

Ideological Scaling of Twitter Users: Evidence from the 2014 Ukrainian Crisis*

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This paper addresses the issue of changes in ideological positions of Twitter users talking about Ukrainian politics during the 2014 Ukrainian Crisis up to Crimean status referendum in March 2014, and tests two hypotheses using the text of tweets as data. I develop an original approach to combine unsupervised Latent Dirichlet Allocation with supervised scaling of texts via Wordscores to score ideological positions of Twitter users and test whether text data from Twitter allows us to recover ideological positions of the general public in a meaningful way. Using this approach, I then explore whether tweets posted by pro-Western and pro-Russian Twitter users demonstrated an increasing cleavage during the crisis. While I show that one can meaningfully score the ideology of Twitter users with the help of the content of tweets, I do not find empirical evidence of an increasing cleavage among Twitter users. I discuss theoretical and practical implications of these findings and present substantively motivated explanations for these results.

1. Introduction

Color Revolutions in Georgia, Ukraine, Kyrgyzstan and Lebanon in 2003 – 2005, and especially the ongoing Arab Spring Revolution started in 2010 have contributed to the growing attention political scientists devote to hybrid regimes and the mechanics of their political evolution. While early research on hybrid regimes¹ was mainly focused on the refinement of the typology

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¹I follow Diamond (2002) and use this term to refer to a broad range of political regimes that combine democratic and authoritarian characteristics.

and description of the institutional design in these countries (Collier and Levitsky 1997; Levitsky and Way 2002; Ghandi and Przeworski 2007), the scholarly emphasis has recently shifted to studies of mass politics, public opinion and various factors that contribute to the dynamics of protests there, as these have proven to be the crucial aspect of the political evolution in hybrid regimes in the past ten years (Tucker 2007; Robertson 2013).

While the main tool for studying mass behavior decades ago was collecting survey data, the situation is rapidly changing nowadays due to the current proliferation of social media around the world. Online networks like Facebook, Twitter, Instagram and others are becoming a tool for both doing and studying politics. Political elites in democracies use social media to inform constituencies about their activities (Ross and Buerger 2014), change their public image (Dimitrova and Bystrom 2013), raise funds for electoral purposes (Weintraub and Levine 2009), and mobilize their supporters (Dimitrova et al. 2014; Goldbeck et al. 2010; Quintelier and Vissers 2008). At the same time, voters can use social media to express their feeling about a variety of issues (O'Connor et al. 2010) and to stay informed about the political agenda (Vaccari et al. 2013). The political opposition uses social media for the propagation of its ideas, mass mobilization, and coordination of protest activities (Lonkila 2012; Morozov 2009; Mungiu-Pippidi and Munteanu 2009; Tufekci and Wilson 2012). In autocracies, social media's role in politics may be very different. In some cases, citizens may use social media to get alternative information about the state of the world and, thus, increase their political awareness (Reuter and Szakonyi 2013). However, elites in autocratic regimes can manipulate Internet content and use social media to dissuade people from participating in protest activities, or even to monitor and suppress different forms of dissent (Pearce and Kendzior 2012). Likewise, autocracies can use social media in order to keep citizens informed about what elites regard as the necessary and important information (Kakachia et al. 2014).

At the same time, online social networks allow political scientists to get previously inconceivable amounts of data at a relatively low price, on a regular basis and without delays that are inevitable when collecting survey data. Social media data also proved to be

relatively successful at predicting electoral results (Ceron et al. 2014; Tumasjan et al. 2010; Wattal et al. 2010), although some concerns about possible biases arose (Gayo-Avello 2011).

This paper focuses on analyzing social media in hybrid regimes and studies changes in the ideological positions of Twitter users talking about Ukrainian politics during the 2014 Ukrainian Crisis up to the Crimean status referendum, i.e. from November 25, 2013 to March 16, 2014.

There are several reasons to be interested in mass-level ideological shifts. First, the political crisis in Ukraine in 2014 has demonstrated a clear evolution from protests against foreign policy decisions of the former Ukrainian President Viktor Yanukovich to a generic anti-Yanukovich movement aimed at reforming the political system of the country (Herszenhorn 2013). Started as a peaceful protest, the so-called “Euromaidan” became, in late February and early March of 2014, an arena of large-scale violence on the part of both special police forces using brutal force to dispel “Euromaidan” (Bonner 2014), and rebel fighters taking over administrative buildings in Kiev and throwing Molotov cocktails at the police (Battle... 2014). Escalation of the conflict between the ruling political elite and protesters was aggravated by the rise of regional separatism and nationalism (Manueco 2014) leading to a secessionist crisis in Crimea which eventually resulted in Crimea joining the Russian Federation. All these happenings were accompanied by a massive pro-protest campaign on social media, especially on Facebook and Twitter.² Analyzing dynamics of mass ideological positions would help shed new light on the evolution of protest in Ukraine.

The rest of the paper is organized as follows. Section 2 provides a theoretical basis for studying mass ideological positions in modern politics. Section 3 gives an overview of the Ukrainian party system and ideological positions of the main parties, as well as provides basic information on the development of the Ukrainian Crisis. Section 4 proceeds with the description of data and methods employed in the empirical analysis. Section 5 presents the

²According to Olga Onuch who surveyed 1203 active protesters in Kiev in November, 2013, 54% of respondents mentioned social media as a source of news about protests (Onuch 2014). This statistics show that social media have been widely popular among protesters in Ukraine and could be used to study this group of Ukrainian population.

main empirical results. Section 6 provides evidence on the robustness of the results. Section 7 concludes.

2. Ideology in Politics after the “End of Ideology”

Ideology as “a set of ideas, beliefs, values, and opinions, exhibiting a recurring pattern” (Freeden 2001) has for a long time been one of the core political science concepts related to scholarly research in a broad range of major topics including – among others – public opinion formation (Page and Shapiro 1982; Fleishman 1986; Durr 1993; Mayer 1993; Monroe 1998; Lahav 2004), voting (Campbell et al. 1960; Nieuwbeerta 1995; Nieuwbeerta and Ultee 1999; Evans and Whitefield 2000; Dalton 2003; Ellis 2012), partisanship (Converse 1969; Box-Steffensmeier et al. 1996; Box-Steffensmeier and De Boef 2001; Lockertie 2002), party competition (Downs 1957; Enelow and Hinich 1984; Hinich and Munger 1994; Hinich and Munger 1997; Adams and Somer-Topcu 2009), coalition government formation (Axelrod 1970; De Swaan 1973; Taylor and Laver 1973; Laver and Schofield 1990), and political economy of redistribution (Moon and Dixon 1985; Persson and Tabellini 2000; Alesina and Glaeser 2004; Huber et al. 2006; Alesina et al. 2012).

However, since the 1960s, there has been significant debate in political science about the role of ideology in shaping politics. Following the seminal 1964 paper by Converse, the belief that citizens are not able to adhere to any consistent system of political attitudes and values (Converse 1964; Billig 1991a; Billig 1991b) has become widely acknowledged among political psychologists. The majority of research about the role of ideology has focused not on people’s beliefs, but on roll-call data analysis, and has aimed to describe legislative behavior as well as provide a summary description of the issue space of politics based on behavioral manifestations of legislators’ preferences (Poole and Rosenthal 1991; Clinton et al. 2004; Hix et al. 2005; Hix and Noury 2009; Poole and Rosenthal 2012). The legislative focus in studies of the ideological space of politics in democratic regimes hinges on the assumption that errors in legislators’ utility functions are uncorrelated (Cox and Poole 2002), which may

be the case in democratic regimes, but deserves serious scrutiny in autocracies and hybrid regimes (Aleskerov et al. 2007). Indeed, political parties tend to be far from independent political actors and crucial decision makers in non-democracies (Slater 2003). Patterns of legislators' voting in hybrid regimes could be motivated by informal rules and rent-seeking rather than following any consistent ideological logic. The pitfalls of studying the role of ideology (at least, as models of how people think (Humphreys and Laver 2010; Laver 2014)) using data on legislators' behavior in hybrid regimes, together with evidence that people do have ideologies that help them organize their attitudes (Milburn 1987), suggest a need for a new approach to the analysis of ideology. I argue for an approach based on an analysis of public discourse about politics in identifying principal lines of ideological cleavages in hybrid regimes, since a politician's public speeches are supposed to signal the electorate about her/his political beliefs and help supporters interpret the political process in compliance with their partisanship. Consequently, text analysis of relevant public declarations that politicians make can be a better option for studying the diversity of ideological cleavages in these countries, even though politicians' public speeches may be regulated by certain informal rules (Anderson 1996; Anderson 1997) as much as their voting behavior. What makes the difference here, is that public speeches are aimed at citizens and are supposed to mobilize, quiet, excite, or just provide the general public with cues about how to interpret political information (Levintsova 2013), while legislators' voting patterns are normally hidden from public scrutiny in hybrid regimes and, as a result, are not very informative from an ideological viewpoint.

Textual analysis of ideological preferences, which I argue for, is based on a vast literature from political psychology and sociolinguistics pointing out that political ideology is closely related to cognitive styles. This literature is grounded in Adorno's et al. (1950) research on the authoritarian personality that revealed a higher propensity for people with right-wing political values and attitudes to score high on the authoritarian personality scale – a finding widely corroborated in later inquiries (McClosky 1967; Sanford 1973; Wilson 1973). Psychological research in 1980s found that right-wing respondents generally appear more dogmatic (Stone

1980). Moreover, Tetlock showed that senators with extremely conservative voting records in the 94th Congress were related to less integratively complex policy statements than their moderate or liberal colleagues (Tetlock 1983).

One of the behavioral manifestations of these differences in cognitive styles is linguistic style (van Dijk 2002). For example, Slatcher et al. recovered six linguistic style categories (cognitive complexity, femininity, depression, age, presidentiality, and honesty) from the public speeches of two U.S. presidential and vice presidential candidates in the 2004 electoral campaign (Slatcher et al. 2007). There is also evidence of ideologically biased selection of topics and examples in politicians' speeches and writings (van Dijk 2002).

Due to these differences in language usage, quantitative analysis of texts is capable of producing sensible results in various scientific fields (Pennebaker and Lay 2002). In political science, textual analysis has been applied to predicting results of presidential and congressional elections by comparing the levels of optimism in candidates' speeches (Zullo et al. 1988), studying the effects of language on coalition formation in multiparty negotiations (Huffaker 2011), and recovering U.S. senators' positions on foreign policy (Tetlock 1981) and parties' policy positions from party manifestos and programs (Laver et al. 2003; Klingemann et al. 2006; Slapin and Proksch 2008).

Although textual analysis of party manifestos may be a fruitful approach to studying the ideological space of politics in a settled democracy with a stable party system, it is probably less useful in the case of hybrid regimes due to the questionable role of parties and their political programs (Gandhi and Przeworski 2007). This approach could become even less efficient in times of national emergency due to the dynamics of political life and, possibly, political transformations. Recent developments involving mass protests around the world might suggest that political scientists should incorporate a broader range of textual data into studying ideology in hybrid regimes, including data from social media (McCurdy 2012). Indeed, it is not only politicians who shape politics even in non-democracies, especially in times of national emergency. Shocks to mass beliefs as well as behaviorally expressed emotions

can trigger major changes in the political system (e.g. Egypt in 2011 – 2012) (Cannistrato 2011), and thus become relevant to political science research. Among the variety of sources that one can use to collect this sort of data, social media are presumably the most reflective of the shifts in public beliefs over time, since politically active users talk about politics on social media, express their attitudes toward specific decisions politicians are making, coordinate future activities and mobilize supporters (Khondker 2011). Social media are becoming a new way to disseminate political ideas and ideology, and are therefore attracting increasing attention from authorities in hybrid regimes (Cottle 2011; Christensen 2011). As a result, for instance, Twitter and YouTube were blocked in Turkey in March 2014 at the government’s request (Parkinson 2014). Another example of increased regulation of mass media by hybrid regimes is the bill the Russian parliament passed in April 2014 making it compulsory for popular bloggers to comply with the general regulations of mass media, which makes it harder to disseminate any unproven information critical of the authorities (Federal Law of the Russian Federation... 2014).

The use of social media to infer public opinion, including ideological positions, and patterns of political communication between elites and ordinary citizens has already proven to give substantively important results. For instance, Beauchamp (2013) shows that political tweets can be useful to predict representative state-level poll results across states and time. Barberá et al. (2014) apply various textual and network analysis techniques in a study of the U.S. congressmen’s political agenda and show that political elites are responsive to their followers on Twitter in their political discussion while having almost no effect on ordinary citizens’ public agenda. Nevertheless, we know much less about political communication in social media outside the U.S., and especially little in hybrid regimes. This paper is an attempt to both narrow the gap in our understanding of social media use in hybrid regimes and recover substantively interesting features of the ideological space in a hybrid regime – Ukraine – in times of a deep political and social crisis. More specifically, this paper focuses on the ideological evolution of Twitter users’ tweets about politics during the 2014 Ukrainian Crisis

in order to test two hypotheses.

***H1:** Politically active Twitter users leaning toward different ideological poles use different vocabulary on Twitter.*

If this is the case, Twitter can be potentially used for a number of purposes by students of political behavior. First, we could possibly obtain an ideological map of both politicians and numerous Twitter users on a regular basis in order to monitor the dynamics of popular attitudes and beliefs. Second, we could presumably identify politicians whose manner of speaking about politics is the most influential, in the sense that they frame the way ordinary citizens discuss politics more than other politicians' ways of speaking (Barberá et al. 2014). If Twitter data do provide us relevant information about citizens' ideological positions, than Twitter can be used for a wide range of research tasks related to studies of mass ideological attitudes.

***H2:** The main political cleavage measured as the difference between average ideological positions taken by pro-Western and pro-Russian Twitter users was becoming more profound in the first stage of the 2014 Ukrainian Crisis (before secession of Crimea).*

This hypothesis is closely related to the aforementioned search for the new predictive power we can get from using Twitter in political science research. It is also motivated by a vast research in political psychology showing that involvement in political activities during crises tends to strengthen and even radicalize activists' opinions (Abelson 1959; Lane and Sears 1964; Krosnick and Milburn 1990). Possibly, an increase in the cleavage found in tweets could be a predictor of the later violent development of the Ukrainian Crisis that lead to a massive use of military power in Ukrainian regions in late April and early May of 2014, as well as numerous victims during fights between pro- and anti-federalization demonstrators in Odessa on May 2nd, 2014. It might also allow scholars to make conjectures about the future dynamics of the party system in Ukraine.

3. Ukrainian Politics on the Eve of Crisis

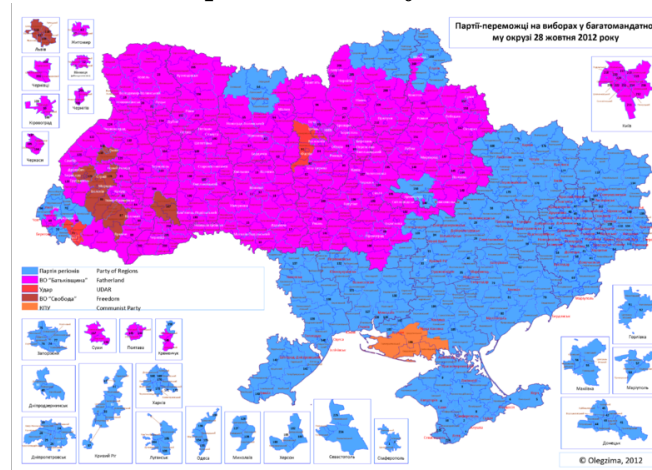
The party system in Ukraine is quite volatile with few parties participating in more than two consequent elections without experiencing major changes (Rybiy 2013). In the 2012 parliamentary election, five parties gained seats in the Ukrainian parliament (Verkhovna Rada). The largest party in the parliament holding 30% of votes was the Party of Regions supporting President Viktor Yanukovich (2010–2014). The second party with 25.5% of votes was “Batkivshchyna” (literally, “Fatherland”) led by former Prime Minister Yulia Tymoshenko, one of the leaders of the 2004 Orange Revolution, who was sentenced to seven years in prison as a result of an allegedly politically motivated criminal case investigation in 2011. Another party, the Ukrainian Democratic Alliance for Reform (UDAR, literally – “Strike”) of Vitaliy Klychko, got the third most votes (14%) although it did not participate in the previous 2007 election and got less than one per cent of votes in the 2006 parliamentary election having been created in 2005. Slightly more than 10% of voters supported the nationalist Freedom Party led by Oleh Tyahnybok. Finally, around 13% of voters cast their vote for the Communist Party led by Petro Symonenko, but due to the structure of districts the communists got less seats than the Freedom Party in the Verkhovna Rada (Herron 2014).

The results of the 2012 parliamentary election revealed a pronounced electoral clustering of regions in Ukraine (see Figure 1.) caused by deep regional divisions. For a variety of reasons, including historical, ethnic, linguistic, religious and other factors, Ukrainian politics has long been characterized by a deep cleavage between the South-Eastern and Western regions (Barrington 1997; Kulyk 2011). Religiously, Western Ukraine is dominated by the Ukrainian Greek Catholic Church, while Eastern and South Ukraine is populated mainly by followers of one of the three Ukrainian Orthodox Churches (Borowik 2002). Linguistically, more than 80% of people in the South and South-East of Ukraine speak Russian in everyday life. In the North-East, the proportion of Russian and Ukrainian speakers is almost equal with a small prevalence of the former and a large group of people using a colloquial mix of the two languages (the so-called “surzhyk”). At the same time, the Center of Ukraine is mainly

Ukrainian-speaking, and an absolute majority (more than 90%) of those living in Western Ukraine speak the Ukrainian language in everyday life (Language Composition... 2001).

Regional cleavages lead not only to electoral clustering, but also tend to produce a cleavage in attitudes towards basic policy issues (Armandon 2013). According to a survey conducted by Kiev International Institute of Sociology in February – March, 2013, 41% of respondents supported Ukraine joining the Eurasian Economic Community Customs Union (Belarus, Kazakhstan, and Russia), while 39% supported the signing of an economic agreement and further association with the EU (Kiev International... 2013). These differences are evident also in attitudes that people from different regions of Ukraine hold about recent political developments. For instance, in April 2014, 70.5% of people living in Donetskaya oblast and 61.3% of those living in Luganskaya oblast³ believed that what had happened on Maidan in Kiev was “an armed coup d’etat organized by opposition with support from the West”, while the percentage of people believing that in the nearby region of Dnepropetrovsk, located to the west of Luganskaya and Donetskaya oblast, was just 31.2% (Kiev International... 2014)

**Figure 1. Leaders in multi-member districts
in Ukrainian parliamentary election of 2012⁴**



Source: Wikipedia. Ukrainian parliamentary election, 2012.

³ These are two regions in Eastern Ukraine with the most active armed unrest and opposition to central authorities in Kiev in March – August 2014.

⁴ *Note:* Blue (a lighter color in black and white) corresponds to districts where the Party of Regions won. Pink (a darker color in black and white) denotes regions where Batkivshchyna won.

Basically, regional differences mark the primary ideological axis in Ukrainian politics making crucial the issues of the national identity (Osipian and Osipian 2012), since the left – right economic and liberal – conservative dimensions are not well articulated (Social Values of the Population... 2013; although also see Herron 2014).

As a result of these differences, public policy in Ukraine has been marked by several crises and radical changes in last 10 years. In 2004, the Orange Revolution brought pro-Western President Viktor Yushchenko and Prime Minister Yulia Tymoshenko to power. However, they left office after the 2010 Presidential Elections gave victory to mainly pro-Russian politician Viktor Yanukovich who had previously, in 2004, lost to Viktor Yushchenko in the third round of the presidential elections (Haran 2011).

Taking into account the almost equal support for association with EU and Russia, Viktor Yanukovich was carrying out a fluctuating foreign policy (Bozhko 2011; Proedrou 2010). Domestic policy style also changed during his presidency, including numerous criminal investigations against the opposition leaders, incarceration of former Prime Minister Yulia Tymoshenko, and conducting allegedly fraudulent local elections in October 2010 (Sedelius and Berglund 2012). This autocratic drift in Ukraine was summarized by the Polity IV democracy index going one point down (from 7 to 6 on a 21-point scale) during 2010–2013 (Polity IV 2013). Altogether, this produced an increase in the popular disenchantment with President Yanukovich's rule (Slivka 2013), and ended in mass protests in the center of Kiev, on Maidan Nezalezhnosti (Independence Square), started on November 21, 2013, immediately after Viktor Yanukovich announced that he would not sign an economic agreement with the EU (Herszenhorn 2013b). Three days after, protesters made a first attempt to take over the building of the Ukrainian government (BBC Monitoring Newsfile 2013). By December 2nd, street fighters took under their control several administrative buildings and used force against police forces (EuroMaidan Rallies... 2013). In mid-January, rebels were fighting against the police on the streets in the proximate vicinity of government buildings, with numerous people being injured (Englund 2013; Englund and Lally 2013). The most violent events happened on

February 20 – 21, when both activists of Euromaidan and policemen were killed by unknown snipers (Traynor 2013). After that, President Yanukovich left the capital (Higgins 2013) and was declared dismissed by the parliament of Ukraine (Walker 2013). The leaders of the Ukrainian opposition came to power, which was supported by the majority of Ukrainian regions, except Crimea and, later, the Eastern regions of Lugansk and Donetsk, where pro-Russian unrest started (Decision of the Presidium... 2014; Ukraine Crisis Fuels... 2014). On March 16, more than 95% of voters in Crimea and the city of Sevastopol voted for joining Russia in a referendum⁵, unrecognized by the international community. As a result, on March 21, Crimea was officially admitted to the Russian Federation after both chambers of the Russian Parliament (State Duma) ratified the treaty between Russia, Crimea and Sevastopol (Goryashko and Korchenkova 2014), marking the beginning of a new stage of the Ukrainian crisis, now related more to ensuring the territorial integrity and economic stability of the country and less to power struggle among different political forces (Petro Poroshenko Claims... 2014).

All the events described above were broadly covered and discussed on Twitter, as well as other social media. This paper uses data from Twitter to analyze ideological shifts of Twitter users talking about Ukraine during the first stage of the crisis.

4. Data and Methods

This paper studies the pro-Russian vs. pro-Western cleavage, which has recently been the main ideological axis in Ukrainian politics (see Section 3), using text as data. This is motivated by the fact that publicly available texts are the basic tool used by politicians to inform a voter about their views, attitudes and activities. Naturally, the text of tweets posted by politicians could also be used to provide information about their ideological positions and can thus be used to infer ideology.

Since ideological preferences tend to be quite stable and not susceptible to extreme

⁵ The turnout on the referendum was 83.01% in Crimea and 89.5% in Sevastopol, although some commentators point out to the fact that opponents to Crimea joining Russia tended to abstain from voting (Morello 2014).

volatility (Feldman 1989; Feldman 2013), I choose the week as the unit of time in my analysis.⁶ On the one hand, in times of a deep political crisis a week seems to be quite a long period of time allowing people to reassess what is going on in the world. On the other hand, a week is a natural time lapse for structuring political activities in time. Additionally, the total number of weeks under study (sixteen) allows us to get an image of the ideological evolution of Twitter users without undue coarsening of the results.⁷

The logic of my analysis is as follows: take tweets posted every week by pro-Russian and pro-Western politically active Twitter users, compare them to tweets posted by politicians and locate them on the ideological scale, given the wording they use.⁸ So, the unit of analysis here is a set of weekly tweets posted by a pro-Western or pro-Russian politically active Twitter user.

In order to fix the direction and the variance of the ideological axis, I use as the training set the tweets posted by the most popular politicians having a Twitter account during the first two weeks of the crisis. For this, I choose 15 Twitter accounts belonging to pro-Western politicians and parties and five Twitter accounts belonging to pro-Russian ones.⁹ The imbalance in the training data set is due to a certain imbalance in Twitter activity between pro-Western and pro-Russian politicians, the first being much more active on Twitter.¹⁰ I

⁶ There is no need for dealing with seasonality in the number of tweets during the week, since I am not trying to decompose the time-series of tweets into components nor make predictions about tweets flow.

⁷ One could possibly argue for using days as units of time for analysis. However, the number of words used by people within a day is too small due a limited number of characters one can put in a tweet (140 characters only). And ideological estimates cannot be reliable enough when computed based on so small texts. So, I had to choose a longer time period.

⁸ Here, I treat retweets as an ordinary type of tweets. I argue that politically active Twitter users normally retweet what people with a close ideological position have tweeted, and they do that in order to express their consent. That is why one can treat retweets as a normal text. Even if somebody occasionally retweets a tweet posted by somebody from the other ideological camp, she will presumably accompany that retweet with critical comments, thus preventing the distribution over words for that ideological group from being too similar to the one of the opposite group.

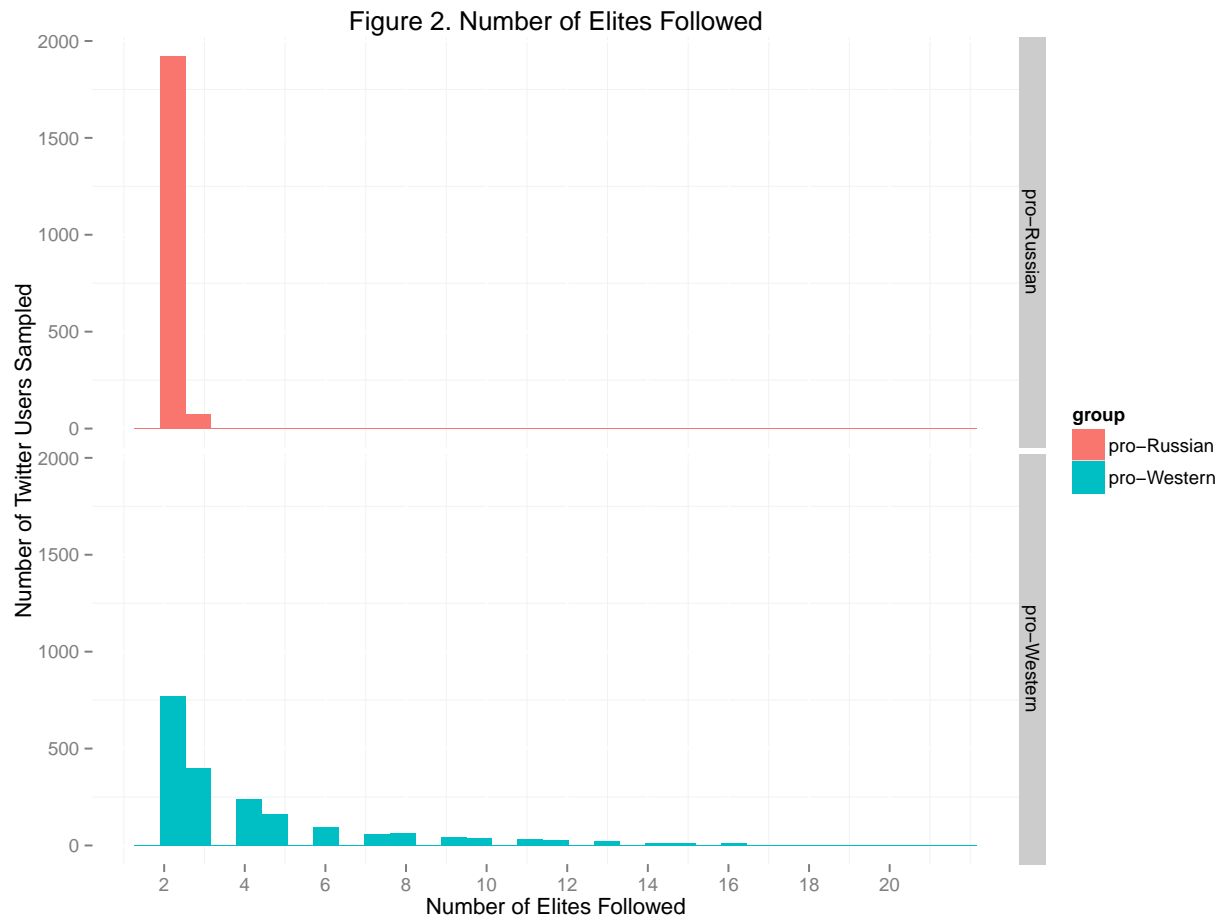
⁹ I use a list of the most popular politicians' Twitter accounts provided by (Rating of Ukrainian Politicians... 2014). Only 5 pro-Russian politicians are mentioned in the list. The 15 pro-Western politicians are those who occupied the first 15 positions in the rating, while the most followed pro-Russian politician, Mikhail Dobkin, appeared only on the 16th position.

¹⁰ For example, Petr Simonenko, the leader of the Communist Party of Ukraine, has a total of 105 tweets, all posted before the crisis; and the Communist Party of Ukraine does not even have a Twitter account. At the same time, Prime Minister Arseniy Yatsenyuk, a well-know pro-Western Ukrainian politician, has an account with more than 600 tweets that are posted on a regular basis.

choose the first two weeks for the formation of the training set for several reasons. First, taking the whole period of time under study (16 weeks) would prevent me from recovering any dynamics in followers' positions. Second, taking a separate training set for each week could wash away a large part of the inter temporal variance in word usage, since politicians are also changing the way they talk about politics during the crisis. Third, taking only the first week would not be appropriate for the sake of my research, since the number of words available from the test set would not be sufficient to implement any meaningful scoring. Finally, I do not take any longer period of time (like three or more weeks), because in the beginning of December the Ukrainian crisis started escalating, and there was no reason to wash away this dynamic.

Apart from the training set, I consider a test set of tweets posted by politicians' followers on Twitter. Since I need to identify what ideology Twitter users lean towards, I focus on politically active Twitter users, defined here as those who follow at least two politicians from one ideological pole and none from the other. So, for instance, politically active pro-Western Twitter users are defined as those who follow at least two pro-Western politicians, and none of pro-Russian politicians. Due to the above mentioned imbalance in the activity of pro-Western and pro-Russian Twitter users and in order to make the pro-Western and pro-Russian subsets of the test set more comparable, I take random samples from all pro-Western and pro-Russian politically active followers and end up with 2000 Twitter users for each ideological group of followers. Hence, the test set is comprised of tweets posted by 4000 Twitter users.

As one can see in Figure 2, a random sample of Twitter users confirms the aforementioned imbalance in how active pro-Russian and pro-Western citizens are on Twitter. While the absolute majority of sampled pro-Russian Twitter users follow just two elites, just a few – three politicians and no one more than three, the pattern is very different in case of pro-Western users whose frequency distribution possesses a much longer right tail.



I use the Twitter API to download tweets posted by elites and all politically active Twitter users and parse these data into weekly subsets for further cleaning and analysis. The pre-processing step of my analysis, both for the training set (elites' tweets during the first two weeks of the crisis) and the test set (ordinary citizens' tweets), includes removing punctuation and numbers, as well as standard stop words from the Russian and English languages as defined by the Snowball Stemmer Project.¹¹

The basic idea of my text analysis is to identify words used primarily by pro-Western and primarily by pro-Russian elites and then look at the way politically active non-elites talk on Twitter. If the content of tweets can actually give us any valuable information

¹¹ The Snowball Stemmer Project was started in early 2000s in order to develop lists of stop words in various languages – contrary to the, probably, more widely known in the English-speaking world Porter's stemmer that supports only English language. Now, Snowball Stemmer is the default option in 'tm' package in R.

about ideological preferences of tweets’ authors, then one would expect to find that followers of pro-Russian elites use mainly words frequently found in pro-Russian elite’s tweets, and analogously for pro-Western followers and elites. Thus, I build my text analysis on the comparison of word frequency distributions from the test and training sets. The more tweets by non-elites resemble tweets of elites of the same ideology, the closer the score of non-elites is to the score of the elites. For example, if the ideological continuum is scaled to the closed interval from -10 to 10 with the left end being assigned to pro-Western politicians, and if the word frequency distribution of pro-Western followers is exactly the same as of pro-Western elites at any time, than pro-Western followers will always get the same score of -10 . If, however, followers’ word frequency distribution is somewhat different from that of pro-Western elites and bear some resemblance to that of pro-Russian politicians, then pro-Western followers will get a score somewhere in between two edges of the continuum.

While one could possibly use tweets posted by followers and pre-processed as described above to score followers’ ideological positions, this approach could induce severe noise into the analysis. People talk not only about politics on Twitter. Even among politicians’ tweets, one could also find essentially non-political ones. Furthermore, even when people are talking about something unrelated to politics, the words they use may coincide with those used by politicians by mere chance. This concern is of special importance in the Ukrainian case, since pro-Russian and pro-Western politicians typically use different languages (in the case of pro-Western elites and people this is either English or Ukrainian, while pro-Russian elites and their followers use mainly Russian).

In order to deal with potential noisiness of the data, I first recover politically relevant words employing Latent Dirichlet Allocation (henceforth – LDA). LDA is a method for automated text classification (Grimmer and Stewart 2013) via recovering the topic structure of the documents. Technically, it is a three-level hierarchical Bayesian model (Blei et al. 2003) treating texts as a bag of words and describing the generative process of text formation. The LDA model includes several parameters:

- $\beta_k \sim Dir(\vec{\eta})$ refers to K latent prior Dirichlet distributions (i.e. topics) over the set V of words with a vector hyperparameter $\vec{\eta}$;
- $\theta_d \sim Dir(\vec{\alpha})$ denotes a latent prior Dirichlet distribution parameterized with a vector hyperparameter $\vec{\alpha}$ over the topics within the $d - th$ document;
- $Z_{d,n}(\theta)$ stands for a latent discrete random variable defined for every document d ($d = 1, \dots, D$) and every word n ($n = 1, \dots, N_d$) in the document and shows what topic the $n - th$ word in the given document comes from;
- $w_{d,n}(z_{d,n}, \beta_{z_{d,n}})$ refers to the only observed random variable in this model that takes on values from the set of words and depends on both what topic it comes from (i.e. $z_{d,n}$) and what the probability of getting this word within this topic is (i.e. $\beta_{z_{d,n}}$).

Given these parameters, one can describe the generative process for the corpus as follows. Step 0: there are D documents with N_d empty slots for words, a set of K topics that represent distributions over the set of words (i.e. β_k), and a set of distributions of topics within each document ($\theta_d, d = 1, \dots, D$). Step 1: the algorithm takes the first document in the corpus and the first word slot, and defines a topic to draw a word from (i.e. $z_{d=1,n=1}$) for this slot. The topic is chosen as a random variable $Z_{d=1,n=1}$ from the distribution of topics within the first document (θ_1). Step 2: the algorithm takes the topic chosen before and draws an observation (i.e. a word) from the distribution ($\beta_{z_{d=1,n=1}}$) corresponding to it. This chosen word fills in the first word slot. Steps 3 – 4: the algorithm repeats Steps 1 – 2 for the second slot of the first document. And so on, up to the final slot of the final document in the corpus.

Estimation of latent parameters in this model is quite tricky, since there are several unobserved variables and only one observable. However, the Bayesian approach allows estimating model parameters through the posterior:

$$p(\theta, z | w, \alpha, \beta) = \frac{p(\theta, z, w | \alpha, \beta)}{p(w | \alpha, \beta)},$$

where the denominator takes the form of

$$p(w|\alpha, \beta) = \frac{\Gamma(\sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i)} \int \left(\prod_{i=1}^K \theta_i^{\alpha_i-1} \right) \left(\prod_{n=1}^N \sum_{i=1}^K \prod_{j=1}^V (\theta_i \beta_{ij})^{w_n^j} \right) d\theta$$

(Blei et al. 2003) and cannot be computed (Dickey et al. 1987). Hence, one typically uses approximate estimation methods. Here, I employ the collapsed Gibbs sampler (Griffith and Steyvers 2002) implemented in R.

As one can see, the LDA model assumes that the number of topics K to be recovered from the corpus is known. However, this is not true for tweets on Ukraine. In order to deal with this problem, I employ the LDA model selection algorithm based on taking harmonic means of samples from the collapsed Gibbs sampler suggested in (Griffith and Steyvers 2004). The use of this algorithm allows me to select an optimal number of topics to be recovered from the corpus of tweets.

After running the LDA algorithm on the training set of politicians' tweets posted during the first two weeks of the crisis, I get topics represented by lists of words with probabilities of appearing within these topics assigned to them, as well as distributions of topics within pro-Western and pro-Russian politicians' tweets corpuses. Using this information together with Bayes' rule, I calculate the inverse probabilities – probabilities of every topic given every word – and predict topics for every word. Thus, I can identify politically relevant words, defined as words for which the predicted topic is a political one.¹²

Finally, I use only politically relevant words to score the test sets (tweets posted by followers of pro-Western and pro-Russian elites). In order to relate test sets to the training ones and score them, I employ the Wordscores method proposed in Laver et al. (2003). Wordscores is procedure allowing for supervised classification of texts from a test set according to the words found there. In order to identify words' ideological relevance, one chooses a training set of r documents (here, they are two sets of tweets used by pro-Western and pro-

¹² I consider political the top half of the topics ordered according to the percentage of political words among the list of 15 most common words in each topic. Political words are those related to politics (protests, voting, public decision making, politicians, etc.)

Russian politicians) and assigns them some score A_r on the ideological scale. For simplicity, I assigned -10 to the set of pro-Western tweets and 10 to the set of pro-Russian tweets. Then, for every word in the training set, one calculates $F_{wr} = Pr(w|r)$, the probability of finding the word w in the text r . This probability is then used to derive the inverse probability $Pr(r|w)$ according to Bayes' rule:

$$Pr(r|w) = \frac{Pr(w|r) \times Pr(r)}{\sum_r Pr(w|r) \times Pr(r)} = \frac{F_{wr}}{\sum_r F_{wr}},$$

where $Pr(r)$ equals to one, since the document is treated as given. Thus, $Pr(r|w)$ is the probability that one is reading document r given that she reads word w .

This probability, $Pr(r|w)$, allows obtaining the ideological score for every word in the training set simply as an expected value:

$$S_w = E(A_r|w) = \sum_r A_r \times Pr(r|w).$$

Finally, we get the ideological position of every document from the test set (S_v) calculating another expected value:

$$S_v = \sum_w S_w \times F_{wv}$$

Employing this approach, I get ideological scores for all test documents for every week under study. This allows me to recover shifts in ideological positions of the followers of the main political forces in Ukraine on Twitter. An assumption I am forced to make here is that words people use on Twitter reflect their ideological positions. This assumption is not a heroic one, first, because people can choose different languages when writing tweets. People can also talk about different topics, stressing different aspects of life – in accord with their ideological perception of reality.

5. Results

I estimate an LDA model on pro-Western and pro-Russian politicians’ tweets posted during the first two weeks of the Ukrainian crisis in order to recover only ideologically relevant words to be used in scaling the test sets of tweets posted during the crisis by elite’s followers on Twitter.

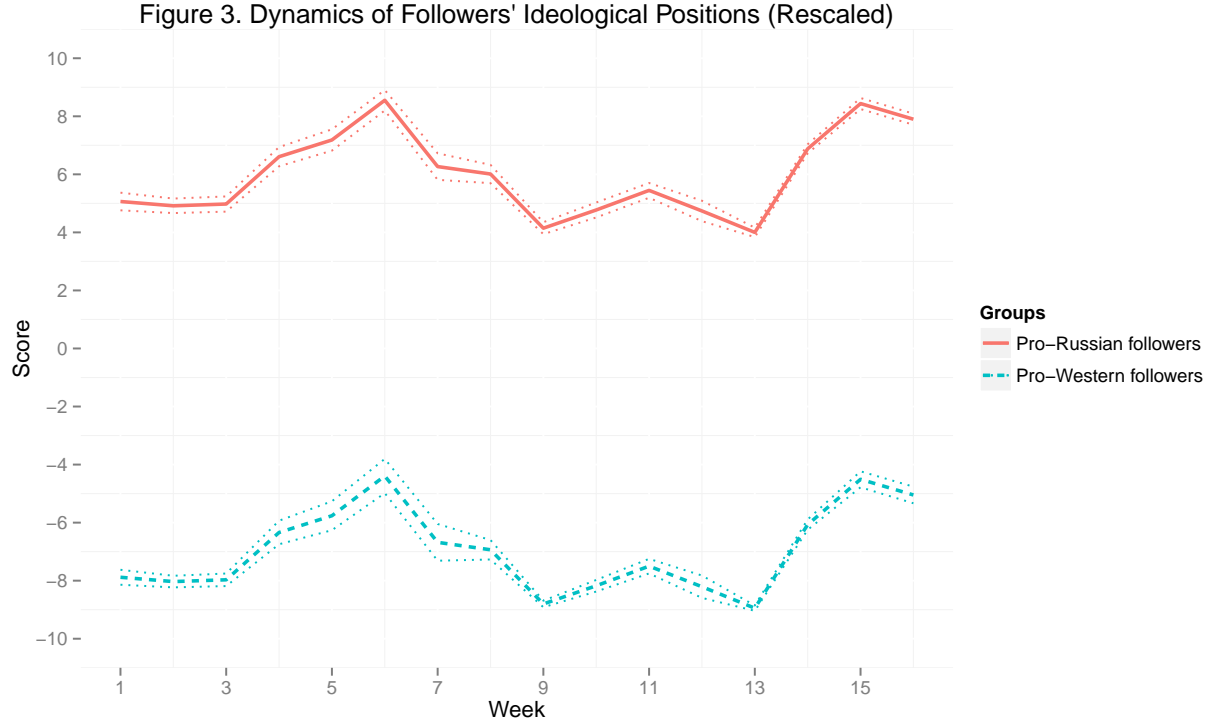
The application of harmonic means approach to the LDA model selection does not necessarily produce a unique optimal number of topics, since it works with different samples from the Gibbs sampler. However, after rerunning the harmonic means algorithm several times, I found that the optimal number of topics typically lies between 17 and 24. After a close inspection of the graph representing log likelihoods when different number of topics are recovered (see Appendix 1), I chose 17 as the “optimal” number with the motivation to choose the smallest reasonable number for the sake of parsimony and interpretability.

Hence, I estimated the LDA model with 17 topics and extracted 15 most frequent words within every topic. Thus, I could identify 8 topics as political ones¹³, since they constitute the top half of the list with topics ordered according to their relation to politics (see Appendix 2 for lists of 15 most used words within each topic with stars marking words considered to be political). Then, applying Bayes’ rule, I predicted the most probable topic for every word and retained only words associated with political topics in the document-term matrix to be used in the Wordscores algorithm. So, the set of all words to be used in scaling was reduced from 988 in the original document-term matrix for the training set before LDA-refinement to 453 after selecting politically relevant words only.

I use the 2×453 document-term matrix from the test set as the reference for scaling followers’ ideological positions on a weekly basis. Tweets posted by pro-Western elites are assigned the value -10 on the ideological scale, while pro-Russian politicians get a 10-points score. Then, I apply Wordscores to estimate pro-Western and pro-Russian followers’ positions separately for each week and rescale the scores in order to make them comparable across time

¹³ Topics 1, 3, 5, 7, 8, 9, 10 and 14 are considered to be political ones.

(Laver et al. 2003). Figure 3 presents the results together with 95% confidence intervals.



As one can see from Figure 3, pro-Russian and pro-Western politically active Twitter users are well separated from each other, with pro-Russian followers lying closer to the top edge of the scale that corresponds to pro-Russian elites, and pro-Western follower being closer to pro-Western politicians (point -10 on the scale). This means that pro-Russian and pro-Western Twitter users talk differently about what is going in Ukraine, which corresponds to the literature about differentiated usage of language by supporters of different ideologies and corroborates hypothesis 1 of this paper. This also means that the wording people use in their tweets can actually convey information about ideological preferences in times of crisis like the Ukrainian one.

However, a close look at Figure 3 reveals that the two sequence curves change in a parallel way, giving the product-moment correlation coefficient of 1. Since this may be an effect of rescaling scores, Figure 3 may not convey reliable information about any increases in the cleavage between pro-Russian and pro-Western followers in time. On the contrary, Figure

4 shows non-rescaled scores for followers' tweets and reveals a clearer pattern. Although sequence curves are still quite correlated, the product-moment correlation coefficient now takes on a more realistic value of 0.74 (p-value ≈ 0.001). The resemblance of the curves I find here may be due to the fact Twitter users reacted to the same events, and the topics they discussed every week would not have been very different.

Even more importantly, one can easily deduce from Figure 4 that there was neither an increasing nor decreasing trend in the ideological positions of pro-Russian and pro-Western followers of Ukrainian politicians during November 2013 — March 2014.

This graphical pattern is corroborated with a formal statistical test. I run an OLS regression of the difference between pro-Russian and pro-Western followers' scores on time. If there was an increase in the cleavage, one should get a positive coefficient on the time variable. Table 1 presents the results.

Table 1. Regression of differences in scores on time

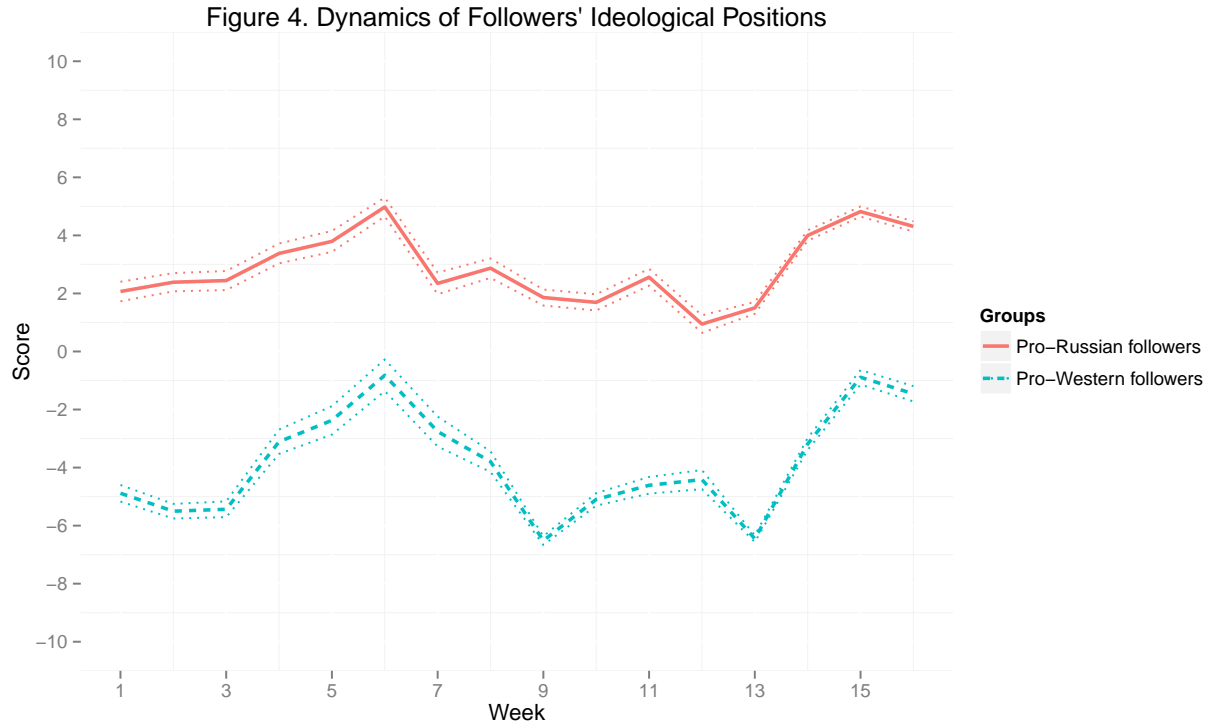
	(OLS)
Week number	−0.07 (0.05)
Constant	5.78*** (0.47)
N	16
R^2	0.13

Note: *** $p \leq 0.01$. Standard errors in parentheses.

As follows from Table 1, the coefficient for the number of the week is not only statistically insignificant, but is even negative. Since the magnitude of the coefficient is negligibly small, there is no grounds for interpreting either its value or even its sign. The conclusion is nonetheless straightforward: no increase in the cleavage of Twitter users is present in the data.

The actual dynamics of the inferred ideological positions of both pro-Russian and pro-Western followers of the elites is also informative. However, one should be careful when interpreting spikes and depth on the presented graphs. Figures 3 and 4 reveal three peculiarities

of ideological scores estimated with the data from Twitter.



First, spikes on week 6 require an explanation. A close look at the data as well as timing of the events reveals that week 6 (December 30 – January 5) corresponds to New Year holidays that are traditionally the most popular holidays in many post-Soviet countries, including Ukraine. Those days people tended to tweet congratulations and discuss their leisure time. Thus, the term-document matrix for the test set during week 6 included numerous words unrelated to protests. Nonetheless, many tweets contained general words about the great future of Ukraine, which were so popular in tweets of pro-Russian politicians in the first weeks of the crisis. This explains the spike toward the pro-Russian ideological pole in the scores assigned to both pro-Russian and pro-Western politicians.

Second, an upward (i.e. towards pro-Russian pole) tendency is noticeable on the graphs during weeks 14 and 15. During these two weeks (March 3 – 16), Crimea became an epicenter of the crisis. A large part of Twitter users were discussing at the that time both a possible response of Ukraine to the deployment of Russian troops in Crimea and possible changes in

life for people in Crimea in case of its secession. This change of the focus of popular political discussions affected the document-term matrix again, making words related to protest less numerous. As a result, we see an increasing trend in the ideological scores for both groups of politically active Twitter users.

Third, there is an overall decreasing tendency of the scores for pro-Russian followers of elites. During a relatively long period including weeks 7 – 12 (except week 11 only), ideological scores of the pro-Russian group of Twitter users were getting closer to the pro-Western pole. This was the time when protests became especially active leading in the end to President Yanukovich’s dismissal on February 22 (week 13). This trend poses the question of whether it reflects only a switch in public attention or indicates also a generic tendency of Twitter users to lean towards pro-Western politicians while the crisis was developing. However, this question is beyond the scope of the paper, since it requires comparison of data from Twitter to public surveys that are currently unavailable.

6. Robustness Checks

The results presented above rely on scaling tweets using Wordscores after selecting politically relevant words via unsupervised LDA. I use a somewhat intuitive but basically arbitrary rule (top half of the topics ordered according to their relation to politics) to define an LDA topic as a political one. Here, I present evidence of how robust my results are to changes in this rule.

Appendix 3 lists all the 17 topics extracted via LDA with the percentage of politically relevant words in the descending order. As an alternative to the rule used above, I both drop the least politically relevant topics of the list used previously, and add the next political topics in the ordered list from Appendix 3. Since three topics out of the previously used eight¹⁴ have exactly the same number of political words, my first robustness check involves implementing Wordscores on the document-term matrix with words related only to 5 (i.e.

¹⁴ These are topics 3, 5, and 8.

8 – 3) topics. Likewise, as the next two political topics in the ordered list¹⁵ have the same number of political words, I use 10 (i.e. 8 + 2) topics to remove possible noise from the document-term matrix employed in the Wordscores procedure.

The new sequence curves presented on graphs 5 – 8 in Appendix 4, as well as regression coefficients reported in Table 2 here reveal a high robustness of the results described in Section 5. In the case of the 10 topics used, the sequence for pro-Western followers ends up marginally closer to the pro-Russian curve, which may be due to the noise introduced by a larger number of commonly used words employed in Wordscores. At the same time, the graphs for the case of only 5 topics being treated as politically relevant, the results are almost the same with a slight drift of both curves to the corresponding edges of the scale. So, slight changes to the number of topics considered to be politically relevant do not result in any considerable changes of the cleavage between pro-Russian and pro-Western politically active Twitter users. A null result is found again for the second hypothesis of this paper, as it follows from coefficients for slopes shown in Table 2.

**Table 2. Regression of differences in scores on time
(robustness check)**

	(10 topics)	(5 topics)
Week number	−0.04 (0.06)	−0.07 (0.05)
Constant	6.89*** (0.60)	7.18*** (0.48)
N	16	16
R^2	0.03	0.12

Note: *** $p \leq 0.01$. Standard errors in parentheses.

Since I found that my results are highly stable to changes in the number of topics considered to be political, one can question the importance of noise in my data. Is it actually necessary to combine unsupervised LDA with supervised Wordscores in order to remove informational noise when analyzing textual data like these? Graph 10 in Appendix 4 presents

¹⁵ These are topics 6 and 12.

unscaled sequence curves for ideological positions of politically active Twitter users. Although one can easily separate pro-Western and pro-Russian users, one could also assert using the graph that pro-Russian followers are quite ideologically far from pro-Russian elites and occupy a neutral zone on the ideological map, while pro-Western followers reside sufficiently close to pro-Western politicians. No doubts, these empirical findings caused by noisy data could end up in erroneous interpretation of the political situation in Ukraine and wrong predictions. Noisy data requires not only reporting standard errors (Benoit et al. 2009), but also a special treatment of noise when dealing with ideological scaling, as this paper reveals.

7. Conclusion

Mass protests have become a major driving force in the political development of hybrid regimes. Meanwhile, the proliferation of the social media made these online means of communication an important tool for political coordination and dissemination of information, especially by the political opposition in non-democracies. Hence, analysis of the social media can shed additional light on the way political unrest is developing in hybrid regimes, and on the psychological forces influencing patterns of mass protests.

This paper focuses on the pro-Western vs. pro-Russian ideological split in Ukrainian politics and attempts to analyze the dynamics of ideological positions of Twitter users talking about Ukraine. The motivation for this analysis is that ideological patterns of political tweets can reflect individuals' attitudes and intentions and, thus, provide information about future acts of the mass behavior.

I use tweets posted by the most popular pro-Western and pro-Russian politicians during the first two weeks as a training set, and tweets by their followers as the test set to be ideologically scored by the Wordscores procedure. I implement an original combination of supervised and unsupervised textual analysis via Latent Dirichlet Allocation to select only politically relevant words to be employed by Wordscores. This approach allows me to get rid of a large portion of noise in the data.

The paper makes use of the data described above in order to test two hypotheses: the

first one speculating that politically active Twitter users with different ideological positions discuss politics using a different vocabulary, while the second one supposes that the difference in scores assigned to pro-Russian and pro-Western Twitter users is increasing in time due to the gradual aggravation of the crisis.

The results presented here corroborate the first hypothesis. The two curves representing dynamics of pro-Western and pro-Russian followers of politicians on Twitter are clearly and statistically significantly separated. This means that Twitter can be a source of public opinion information relevant for political science research.

However, the second hypothesis finds no empirical support. One can explain this finding in several different ways. First, it could be the case that tweets reflect the current mood and emotions of the users, and may lack systematic relation to actual actions people take.¹⁶. Second, the cleavage among pro-Western and pro-Russian politically active Twitter users may already be so deep that aggravation of the conflict was itself a reflection of the existing cleavage and could not produce any visible growth of the split, or the cleavage was increasing among less politically active people. Third, the null finding may be due to the Crimean crisis and deployment of Russian troops on the peninsula. The latter may have affected the mood of the general public switching the topics of the tweets from protest activity to the protection of the territorial integrity of Ukraine. While the first explanation is, from a substantive viewpoint, somewhat discouraging, since it reveals large limitations for the use of Twitter (and, probably, social media in general) data in political science research, the last two explanations do not challenge the scope of questions we can ask of social media data and only refers to the specifics of the 2014 Ukrainian Crisis. However, further research is required in order to assess the feasibility of the explanations proposed.

Finally, I found that ideological scaling based on tweets may be sufficiently affected by the noise present in the data due to the non-political substance of a great deal of the tweets. This finding highlights the importance of a careful pre-processing of the text data

¹⁶ On the distinction between having a radical opinion and taking radical actions see, for example (McCauley and Moskalenko 2014).

and encourages combining supervised machine learning techniques (like Wordscores) with unsupervised methods (like Latent Dirichlet Allocation). This paper also reveals a need for a more unified way to test statistical hypotheses (including the ones about time trends) within the common framework of scaling texts. A Structural Topic Models approach could possibly also be used in order to corroborate the results presented here via LDA and an OLS regression.

Another issue of significant substantive interest for political science raised indirectly by this paper is how much the results one can get from ideological scaling of tweets correspond to the pattern one can reveal from survey polls. Actually, this is a twofold question, since it embraces both the reliability of the scores we get from Twitter and the selection bias of Twitter users with respect to the whole electorate. One could possibly address the first part of this question by looking at the patterns of ideological scores (or just politicians' ratings) on Twitter and in survey polls during an electoral campaign, since this is the time when polls are conducted on a regular basis. The second part of the question could be addressed by comparing survey data for all respondents to data about politically active respondents who also use social media.

Naturally, my analysis is but the first step in studying the pros and cons of using social media text data for recovering ideological positions of political elites and the general public in times of national crises in general and during the Ukrainian crisis in particular. We should engage in a larger scale research project to reveal the actual potential of the social media to predict social conflicts. We can also make more use of the fact presented here that textual data from Twitter does allow us to estimate the ideological positions of ordinary people.

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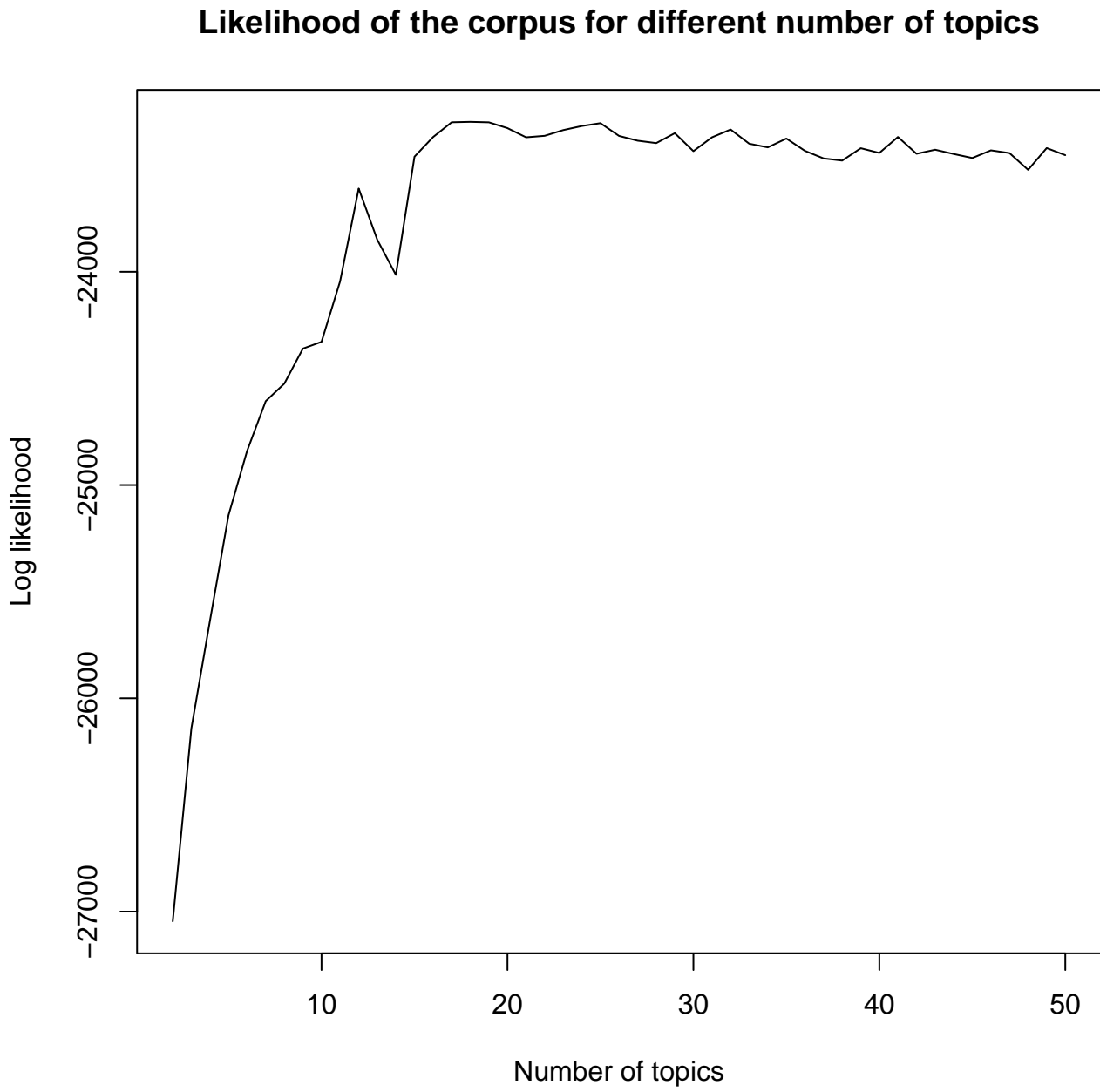
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Appendix 2

Table 1. 15 most frequent words within topics.

Topic 1 *украины *президент виктор *глава *государства *янукович *президента *обращение провел случаю *встречу *сотрудничества *украина *участие *встреча	Topic 2 *эвромайдан зараз *друзу *людей мене завтра ustream але сьогоднү вже *революція *aronets хто *тисяч аронець	Topic 3 *азаров николай vladimir *рыбак александр *ефремов *украина *украины *экономики анатолий *год *кинах *янукович будут виктор	Topic 4 *эвромайдан youtube *сьогоднү *майдану *турчинов cont uploaded video влада пүд *turchinov буду завтра знайти можно
Topic 5 *эвромайдан *друзу *сьогоднү вже *укра»ни *sos *день *людей пүд вүд дякую його *звернення *януковичу буде	Topic 6 это *ukrpravdanews елки или так *украины *харьковчан *batkivshchyna winny вот *врал *киев *ленину любовь *оппозиции	Topic 7 *януковича *день *эвромайдан хто *сьогоднү *майдану *укра»ни *янукович *людей буде грудня *майдану але пүд *завтра	Topic 8 *зараз *aronets бүля live *майдану *эвромайдан *друзу *людей вони *революція дякую мене *тисяч вүталүя *киэвү

Table 1. (continued) 15 most frequent words within topics.

Topic 9 *эвромайдан *майдан *майдану хто *янукович але бути вже ефур *майдану *прапорув *проти *agrytsenko *euromaydan *арму»	Topic 10 *сейчас это *аваков *вместе все *михайловской *portnikov svakarchuk tviuaofficial *беркут *беркута вот *вчера *эвромайдан *киеве	Topic 11 *укра»ни live грн грудня день дпс сьогодн *novosti вутаю його нудпсу тому irpen osvita.ua *вудбудеться	Topic 12 *эвромайдан всх *майдан уряду *вимога *вудставку *президента щоб *янукович весь *вибори вуд вони *достроков завтра
Topic 13 *удар *кличко вуд *донуй *klitschko *сьогодн ofeliyadd *korrespondent але день дякую *помощью хто markorachevski via	Topic 14 *революциягудност *эвромайдан *бесарабц олег *тягнибок бүля боку *зараз *күнець *ләнүна *революция *майдан *людей *янукович *януковича	Topic 15 *свобода *активүстүв *майдану влада грудня якү *майдан *укра»ну *участь вже вуд вудпущено гүрнику *госпүталүзовано двоэ	Topic 16 *эвромайдан *студенти *kyrylenkovyach сьогодн всү пүд *регүонали вже вуд *людей ua.ua але бүля будуть *эвромайдану

Table 1. (continued) 15 most frequent words within topics.

Topic 17
*состоится
*днепропетровске
*открытие
года
*украины
города
городского
декабря
молодежи
начала
ноября
бадминтону
*брифинг
воспитания
*встреча

Appendix 3

Table 2. Ordered list of LDA topics with percent of political words.

Number of the Topic	Political Words (%)
1	80
14	80
7	66.7
9	66.7
10	66.7
3	60
5	60
8	60
6	53.3
12	53.3
13	46.7
15	46.7
2	40
16	40
17	40
4	33.3
11	20

Appendix 4

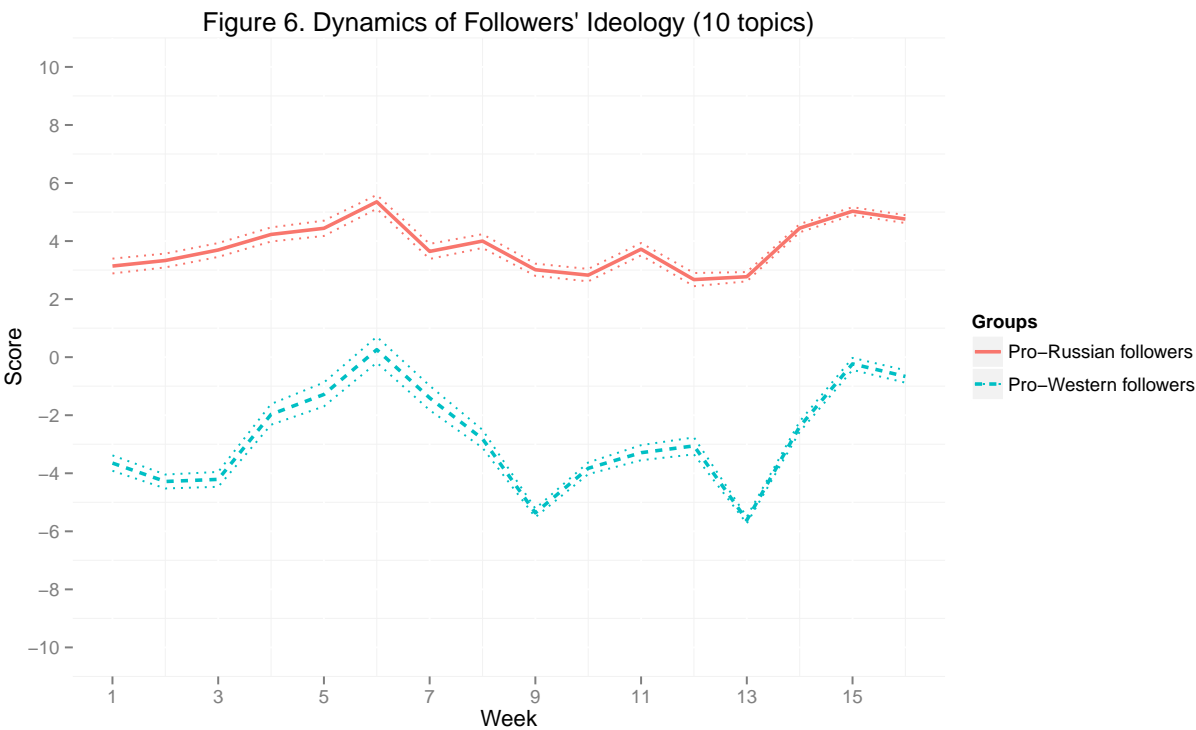
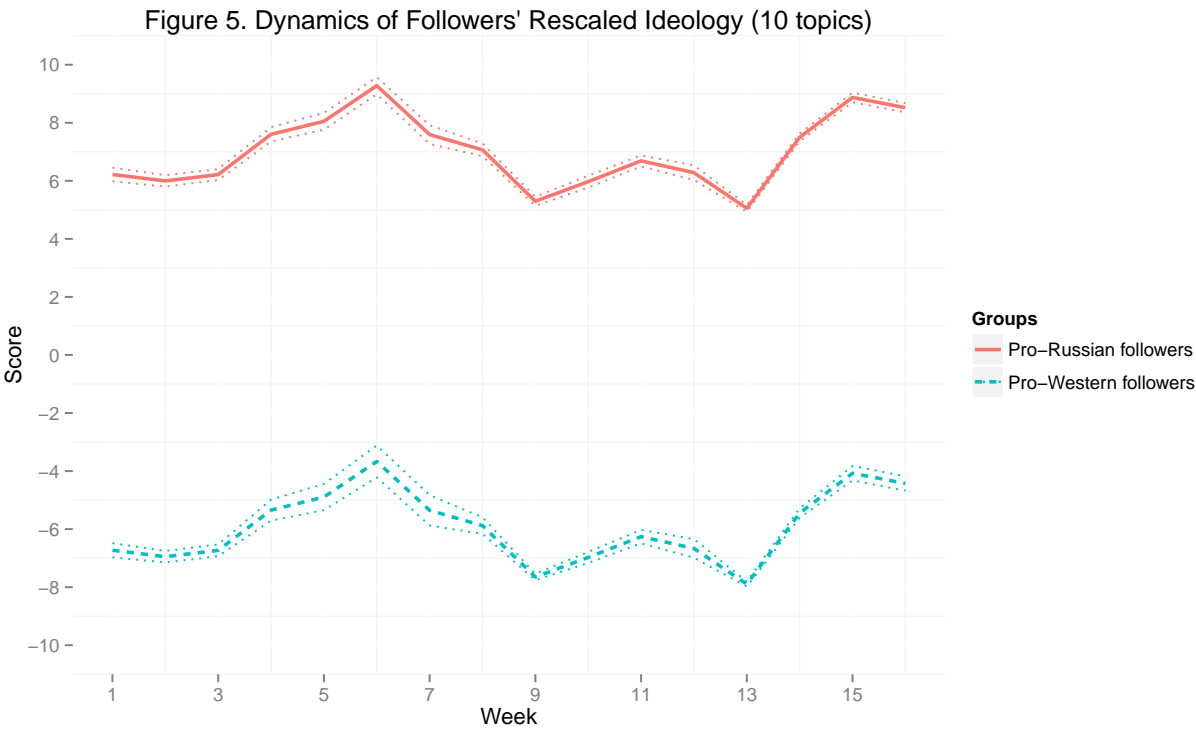


Figure 7. Dynamics of Followers' Rescaled Ideology (5 topics)

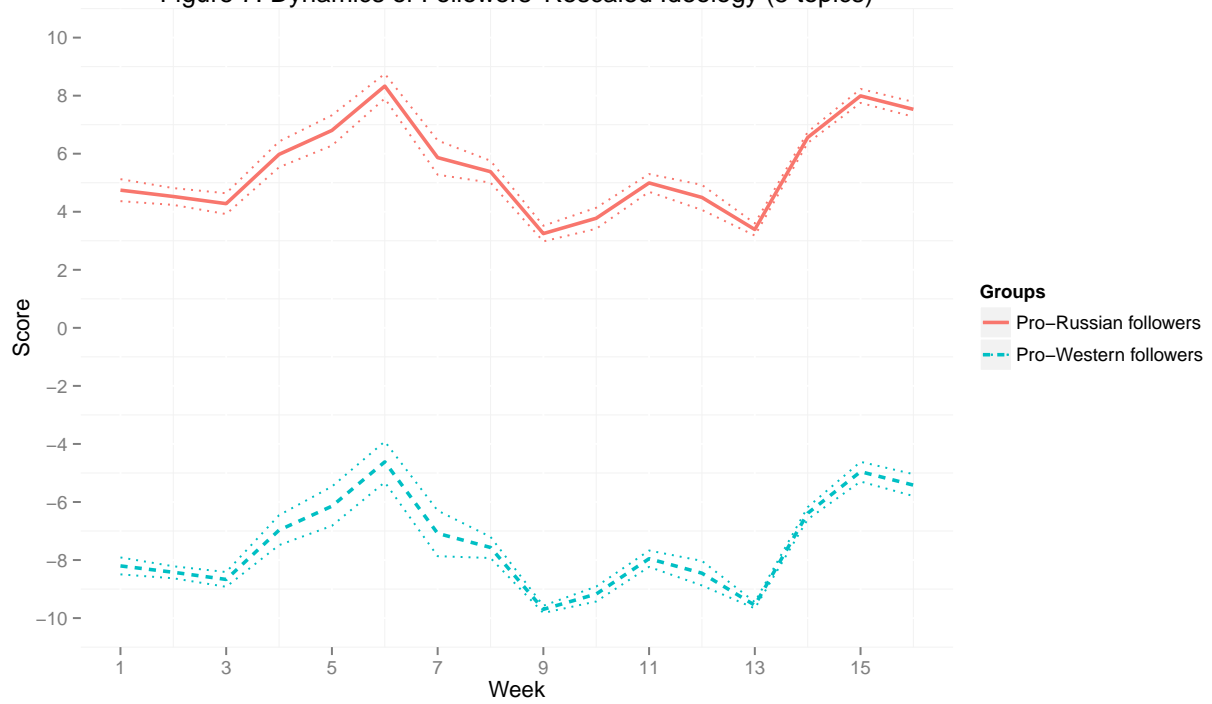


Figure 8. Dynamics of Followers' Ideology (5 topics)

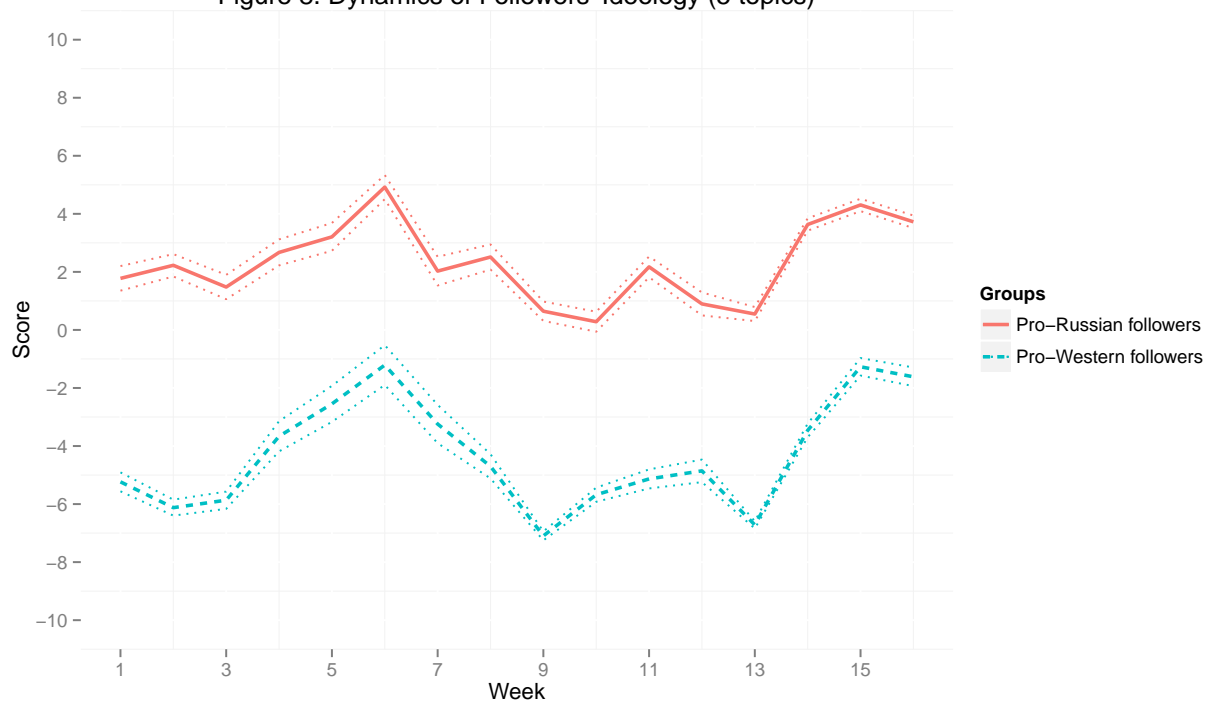


Figure 9. Dynamics of Followers' Rescaled Ideology (no LDA)

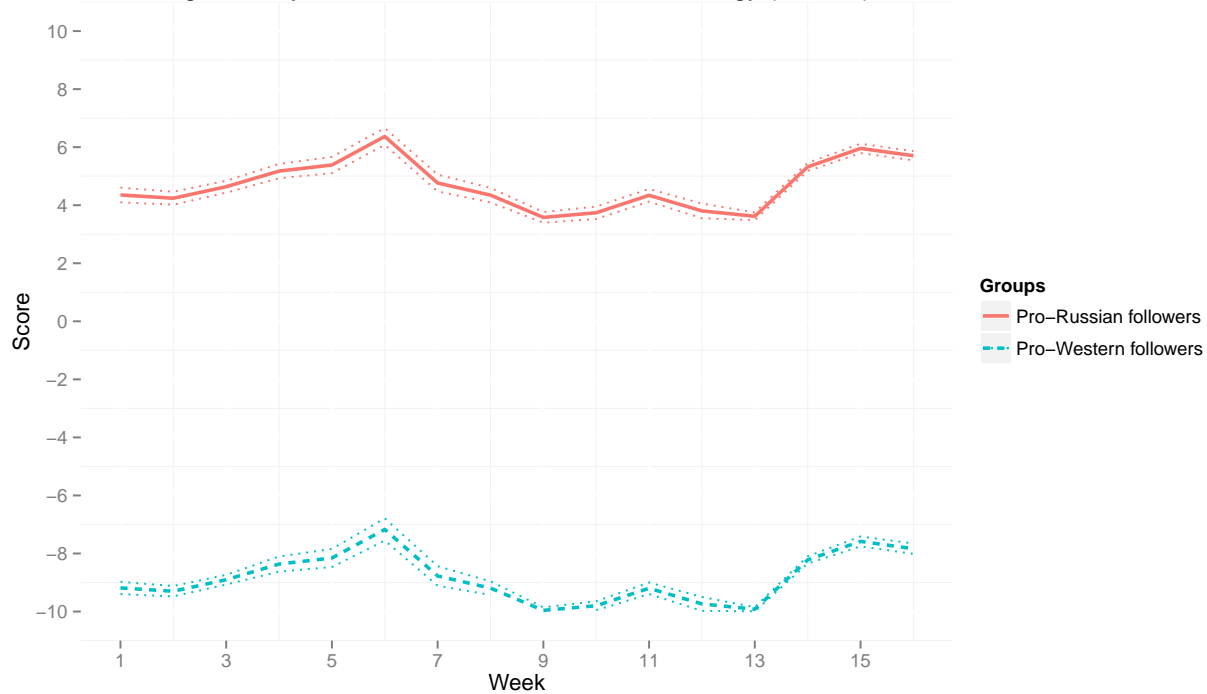


Figure 10. Dynamics of Followers' Ideology (no LDA)

