corresponding probability for the nonsystematic co-occurrence of two or three words. The null hypothesis is thus rejected if *p* is very small ($p < 0.01$ or $p < 0.05$). Maximum likelihood estimation was used to compute the likelihood that word A and word B (and word C) co-occur in the analyzed text (see Supplementary Information S2.1 for further details). The student's *t* test statistic was used as a bigram (BAS) or trigram (TAS) association score (Perkins, 2010). These scores reflect the frequency of the collocations. The *t* test is particularly

useful to rank collocations to identify the most dominant collocations in the discourse. Significance testing is less reliable due to the normality assumption of the *t* test, which is violated for natural language (Manning & Schuetze, 1999, p. 156). Generally speaking, the association score should be at least around 2.5, which corresponds to a confidence level of $\alpha = 0.05$ (Manning & Schuetze, 1999, p. 153). Only scores similar or larger than this value were considered for ranking. Association scores in our analysis then ranged from 2.45 to 13.27. Note that trigrams generally have a lower association score within this spectrum.

In order to understand the potentially distinct dynamics underlying the discourse in each of the two main political camps—the opposition camp and the pro-Putin camp—it is first necessary to identify these two camps in our data set. This is a difficult task because we can only rely on what users write given that typically no official affiliation information is available. We therefore proceeded as follows: first, we identified the unique users in our Twitter data based on the value of their “screen_name.” We then used keywords (see full list of keywords in Supplementary Information S2.2) in combination with the sentiment analyzer SentiStrength and scored the tweets of identified users on a scale between -3 and 3 , with negative scores indicating a pro-Putin tweet, positive scores an oppositional tweet, and a 0 score a neutral tweet. We classified users by the average score of all their tweets as either belonging to the pro-Putin or opposition camp by invoking that users would express positive sentiments about terms associated with their own camp and/or negative sentiments toward terms associated with the other camp (see Supplementary Information S2.2 for further details). Thus, the combination of keywords and sentiment analysis allowed us to understand the framing of the keywords used, since the keywords on their own do not indicate a political affiliation. For instance, if the keyword is Putin and it appears with negative sentiment words, we can derive that the user posting this tweet is critical of Putin; if on the other hand it appears with positive sentiment words, then the user is rather likely to be a Putin supporter. Note that we focused on and classified only the 1,000 most active users among the more than 140,000 unique Twitter users in our data. The 1,000 most active users accounted for 51% of all

tweets in our data set, that is, these users were the most influential contributors in the debate. With our focus on the political debate and the communication strategies used to affect popular perceptions, it is sensible to focus on these most active and influential users, who are most likely to affect popular perceptions. On the other hand, the specific focus allows us to investigate the Twitter users involved in the political discourse more closely, that is, to examine who they are and how they are connected with each other.

Classification of users was particularly challenging because the Russian oppositional camp is highly fragmented and the often harsh criticism voiced in tweets is not only directed against Putin and his supporters but also sometimes against other oppositional groups and figures. For this reason the automatic classification may from time to time misclassify Twitter users as pro-Putin because it detects emotionally negative tweets targeted toward the “other” opposition. We therefore extended the classification procedure to include weights and additional “context” information (e.g., retweet information; see Supplementary Information S2.2 for further details). We estimated the quality of this classification method by selecting a sample of 100 users and manually assessing their political orientation based on their user profiles and tweet activities. By comparing this manual categorization with the result of the automatic classification, we found that around 70% of political orientations were classified correctly by our automatic routine. This accuracy level is comparable to classification accuracy achieved by common machine learning text-based classification methods (Bensusan & Kalousis, 2001; Bird, Klein, & Loper, 2009). Note also that the results of our subsequent discourse analyses for the two camps, which reveal clearly pro-Putin and oppositional discourses, further lend credibility to our classification.

To get a better understanding of who the most active users are and how they are connected, we extracted and analyzed their full names and profile descriptions and the timing when they set up their Twitter accounts. Moreover, we studied their social networks based on whom they are following within the 1,000 most active Twitter users.⁷ These

follower network structures, then allowed us to understand the communication flows and thus to what extent messages from certain camps are also noticed by the other political camps. Note that a retweet-based social network would underestimate the links between different political camps given that oppositional Twitter users may for instance follow pro-Putin followers to stay informed about their plans and actions. Yet they are rather unlikely to retweet pro-Putin messages, particularly because the commenting retweet function was not available on Twitter for our period of analysis. Furthermore, the social network analysis reveals who are the most influential Twitter users in the respective camps in terms of the number of their followers and how they are linked to the other Twitter users in their own but also in the other political camps.

Finally, to analyze the political communication strategies used by the different political camps between November 2011 and March 2012, we adopted a qualitative research method approach (Saldana, 2013) and manually coded the main extracted n-grams, that is, those with significantly high association scores, in each camp according to the four communication strategies described in the theory of communication power by Castells (2009): framing, priming, agenda-setting, and indexing (see second section). We used five additional ad hoc codes (Flick, 2006) for n-grams that did not fit in either of the four categories but are important with respect to how the population perceived oppositional mobilization: *fact*, when an n-gram merely reported a fact; *demand*, when an n-gram expressed a political demand such as “fair election”; *self-criticism*, when an n-gram expressed an in-camp criticism; *hijacking*, when a core demand or idea from the adversary political camp was hijacked and misused by a political camp in an n-gram, and *mobilization*, when an n-gram informed about an upcoming or ongoing political action.⁸

Results

We first describe briefly the evolution of the protest movement and discourse following the Duma elections of December 4, 2011, showing its rise and decline in the overall Twitter discourse. We then

analyze the different political camps, their most active and influential members, their social networks, and their respective political discourse to understand how the communication strategies and reactions of each side contributed to the disintegration of the oppositional movement on Twitter shortly after the second elections in March 2012.

Rise and fall of the Russian protest movement on Twitter

The election and protest events in 2011–12 were all mirrored and reflected on Twitter (see Supplementary Information Figure S3 and S4). The December election was officially an overwhelming victory for the governing party, “United Russia.” This victory was reflected in the Russian Twittersphere in the number of mentions of each party and in the number of statements referring to the parties for which people had voted, for instance, “for Jabloko” (liberals) (BAS = 5.08), “for KPRF” (communists) (BAS = 4.65) or “for United Russia” (BAS = 9.24).

The Twittersphere discourse, however, also shows that the Duma elections were generally perceived as having been manipulated. The bigram “fraud elections” (BAS = 6.63) was one of the most common bigrams for the December 4, 2011, discourse. People reported voting against United Russia in an attempt to demonstrate the inaccuracy of the allegedly manipulated official results, and demanded to “cancel elections results” (TAS = 3.51) and to “conduct new elections” (TAS = 4.11). Major protests followed, attended by tens of thousands of Russians on December 6, 10, and 24; on February 26; and on March 5 and 10. Here, Twitter was used as a tool for mobilization. For example, specific protest mobilization hashtags (e.g., #6Dec, #Triumfalnaya) were used to spread information on the timing and location of protests. Furthermore, new prominent oppositional figures emerged during the first days of protest, for example, unaligned oppositional figures such as Alexey Navalny.

The political discourse on Twitter in December 2011 was largely dominated by critical, oppositional voices. Putin was portrayed as a thief of votes (“Putin thief,” BAS = 3.00), and United Russia as a “party (of) thieves” (BAS = 5.14). At

the same time the discourse reflects the euphoria and appeal associated with revolutionary sentiments. Tweets such as the one on December 18, 2011, referring to a “new level (of) evolution (of) Russian political culture” (combined TAS = 3.71, see Supplementary Information S2.1. for explanation of combined TAS and BAS) were posted frequently. A strong identification with the protest movement was shown by statements such as “you are (the) movement” (TAS = 3.97), “Balotnaya (Square) we come” (TAS = 4.78) or “be one white-ribbon” (TAS = 3.54). The largest protest event on December 24, 2011, was accompanied by enthusiastic feelings among supporters of the oppositional movement: “demonstration (was) great, thanks” (TAS = 3.44).

However, support for the protest movement began to weaken on Twitter in January 2012, despite continuing demands for fair elections and worries about the declining Russian democracy (e.g., “end (of) era (of) democratic governing” with combined TAS of 3.04). Sympathy with Putin was now expressed more frequently (e.g., “God save Putin” with a TAS score of 3.58). Moreover, already in the wake of the first oppositional protest, the pro-Putin forces organized rallies supporting Putin and United Russia. Even though these rallies were initially small, attempts to delegitimize them as fake protest events appeared on Twitter immediately (e.g., “The so-called excursion turned out to be an excursion to a rally pro-United Russia,” combined TAS = 2.75).

At the same time and in line with a widening split in the protest movement (Sakwa, 2014), the divisions between various political opposition factions also became visible on Twitter (e.g., “Prokhorov against Ziuganov” TAS = 2.92, or “LDPR gives Ziuganov Stalin mask” combined TAS = 2.52). These internal disputes created the impression of a dissolving opposition incapable of seriously challenging Putin. Increasingly, people began to express their discontent with the opposition, for instance “Our so-called opposition, unsatisfied with elections, (but) nobody resigned” (combined TAS = 2.45).

By the end of January, tweets expressing support for Putin increasingly dominated the political Twittersphere and became more frequent than tweets expressing opposition to Putin (see Figure 1).⁹ In February, an increasing number of

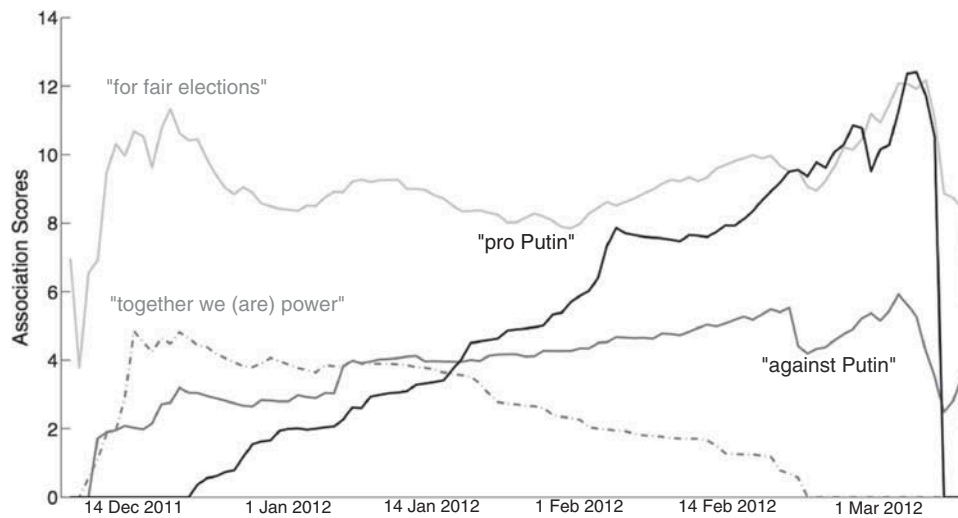


Figure 1. Smoothed trend lines for four important bi- and trigram collocations starting with the Duma elections on December 4, 2011. We controlled for linguistic heterogeneity and found that our estimated scores for the pro-Putin bigram may be even underestimated (see endnote 8).

pro-Putin protest events were organized, yet support for the protest movement on Twitter was still very visible. The new slogan “Putin go home” (BAS = 7.48) was frequently used and statements of reassurance such as “Welcome political spring” (TAS = 3.80) as well as identification statements such as “I took part in the protest event” (combined BAS = 4.69) were tweeted frequently. Moreover, attempts to delegitimize the pro-Putin demonstrations were intensified with users spreading statements such as “How I started (to) love Putin for 500 rubel” (combined TAS = 3.00), suggesting that supporters for the pro-Putin demonstrations were bribed.

At the same time, however, attempts to delegitimize the oppositional protest—the opposition was accused of having been paid and directed by the United States—were also spread on Twitter, as expressed for instance in the statement “We believe Putin, against U.S.’s revolution” (combined TAS = 3.65). The pro-Putin camp instigated popular fear of chaos and revolution, suggesting that only Putin will ensure peace and order. This resonated with an apparently growing feeling of futility and disillusionment on the side of the protest supporters. Protests were even deemed increasingly senseless at a time when the political momentum appeared to have shifted toward the pro-Putin side (e.g., “pointless protest” with BAS = 4.34 on February 26, 2012).

Despite accusations of election irregularities after the presidential election on March 4, 2012, it then seemed indisputable that Putin enjoyed broad support among Russians and the protest movement began to dissolve quickly. This is also visible in the decline in the frequency of protest-related and mobilization keywords on Twitter following the second elections (see Supplementary Information Figure S4). At the same time, the anger of those who had supported the movement turned against the oppositional leaders who were blamed to have failed: “Opposition incompetent, failed to take up people’s discontent” (combined TAS of 2.58 on March 10, 2012).

Power struggle between different political camps on Twitter

The analysis of the overall political discourse on Twitter already suggests that communication power was indeed used to instigate a discursive shift in favor of Putin and to weaken support for the opposition on Twitter. Critical voices were discredited and political elites were represented as legitimate. We now turn to a more specific analysis of each political camp (pro-Putin and opposition) and their discourse. We further contrast these against the unclassified camp in our Twitter data, which may be regarded as the general public. We will in particular focus on the pro-Putin camp’s efforts to affect people’s perception

with respect to the oppositional movement to discourage further mobilization. First, we consider the overall activity patterns in the three camps (pro-Putin, pro Opposition, unclassified). The distributions of tweets per user across the full period covered by our data—overall and in all three camps separately—consistently show relatively similar heavy-tailed signatures (Figure 2). Gray lines mark the best fit of the heavy (or power law) tail of the distribution with 95% confidence intervals. Fits were calculated using maximum likelihood estimation. The corresponding power law exponent α and cutoff x_{\min} at which the tail begins are provided in the figures. This implies two important empirical characteristics of user activity in the Russian Twittersphere: First, the number of very active Twitter users is much larger than one would, for example, expect under the assumption of a normal distribution of tweets per user. Second, there is no typical or mean number of tweets per user. For the full sample of the 1,000 most active users this implies that, although 90%

of users contributed less than about 70 tweets over the full period considered, some users in the remaining 10% contributed over 400 tweets (Figure 2a). Consequently, these 10% most active users account for more than 46% of all tweets.

It is important to emphasize here that among the 1,000 most active users the pro-Putin, opposition, and unclassified camp are not equally represented. In fact, the pro-Putin camp is by far the largest, with 439 of the 1,000 most active Twitter users classified. In comparison, the opposition camp makes up only 285 Twitter users and the unclassified camp 276. This relative difference in the size of the three camps varied little throughout the whole period analyzed and in fact already suggests a communication power disbalance in favor of the pro-Putin camp.

Furthermore, we found that there is a marked statistical difference between the distribution of tweets per user in the pro-Putin camp and both the opposition and unclassified camp: the statistic for the pro-Putin camp visibly deviates from the others in that the heavy-tailed signature only statistically holds

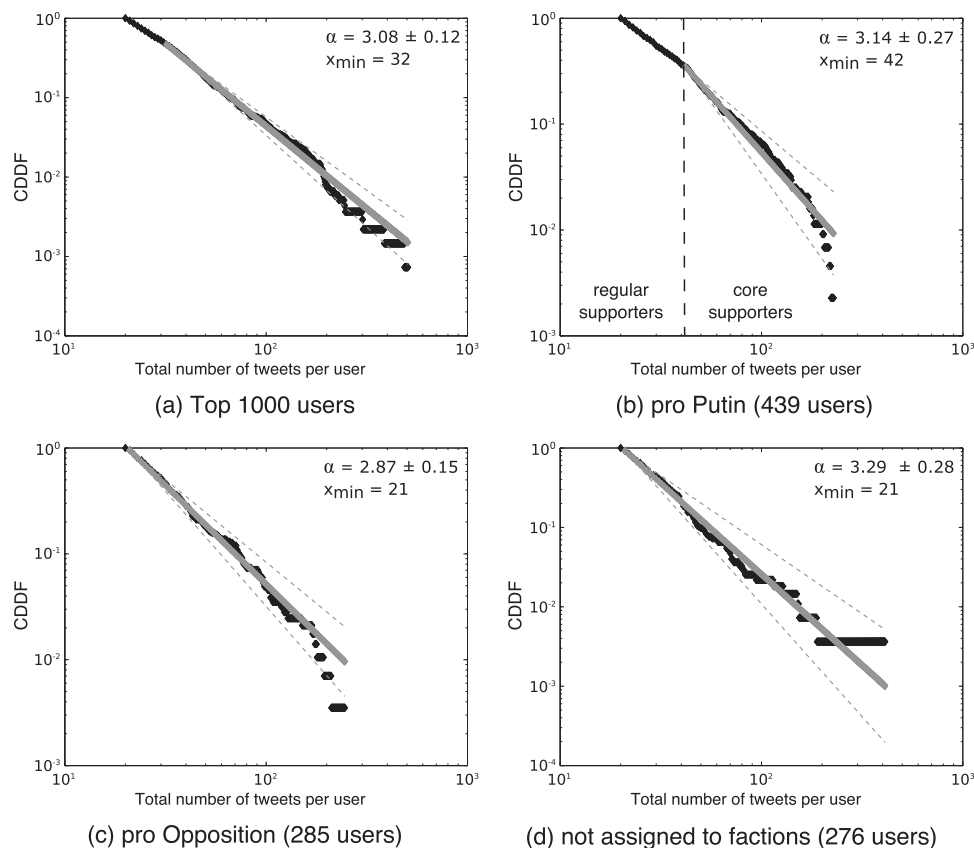


Figure 2. Distribution of tweets per user (a) for the 1,000 most active users, (b) pro-Putin users, (c) pro-Opposition users, and (d) users assigned to neither camp.

true for users with 42 tweets or more. In other words, there is a systematic difference between the activity of very active and less active users in this camp (Figure 2b). In contrast, the distribution of tweets per user follows the same regularity across all levels of individual user activity in the oppositional and unclassified camp (Figure 2c and d). This suggests that there were two distinct subcategories of pro-Putin users: the most active users ($n = 157$) in the tail of the distribution who contributed at least 42 tweets over the full period analyzed, and the remaining less active pro-Putin supporters ($n = 282$). Note that throughout the whole period analyzed the most active users—the core Putin camp—contributed relatively more tweets to the Twitter discourse than any of the other camps, thus effectively dominating the Russian Twittersphere (see also Supplementary Information Figure S5).¹⁰

We can identify a notable effect of the core pro-Putin camp on the political discourse. Figure 3 shows that the “pro-Putin” sentiment is almost exclusively carried by the core pro-Putin camp throughout January. The fact that the share of tweets tweeted by the different camps is comparably stable over time ensures that the effect of the core pro-Putin camp on the bigram “pro-Putin” is not an artifact of activity: the camp indeed began to express pro-Putin sentiment weeks before this was visible in the overall Twitter discourse.

A closer inspection of the core Putin supporters reveals that the camp is dominated by

professional Twitter users, that is, United Russia party, official governmental information outlets, and major pro-governmental media outlets, such as Russia Today (see Table 1).

Through loyal party, institutional, and media officials, the government thus seems to have had the ability to influence the discourse on Twitter more effectively than the opposition. These Twitter users have sufficient resources and leverage for flooding Twitter with dedicated messages. Among the regular Putin supporters there are also media outlets, but not the major ones. Instead, we see more single individuals supporting Putin (see Table 1). These users have lower capabilities (available time, support by a team of operators) to massively spread their views across Twitter.

The most influential Twitter users from the opposition camp on the other hand combine major oppositional media outlets, notably the popular TV Channel RAIN, but also individual activists, journalists, or bloggers. We may assume that their resources are again rather limited compared to the main media and governmental outlets on Twitter. The appearance of Voice of America in the list of most influential oppositional Twitter users shows the strong foreign support of the Russian oppositional movement (see Table 1). Expectedly, the list of most influential unclassified Twitter users contains news and individual accounts that are rather unknown and that do not display a clear political alignment. The fact that major and minor “traditional” media outlets are

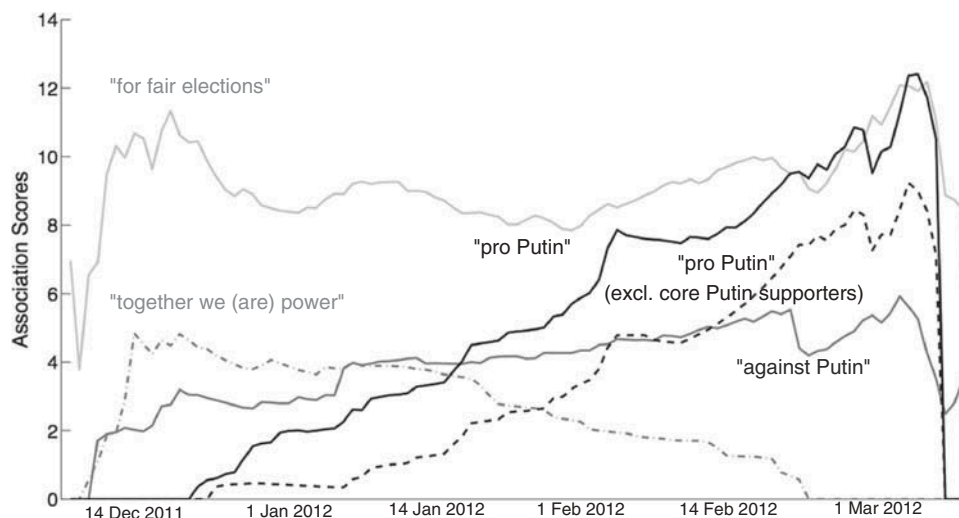


Figure 3. Smoothed trend lines for four important bi- and trigram collocations disaggregating the effect of core Putin supporters on the “pro-Putin” bigram.

Table 1. The most influential Twitter users in each political camp (In-degree shows the number of followers).

User name	Full name	Description	Political camp	In-degree
GazetaRu_Lenta	Chronic of Daily News, gazeta.ru	Own information coverage as well as reports from major Russian and international news agencies (Gazeta.ru is the most popular Russian language news Web site)	Core pro-Putin	135
interfax_news	Interfax	News from Interfax (Interfax is the major Russian news agency)	Core pro-Putin	110
RU_Today	Russia Today	Peace to the World (Russia Today is seen as the main propaganda channel of the Russian government)	Core pro-Putin	109
rgrus	Russian Newspaper	Russian newspaper—outlet of the Russian Federation Government. Published since November 11, 1996. RG and RG.RU publish official documents and operational news	Core pro-Putin	97
radio_kp	Komsomolskaya Pravda	Informative-talkative radio station, 24 hours, format story channel. Radio of real people and nonfiction stories (<i>Komsomolskaya Pravda</i> , used to be the official organ of the Communist Union of Youth, Komsomol; in 1990 it became a daily Russian tabloid.)	Core pro-Putin	96
er_novosti	United Russia	Official Twitter account of the United Russia party	Core pro-Putin	93
topoprf	Tribuna OP	TOP—Public Chamber Tribune—search organizations and persons, news, interviews, blogs, discussions (News Web site)	Core pro-Putin	71
VRSoloviev	Vladimir Soloviev	No description available (journalist on Rossiya 1 TV Channel)	Regular pro-Putin	65
izvestia_ru	Izvestia	Official microblog of the newspaper <i>Izvestia</i> . From news we create insights. (Long-running, high-circulation daily broadsheet newspaper in Russia, previously official Soviet Union government newspaper)	Regular pro-Putin	42
burmatoff	Vladimir Burmatoff	First Deputy Chairman of the Education Committee of the State Duma	Regular pro-Putin	41
ntvru	NTV	Official Twitter account of NTV and NTV.ru site (TV channel, controlled by Gazprom Media)	Regular pro-Putin	34
KFM936	Kommersant FM	Official Twitter account of the radio station Kommersant FM	Regular pro-Putin	24
AdvokatKubany	Victor Mikhaylov	Foundation of legal support for compatriots in the United States. Only proven layers, immigration consultants, notaries	Regular pro-Putin	23
kurginyanRU	Time Will Show	Club “Sut Vremeni” (Time Will Show). This is the Twitter account of the club members. (Russian, left, conservative political movement supporting the Putin government).	Regular pro-Putin	15
tvrain	TV Channel RAIN	The independent Russian TV channel. News RAIN. (Most popular oppositional TV channel in Russia)	Opposition	112
KSHN	Kashin	We have kondopoga, we have khokhloma. Russian journalist and novelist.	Opposition	98
kmrsFM	Kommersant FM 93.6	Non-official Twitter account of Kommersant FM (Oppositional pendant to KFM936).	Opposition	62
lentaruofficial	Lenta.ru	Daily News (Lenta.ru is an online newspaper and the second most popular Russian language news Web site)	Opposition	61
GolosAmeriki	Voice of America	Welcome to the official Twitter community service of the Russian VOA (Voice of America). (Voice of America is the official external broadcast institution of the United States federal government).	Opposition	54
korobkov	Korobkov	No description available (Russian political activist, journalist, and blogger).	Opposition	36
Moscow_advokat	Zemljanskij Nikolaj Polozov	Everything you did not want to know about the Russian justice and feared to hear. Infamous farce. (Pussy Riot lawyer).	Opposition	34
ddb777	Different News	A journalist, not a blogger. This account has no relation to the program “Vesti” and does not reflect the information policy of VGTRK	Unclassified	26
san4izz	Baturin	Medicine, politics, West Caucasus, Middle Volga (blogger)	Unclassified	23
crimerussia	Crime Russia	Notes of organized crime and on shadow and legal economic activities with corrupt links to Russian governing bodies	Unclassified	23
Toporintv	Toporin Aleksander	24/7, Editor-in-Chief (journalist)	Unclassified	22
bicotender	bicotender.ru	Bicotender—search system of tendering and procurement of Russia in CIS. All for success in tendering.	Unclassified	14
b111org	b111org	Service of entertaining blogs	Unclassified	14
arl_spb	Romik(18-)	Patriotism—the last refuge of scoundrel. It's better to be a fool, but smart rather than being a smart fool ... wife@Elisavetatheone	Unclassified	13

among the most influential Twitter users in all camps shows how strongly interlinked social media such as Twitter still are with more traditional media outlets such as TV or newspapers (Chadwick, 2013).

Figure 4 shows the social ties between the most active Twitter users in our data. Additionally, official government accounts such as Medvedev Russia (light violet blue), and central oppositional figures'

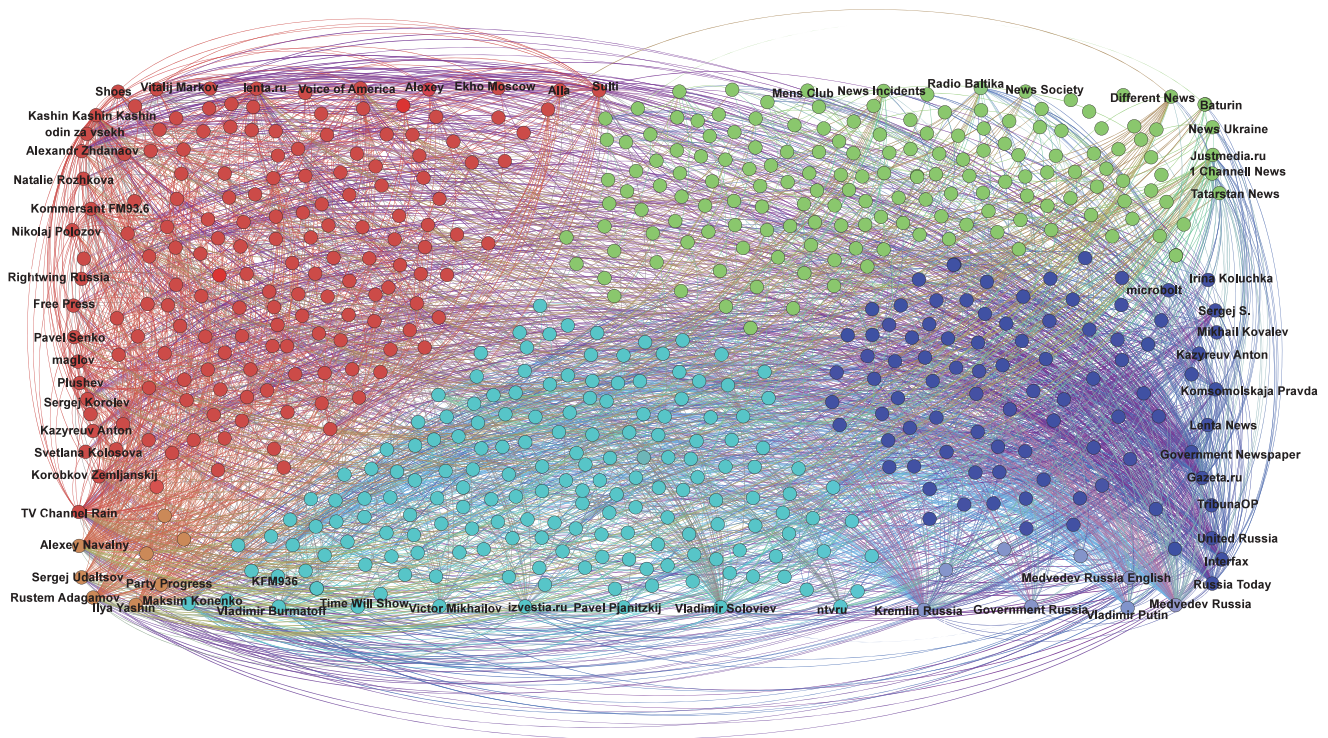


Figure 4. Social network based on whom the respective Twitter users followed. Nodes are Twitter users, directed edges are based on follower relations, thus spanning the whole social network with all political camps and their ties. Red nodes are depicting the oppositional Twitter users, green nodes the unclassified and blue (core) and turquoise (regular) the pro-Putin camp.

Twitter accounts such as Alexey Navalny (orange) were added. Note that these prominent Twitter users were not in the original data among the 1,000 most active Twitter users but were added to show their influence on other Twitter users. Major hubs (nodes with highest in-degree) in each political camp are named. Interestingly, we see that the two main rival political camps, the pro-Putin and the opposition camps, are well interlinked (see also Supplementary Information Figure S6).

We can thus conclude that topics or issues raised by the pro-Putin camp reached the opposition and their supporters and vice versa. And respectively, it is therefore also realistic to assume that any political communication strategy adopted by any of the political camps would have indeed had a direct effect on the respective political opponent. Figure 4 (see subgraphs Supplementary Information Figures S6 and S7) moreover shows that regular Putin supporters are closely following the Twitter users in the core pro-Putin camp. This enabled the core pro-Putin camp to issue targeted political messages that are subsequently taken up, echoed, and further spread by the regular pro-

Putin Twitter users, reinforcing the overall pro-Putin communication (Barberá et al., 2015).

Figure 4 (see also Supplementary Information Figure S7 and S8) shows also that the unclassified Twitter users, which we interpret as the general public, follow the pro-Putin and the oppositional camp. We can thus assume that pro-Putin and oppositional messages reached the general public and could potentially influence perceptions of the general public.

The analysis of the discourses in the different camps (Table 2, see extended Table S1 in Supplementary Information with BAS and TAS scores) shows the various communication strategies employed by the two pro-Putin camps and by the opposition. Table 2 shows the evolution of the political discourse described in the previous section, but additionally highlights how the different political groups contributed to the evolution of this discourse.

Initially, the opposition *set the agenda* by challenging the Duma election results. Table 2 shows that in the beginning the unclassified camp also expressed strong sympathy for the protest movement and similar indignation over election irregularities. Thus, at

Table 2. Time evolution of the discourse based on bi- and trigrams in the three camps, opposition, pro-Putin (core and regular), and unclassified.

Time line	Core pro-Putin	Regular pro-Putin	Opposition	Unclassified
December 4, 2011	For United Russia (framing) KPRF refuses to allocate votes to Jabloko (agenda-setting & framing)	For United Russia (framing) LDPR buys votes with vodka (agenda-setting & framing)	We voted against United Russia (framing) Mafia throws in ballots (agenda setting & framing)	In Moscow journalists observed ballots thrown in (agenda-setting & framing) Duma elections (fact)
December 5, 2011	LDPR considers coalition (agenda-setting & framing) United Russia meets in Moscow (fact)	For United Russia (framing) Putin is better (framing)	Putin's criminal gang totally forged elections (agenda-setting & framing) Dec 5, ChP against forged elections (agenda-setting & mobilization).	People stopped being silent (framing) Demonstrators shouted "freedom," well done (framing)
December 6, 2011	Demonstration Putin supporters (agenda-setting & framing)	Demonstrations split country (framing) Navalny's arrest political mistake (self-criticism)	Dec 6 Triumfalnaya rally for fair elections (agenda-setting & mobilization) Navalny blogger anticorruption project (agenda-setting & priming)	Dec 6 Triumfalanya rally for fair elections (agenda-setting & mobilization) Union of democratic forces (framing)
December 9, 2011	For fair elections (hijacking & demand) Udaltsov released (agenda-setting)	Damned White Ribbon, keep children away (framing) No revolution, thanks (framing)	White Ribbon Snow Revolution (framing) United Opposition demonstration, on Bolotnaya they have to see masses (framing & mobilization)	Honesty best policy (priming) Tomorrow provocation against protesters planned (agenda-setting)
December 10, 2011	Demonstration Medvedev supporters in Moscow (agenda-setting & mobilization)	Our democratic bastards sully our country (framing) You demonstrated, those in power understood (framing)	Dec 10 Demonstration Revolution Square (agenda-setting & mobilization) Shouted "Putin is a thief, against Putin" (framing)	Demonstrations in Moscow (fact) KPRF says illegitimate elections (agenda-setting & framing)
December 23, 2011	Thousand resolute Nashi members (framing) God save Putin (framing)	Modernization supporters, Yes Medvedev Russia (priming) For fair elections (hijacking & demand)	Dec 24 demonstration for fair elections (agenda-setting & mobilization) Revolution creative class, support political reform (framing & priming)	Demonstration for fair elections (fact) Honesty best policy (priming)
December 24, 2011	Burned white ribbon (agenda-setting & framing) Huge Putin portrait launched (agenda-setting & framing)	25,000 demonstrate on Bolotnaya for fair elections (framing) Opposition overstates numbers of protesters (framing)	Multiple tens of thousands people came (framing) Highest level of dignity (framing)	
January 4, 2012	Political action pro-Putin (agenda-setting & framing)	God save Putin (framing)	Udaltsov was arrested (agenda-setting)	
January 18, 2012	Meeting opposition leaders with U.S. ambassador (agenda-setting & framing) Support Russia, support Putin (framing)	Meeting opposition leaders with U.S. ambassador (agenda-setting & framing)	Opposition unsatisfied, but nobody resigned (self-criticism)	
February 4, 2012	Demonstration against fraud elections on Bolotnaya (fact) For fair elections (hijacking & demand)	Demonstration, Navalny promised a million will come (framing) Feb 4 Bolotnaya demonstration bought (framing)	Navalny calls to Bolotnaya Feb 4 (agenda-setting & mobilization) Corrupted idea of first Bolotnaya protest (self-criticism)	Honesty best policy (priming) U.S. happy with Putin, who benefits from protest? (framing)

(Continued)



Table 2. (Continued).

Time line	Core pro-Putin	Regular pro-Putin	Opposition	Unclassified
February 18, 2012	Medvedev Modernization Innovation, support stable progress (priming) Believe Putin, against U.S.'s revolution (framing)	Demonstration in support of Putin (agenda-setting & mobilization) Believe Putin, against U.S.'s revolution (framing)	Whom Putin needs against revolution (agenda-setting & framing) Putin go home (framing)	
February 23, 2012	Demonstration pro-Putin Feb 23 (agenda setting & framing)	Demonstration pro-Putin Feb 23 (agenda setting & framing)	Demonstration pro-Putin not many people, about 1000–2000 (framing)	Zhirinovskii ranting retweet (agenda-setting & framing)
March 4, 2012	FEMEN provocation (framing) Emotional election (framing)	Elections Russian president (fact) Pro-Putin demonstration thousands (agenda-setting & framing)	For Russia's future (framing) We invite to come to Pushkinskaya (mobilization)	Polling station opened (fact) Fake election observers exposed (agenda-setting & framing)
March 5, 2012	On Pushkinskaya they pay money (agenda-setting & framing) World leaders congratulate Putin (framing)	Police bashed people (agenda-setting & framing) Kasparov was welcomed by thousandfold "boo" (framing)	Election observers say correct elections (fact) Demonstration for fair elections (agenda-setting & mobilization)	OMON forces arrested protesters, dissolved demonstration (agenda-setting & framing)
March 6, 2012	Opposition demonstration so far hardly attended (framing) Protest blown away (framing)	Majority voted for Putin (agenda-setting & framing) Political columnist beaten up (agenda-setting)	Press conference of Electoral Association (fact) Home Office, police state (framing)	Overview regions love Putin (agenda-setting) Every damn day demonstrations (framing)
March 9, 2012	Navalny is dead, proclaimed (framing)	Obama congratulates Putin (framing)	Putin insulted Russian people (framing)	And the next protest (framing)
March 10, 2012	Million protesters promised (framing) Nationalists leave opposition demonstration (agenda-setting & framing)	Election results approved (agenda-setting & framing)	Mar 10 demonstration central on Rostov (agenda-setting & mobilization) Thugs are afraid of an orange revolution (framing)	Attempt of nonauthorized demonstration (agenda-setting) Opposition speakers insulted (agenda-setting)

this stage there was a high mobilization potential, particularly since the number of protest participants was growing with each oppositional protest, as highlighted in the opposition's Twitter communication (see Table 2, December 24). In reaction to the strong pro-oppositional momentum in the political discourse, the pro-Putin camp increased its efforts to shift it back in its favor. Putin supporters predominantly used a *framing* communication strategy, belittling (e.g., reporting lower participants numbers; see Table 2, December 24) and delegitimizing the protest movement. A key event here seems to have been the meeting of opposition leaders with the U.S. ambassador on January 18, 2012 (see Table 2). Both pro-Putin camps immediately took advantage of the unique possibility to discredit the oppositional movement as being steered and financed by the United States. The pro-Putin camp went beyond its *framing* strategy in this case and managed to *set an anti-opposition agenda* by revealing the secret meeting and questioning the independence of prominent oppositional leaders.

The two Putin supporter subcamps adopted slightly different *framing* discursive means to delegitimize the opposition and challenge its quantitative (i.e., reporting lower numbers, e.g., Table 2, March 6) and qualitative (i.e., reporting bribed participants, e.g., Table 2, March 5) mobilization success. The core Putin supporters seem to have acted more strategically, reporting alleged facts about discords and splits within the opposition, about the failures of oppositional leaders, and about the decreasing support for the opposition or even firm rejection of the opposition in the population. On the other hand, they continuously stressed the strong support for Putin in the general population. The regular Putin supporters seem to have communicated without a systematic strategy. Their tweets generally appeared to be more spontaneous reactions and more frequently attacked the opposition directly and offensively instead of reporting matter-of-factly (Table 2).

Besides delegitimizing the opposition, the pro-Putin camp seemingly also adopted a *priming* strategy, using Twitter to propagate a political program of stable progress, modernization, and innovation (see Table 2, February 18). The opposition, on the other hand, failed to communicate a political program beyond demands for fair elections. In fact, the demand “for fair elections”

prominently appeared also in the pro-Putin camp (Table 2). This points to a key strategic move by the pro-Putin camp: it appears as if they took over the demand for fair (presidential) elections and presented it as a genuine goal that they themselves were to pursue in the upcoming elections. This *hijacking* communication strategy deprived the opposition of one of its core political demands—a demand that, in fact, formed the basis for the union of different oppositional forces.

Meanwhile, the unclassified camp also underwent changes in its political discourse that are worth noting. After initial support for the opposition, it rather quickly began to lose interest in the political events and discourses: clear support for the oppositional camp was no longer expressed after December 2011, and after the presidential elections the unclassified camp showed even tiredness of the constant political upheaval, apparently preferring a return to normality (see Table 2). The intense discrediting campaign by the pro-Putin camp, which became more and more prominent on Twitter over time, thus seems to have not only contributed to increasing disillusion within the wider protest movement itself (e.g., “Corrupted idea of first Bolotnaya protest” on February 4, 2012, Table 2), but also decisively to the weakening sympathy for the oppositional movement among unaligned Twitter users, thus contributing to a failure of further oppositional mobilization.

Conclusion

In this study we have analyzed the political discourse in the Russian Twittersphere from November 17, 2011, to March 12, 2012. We demonstrated that the discourse on Twitter mirrors major political events and developments quite accurately: all that happened between November 2011 and March 2012 was communicated on Twitter and all that was communicated on Twitter had an actual “real-world” reference. The fact that we find evidence for strategic communication on Twitter that coincides initially with a broad support for the opposition and later with an increasing support for Putin on the one hand and a decline in oppositional mobilization on the other hand additionally underlines the importance of social media as a forum of political dispute. Can we then draw direct inferences from our analysis of Twitter on the fate

of the protest movement more broadly? A direct causal analysis is certainly not possible. For example, analyzing the Twitter discourse did not allow us to derive quantitative predictors for the frequency or timing of protest events. But understanding how the discourse on Twitter shifted in favor of the government can certainly inform our understanding of the rise and decline of the protest movement more broadly.

Our study in particular shows that while both pro- and anti-Putin Twitter users tried to influence the political discourse on Twitter, over time the balance of communication power visibly shifted toward the pro-Putin factions. The strategic communication of Putin supporters in the weeks leading up to the presidential election evidently shifted the perceptions of the protest movement on Twitter to the movement's detriment. This may thus have significantly weakened the oppositional voice on Twitter at a time the movement was already struggling to regain momentum, further mobilize, and overcome internal divisions.

Our analysis highlights that the growing feeling of futility and disillusionment affecting the oppositional movement more broadly (Sakwa, 2014) was clearly reflected on Twitter in the weeks leading up to the presidential election. With the political discourse on Twitter beginning to noticeably shift in favor of the Putin supporters, oppositionally minded people on Twitter may have started to slide into a so-called "spiral of silence" (Noelle-Neumann, 1974, 1993). They perceived their political view to be in a shrinking minority, finding insufficient resonance in the discourse on Twitter, and gradually stopped to speak up, turning rather inward in growing self-doubts and disillusion. The weakening sympathy and increasing indifference of the general public—as represented by the unclassified camp in our analysis—presumably contributed to this escalating demobilization process. At the same time the opposition movement was increasingly confronted with discrediting allegations against its leaders, aggressively reproached by the pro-Putin camp on Twitter (and certainly on other media channels), which invoked merely disappointment among the protesters and skepticism among unaligned Twitter users.

The pro-Putin faction's communication strategies on Twitter seem to have been more successful

than the communication strategies of the opposition. However, it is important here to reemphasize the importance of the "institutionalized" pro-Putin support on Twitter led by loyal core supporters, which was likely instrumental in shifting the discursive power to the government-aligned camps. We could clarify, in particular, that already a relatively small camp of very active and loyal core Putin supporters seems to have effectively enabled the government to decisively influence the discourse on Twitter in its favor (see Figure 3). Short of open technical manipulation, the activity of the core Putin supporters thus amounts to clear and deliberate influence of public perceptions on Twitter in favor of those in power.¹¹

It is not possible from our analysis to conclusively establish to what extent the government used paid "Internet trolls" to spread pro-governmental propaganda, as reports revealed later with reference to the Russian-Ukrainian conflict of 2014–15 (Walker, 2015). Given that the protests of 2011–12 seemingly took the Russian government by surprise, their political communication strategy would in all likelihood have been a reaction to these protests. Thus, if the government would have hired Internet trolls to drive its communication strategy on Twitter, we would expect that many of the pro-Putin users joined Twitter after the first protests sparked in December. We checked this for the 1,000 most active Twitter users and did not find an unusual increase of newly created Twitter accounts in the pro-Putin camps following the December 2011 protests (see Supplementary Information S3). This does, of course, not exclude the possibility that existing users were directed and/or paid to support the government on Twitter.

On digital communication channels such as Twitter, it is generally difficult to obtain reliable proof for whether the support for established powers is real or just "simulated." Researchers have observed "campaigns disguised as spontaneous, popular 'grassroots' behaviour that are in reality carried out by a single person or organisation ... to establish a false sense of group consensus about a particular idea" (Ratkiewicz et al., 2011, p. 297–299) on the Internet. Castells (2009) pointed out that although there is no domination by one group on the Internet, those actors who have resources are capable of manipulating the

discourse in their favor. The resource asymmetry between the two main camps—pro-Putin and opposition—seems to have decisively contributed to the advantage of the pro-Putin side.

This is particularly visible in the activity patterns and discursive behavior of the core Putin supporters, who sent massive amounts of pro-Putin tweets. But there was clearly also genuine support for Putin on Twitter, as represented by the regular pro-Putin camp. Note though that our analysis also suggests that this camp of “regular” Putin supporters was generally much less active than the opposition camp on Twitter (see Supplementary Information Figure S5).

In the end, no matter how much “real” support Putin had, our analysis of the political discourse suggests that the perceived support had a real effect on the opposition and general public on Twitter. This shows that regardless of the promises that new digital technologies hold in terms of empowerment of marginalized or weaker (political) actors, these technologies are still part of the overall system of power—in particular, uneven resource distributions—and may therefore still be utilized by governments in their favor. In other words, our study empirically confirms that indeed “whoever has enough money, including political leaders, will have a better chance of operating the switch in its favour” (Castells, 2009, p. 52). And this applies not only to the specific case study of the Russian political discourse during the 2011–2012 elections and protests. A study on Chinese government’s massive propaganda activities on social media (King, Pan, & Roberts, 2016), for instance, or reports on Erdogan’s social media strategy to mobilize the population against the military coup in Turkey in 2016 (Srivastava, 2016) show clearly that the patterns we find generalize to other countries as well. The question of whether social media are at the end of the day liberative or oppressive is relevant in every political context.

Finally, our study demonstrates how Twitter data may be used for informative political science. In this paper, we conducted a new kind of computational dynamic discourse analysis that is based on quantitative time-series measures (word counts, n-gram association scores) but also on theory-guided and contextually embedded coding and interpretation of these measures. In the future, this method

could be refined for even more precise and elaborate analysis of Internet data.

Notes

1. We used the freely available Twitter Streaming API Spritzer Sample, which collects 1% of all public tweets in real time, <https://dev.twitter.com/streaming/overview>. The retrieved data is in JSON format (see Supplementary Information S1.1).
2. The Berkman Center’s Report “Mapping Russian Twitter” (Kelly et al., 2012) is a notable exception providing groundbreaking insights into the structure of the Russian Twittersphere. See Supplementary Information S1.3 for details.
3. Although the Russian Twitter space extends beyond the Russian Federation and includes former Soviet states as well as Russian immigrants in other countries, the overwhelming majority of Russian language Twitter messages originate from Russia. Also note that the use of Twitter is not limited to large cities such as Moscow or St. Petersburg but also includes more rural and remote areas (Kelly et al., 2012).
4. The only underrepresented political groups were Russian right-wing extremists (Kelly et al., 2012).
5. In particular this included online news sites such as <http://www.bbc.co.uk>, <http://tvrain.ru>, <http://lenta.ru/rubrics/russia>, <http://en.wikipedia.org/wiki/2011-2013Russianprotests>, <http://www.ria.ru>.
6. The term discourse analysis is often associated with a specific qualitative methodological approach advanced by Foucault, Laclau, Mouffe, and others (Laclau, 1993; Weiss & Wodak, 2003). In this paper we use the term more generally to describe our analysis of written language use on Twitter in the context of political communication.
7. Because a belated follow-up extraction of followers of Twitter users is not facilitated by the Twitter API, the social network analyses are based on follower relations in 2015. See Supplementary Information S3 for further details.
8. No intercoder reliability can be provided for the collocation labeling or the manual classification of the sample of 100 active users in order to validate the automatic classification results, because only Viktoria Spaiser was a Russian speaker in the research group and thus only she could read and understand the Russian tweets and collocations.
9. We tested whether the association scores are distorted by the difference in linguistic heterogeneity between different groups, that is, we wanted to check whether the pattern we see in the data is a result of pro-government users being more coordinated in the hashtags and phrases they use, and because of this consistency the collocations they use are more likely to be prevalent in the data set. The opposition could still be dominating the Twittersphere in terms

of number of tweets, but they could have expressed their regime criticism using more heterogeneous language, with less coordination, leading to fewer collocations showing up in the analysis. We therefore calculated the linguistic heterogeneity (lexical diversity) for each camp by dividing the number of all words from the number of unique words (Bird et al., 2009). We found that the pro-Putin camp had in fact the highest linguistic heterogeneity with a score of 4.7366, while the oppositional camp had a lexical diversity score of 4.3156 and the neutral camp the lowest with 4.1295. Overall, however, the scores are rather comparable.

10. The overall distributions of tweets per user in the camps are quite similar. Hence the pro-Putin faction can be expected for any given day to represent the largest share of both active users and tweets posted. Because this advantage exists throughout the whole period analyzed, we can be sure that any shift in the political discourse is not simply an artifact of a change in the relative number of pro-Putin versus opposition users.
11. We examined our data for evidence of direct (technical) manipulation of the political Twitter discourse, particularly by the pro-Putin camp, but did not find any clear evidence for bot-produced and -disseminated pro-Putin messages. The Berkman Center researchers found that after applying a filter to the Russian Twitter data to clear the data from spam, the filtering also eliminated a number of pro-government thematic clusters (Kelly et al., 2012), that is, especially pro-government political initiatives may have adopted aggressive online marketing strategies on Twitter. Such tweets may thus have been removed by filtering heuristics such as those applied by Twitter's Streaming API.

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