

Investigating Independence vs. Control: Agenda-Setting in Russian News Coverage on Social Media

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Abstract

Agenda-setting is a widely explored phenomenon in political science: powerful stakeholders (governments or their financial supporters) have control over the media and set their agenda: political and economical powers determine which news should be salient. This is a clear case of targeted manipulation to divert the public attention from serious issues affecting internal politics (such as economic downturns and scandals) by flooding the media with potentially distracting information.

We investigate agenda-setting in the Russian social media landscape, exploring the relation between economic indicators and mentions of foreign geopolitical entities, as well as of Russia itself. Our contributions are at three levels: at the level of the domain of the investigation, our study is the first to substructure the Russian media landscape in state-controlled vs. independent outlets in the context of strategic distraction from negative economic trends; at the level of the scope of the investigation, we involve a large set of geopolitical entities (while previous work has focused on the U.S.); at the qualitative level, our analysis of posts on Ukraine, whose relationship with Russia is of high geopolitical relevance, provides further insights into the contrast between state-controlled and independent outlets.

Keywords: Digital Humanities, Social Media Processing, Text Analytics

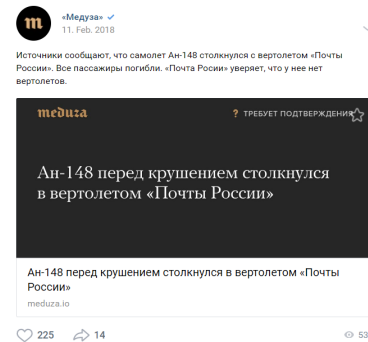
1. Introduction

A major challenge in the media and information industry has always been its targeted manipulation. In a democratic setting, the media are expected to fulfill fundamental functions such as providing the public with information of general significance and contributing to the formation of opinion by criticism and discussion, to enable political participation (Lippmann, 1922; Valenzuela and McCombs, 2019). While it remains open to what extent the media are able to fulfill this role in democracies (Meyer, 2002), it is indisputable that they are strategically used to manipulate and distort the spread of information in autocratic political systems (King et al., 2017).

Agenda-setting, as explored in this paper, is a well-known notion in political and social sciences. It targets the identification of control strategies exerted by governments (or powerful stakeholders) on the output of the media that, in turn, hold the power to influence the public opinion (Damstra et al., 2018; Soroka et al., 2015; Soroka et al., 2018). Among others, previous methods employed for modeling on agenda-setting retrieve a set of topics (e.g., types of reported events, mentions of foreign entities) and interpret their (unequal) frequency distributions in relation to economic variables (Kim et al., 2017). If topic distribution modulates in terms of the economic trends (e.g., negative trends/entertainment news; positive trends/mentions of the local government), further interpretations can be made regarding the presence of media manipulation strategies (Huang, 2017; Rozenas and Stukal, 2019).

We examine agenda-setting in the Russian social media landscape.¹ More specifically, we propose to test whether Russian state-controlled media outlets use subtle manipulation strategies in news on Russia’s largest native social media platform *VK* (former *VKontakte*), where public figures or news outlets can set up official accounts and publish posts like those in Fig. 1 on their walls, similar to Facebook or Instagram. In previous work on subtle media manipulation strategies in non-democratic political settings, investigations of the case of Russia have been limited to news that is a) published by media outlets *owned* or *heavily controlled* by the state (Field et al., 2018; Rozenas and Stukal, 2019), and b) distributed via traditional news channels. However, Russia comes with a much richer ecosystem of first Soviet and later Russian media that cannot be diminished to a uniform system only carrying out a well-coordinated state propagandist effort (Koltsova and Bodrunova, 2019). Even with current evidence of such activities, there has been little systematic analysis of today’s complex structure and deep historical roots of the Russian media system (Kiriya, 2018; Bodrunova and Nigmatullina, 2020). To the best of our knowledge, this is the first study which aims at directly comparing state vs. independent outlets in terms of agenda-setting.

¹Please note that the work presented in this paper was completed before the Russian invasion of Ukraine on February 24, 2022. Since then, the Russian media landscape has started and will continue to change. Nevertheless, we believe that our findings can provide valuable insights into the Russian media eco-system that – and this is not a finding, but our hope – will continue to be more than a uniform propagandist system.



TASS. “Russia considers U.S. interference in the internal affairs of dozens of countries as a neo-imperial approach. Moscow will never do something like that, Sergei Lavrov (*Foreign Minister of the Russian Federation*) said: <http://go.tass.ru/fYUF>.”

MEDUZA. “Sources say that the An-148 plane collided with a Russian Post helicopter. All passengers were killed. The Russian Post assures that it has no helicopters.”

Figure 1: Example posts from the state-controlled news outlet TASS (left) and the state-independent news outlet Meduza (right). The provided translations correspond to the text above the images. Each text constitutes a post, excluding image content (Judina and Platonov, 2018). To facilitate understanding, explanations are added in italics.

We provide an approach to test whether agenda-setting, i.e. *what* topics are covered in the media at the exclusion of others, is used by state-controlled and state-independent media outlets as a response to downtrends in the economy. While previous research concentrates on distraction in Russian media by restricting the space of topics to mentions of the U.S. (Field et al., 2018), we maximize the range on our dataset (Judina and Platonov, 2018) by considering a set of 13 relevant foreign entities (plus Russia itself). We include single countries, such as Ukraine, as well as country groups, such as the EU. We employ regression analysis, bringing news coverage values and Russian economic performance indicators together under the consideration of various factors such as time. The breadth of the scope of the investigation is thus the second contribution of this paper with respect to previous work. After having built a comprehensive picture for all 13 foreign entities, we deep-dive into our data and conduct a qualitative investigation of the media coverage with respect to a foreign entity whose relationship with Russia is of clear relevance: Ukraine.

2. Background and Related Work

Strategic Distraction. In this paper, the concept of strategic distraction is understood as King et al. (2017, p. 496) aptly put it: “Distraction is a clever and useful strategy in information control in that an argument in almost any human discussion is rarely an effective way to put an end to an opposing argument. Letting an argument die, or changing the subject, usually works much better than picking an argument and getting someone’s back up (as new parents recognize fast).” While discussing and reasoning are generally perceived as a means for knowledge improvement and decision-making optimization, Mercier and Sperber (2011) argue that the function of human reasoning ultimately lies in winning an argument rather than finding out the truth. Furthermore, dis-

traction is suggested as an effective strategy for rapidly reducing anger (Denson et al., 2012) and pain (McCaul and Malott, 1984). Finally, distraction is very effective when coming in form of multi-channel, rapid, and continuous information flows, making it hard to disseminate (partial) truths from outright fiction. Thus, distraction paves the way for spreading inconsistent and partially or completely false information without the recipients knowing (Paul and Matthews, 2016).

The Russian Media Landscape. Russian media are often accused of not fulfilling their role as democratic institutions by giving in to state pressure and actively acting as instruments to carry out such pressure, for example in form of censorship or passively succumbing by making themselves dependent on state funding (Kiriya, 2018). However, this is not the full picture as the media in competitive authoritarian regimes like Russia are often not only legal but also act as meaningful democratic institutions, critically observing the leading parties and channeling opposition forces (Koltsova and Bodrunova, 2019; Levitsky and Way, 2010). In recent years, the not only dualistic but generally fragmented nature of the Russian media landscape has become more visible through an increasing opposition of media owned or controlled by the state and media considered to be rather independent (Kiriya, 2019; Bodrunova and Nigmatullina, 2020). While the former are assumed to not fulfill their role as democratic institutions, broadcasting false news or actively selecting what topics are covered, state-independent media experience state pressure by means of legislation, being frequently accused of depending on foreign financing or attacked as foreign agents (Sherstoboeva, 2020).²

²In 2021, this happened with the state-independent news outlet Meduza: on April 23, 2021, the Russian government has labeled them as so-called “foreign agents”. Besides the

Computational Analyses of Agenda-Setting. The concept of agenda-setting refers to the idea that “the press is significantly more than a purveyor of information and opinion. It may not be successful much of the time in telling people what to think, but is stunningly successful in telling its readers what to think *about*.” (Cohen, 1963, p.13, emphasis by the author). In other words, the media are able to influence the importance attached to an information by selecting to cover that information at the exclusion of others (McCombs, 2005; Scheufele and Tevksbury, 2007).

Since its beginnings in the 1970s (McCombs and Shaw, 1972), an increasing amount of researchers has studied agenda-setting from a variety of perspectives (see Kim et al. (2017) for a detailed overview). Among others, one line of work implements the notion of *Granger-causality*, grounded in the field of economics (Granger, 1969). Its main premise postulates that the past determines the future and not vice versa, i.e. cause precedes effect. A time series X is thus said to Granger-cause Y , if X contains statistically different information about future values of Y . Most research concentrates on modeling relations between textual news data and economic performance indicators such as stock market values use approaches including *keyword frequencies* (Kogan et al., 2009; Nardo et al., 2016), *tonality*, *sentiment* (Bollen et al., 2011; Chen and Lazer,), and *structured events* (Ding et al., 2015). However, Field et al. (2018) reverse the direction and use economic indicators to reveal agenda-setting in news articles as a strategy of distraction by drawing on Granger-causality to demonstrate that a negative trend in Russia stock market data precedes a positive trend in news coverage on the U.S., using 100,000+ articles from the Russian state-controlled newspaper *Izvestia*, for a time span of 13 years. Rozenas and Stukal (2019) also harness economic indicators to analyze news coverage from Russian state-controlled TV *Channel 1*, showing that good news tend to be attributed to Putin and Russian officials and bad news are more likely to be attributed to foreign economy and powers (selective attribution).

Another perspective on agenda-setting targets phenomena resulting from the emergence of new media platforms and a growing, ever-changing media landscape (McCombs et al., 2014; Haim et al., 2018). This is also true for the case of Russia, where social media have become a new point of access into the digital media landscape and in some cases even replaced the traditional public sphere in terms of political and cultural agenda-setting (Glenski et al., 2018; Glenski et al., 2020; Vartanova, 2020). There has been a considerable amount of work on Russian social media data including Twitter, Facebook, and VK as well as the role of an outlet’s *status* (controlled or independent) encompassing research on topics such as *ideological bias* (Potash et al., 2017), and *protest mobilization* and *participation* (Enikolopov

consequences this has for Meduza journalists, the branding also leads to a high loss of advertisers.

et al., 2015; Rogers et al., 2019). Moreover, Judina and Platonov (2018) explore *agenda-setting* and *public concern* in news on VK and compare topic coverage and engagement rate for two state vs. two private news outlets. Whilst their work presents an important step into the direction of replacing manual efforts by computing metrics, the scope is limited by manual annotation efforts. Thus, to the best of our knowledge, drawing on agenda-setting to explore distraction as a subtle media manipulation strategy in news on Russian social media has not been addressed yet.

3. Resources

Corpus. Throughout our experiments, we draw on the VK corpus (Judina and Platonov, 2018), consisting of carefully curated posts published by one of the four Russian media outlets *Russia Today* (RT), *TASS*, *Meduza*, and *RBC*. It encompasses a total of 14,910 posts collected during the time frame of January 17, 2018 to March 09, 2018. By asking the question of how a news outlet is financed, Judina and Platonov (2018) provide a categorization of the news outlets into the subsets *state-controlled* (RT and TASS) and private or *state-independent* (Meduza and RBC).

The posts’ distribution is relatively uneven, with two thirds from the state-controlled media outlets RT (7,632) and TASS (3,555), while the share of posts from the state-independent media outlets Meduza (1,900) and RBC (1,823) constitutes the smaller part of the corpus.

Corpus Preprocessing. The goal of the experiments on agenda-setting is to investigate whether media attention is disproportionately focused on a certain topic to divert public attention from certain events, namely, in our case, negative economic trends. Thus, we implement the following preprocessing steps: First, we apply NER (Nadeau and Sekine, 2007) on raw post texts using the ISPRAS (texterra) API.³ Then, extracted references pointing to the same topic are merged into one label, considering all entities referring to a country that occur more than twice in the whole corpus. Next, extracted references are either grouped to single country labels, e.g. including all references for Ukraine (label UKRAINE), or to country groups, such as the EU and geopolitically connected countries (label EU+NEIGHBORS), as listed in Table 1.⁴

In accordance to best practices for tweets (HaCohen-Kerner et al., 2019), we implement basic post text preprocessing, including the substitution of user handles, numbers, hashtags, and currency symbols, as well as the removal of emojis, punctuation, and posts no longer containing a word character. Finally, we tokenize and lowercase all text. An overview of the complete VK corpus in terms of types, tokens, and posts is shown in Appendix (App.) 6.3, Table 5.

³Our code is available here.

⁴App. 6.1 provides a list of references used to collapse the extracted entities, and App. 6.2 a description of reasonable extensions and restrictions implemented for individual labels.

Label	Countries and Regions
Africa	Angola, Algeria, Ethiopia, Guinea, Nigeria, South Africa
Australia + Oceania	Australia, New Zealand, Tonga
China	Hongkong, People’s Republic of China
CIS	Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Moldova, Tajikistan, Turkmenistan, Uzbekistan
EU + Neighbors	All EU member states, Albania, GDR, Liechtenstein, Montenegro, North Macedonia, Republic of Ireland, Switzerland, United Kingdom
Korea	North Korea, South Korea
Near East	Egypt, Iran, Islamic State, Israel, Iraq, Jordan, Kurdistan Region, Libya, Macedonia, Qatar, Palestine, Saudi Arabia, Turkey, Yemen
North America	Canada, Mexico
Russia	Crimea, Russian Federation
South Americans + Caribbeans	Argentina, Brazil, Chile, Cuba, Ecuador, Haiti, Peru, Venezuela
South and East Asia	Afghanistan, Georgia, India, Japan, Myanmar, Mongolia, Pakistan, Papua New Guinea, Sri Lanka, Thailand, Western New Guinea (Papua)
Syria	Ghouta, Syria
Ukraine	Ukraine
U.S.	U.S.

Table 1: Overview of country (group) labels (left) and included countries (right).

Russian Economic Performance Indicators. The Russian Trading System Index (RTSI) is one of the two stock market indices of Russia’s largest exchange groups, Moscow Exchange (MOEX). Including a comparably broad spectrum of up to 50 of Russia’s largest listed companies, the RTSI is calculated in US dollars and considered the international benchmark for Russian trading and thus, Russian economic performance. We harness daily stock market closing prices from the Moscow exchange website for the time period from January 17, 2018 to March 9, 2018, following previous work. Since no data is provided for weekends and public holidays, missing values are estimated by linear interpolation.

4. Exploring Agenda-Setting

In this section, we present the results of our agenda-setting analysis, which is composed of three main building blocks: 1. mentions of political entities (objects of projection, in the agenda-setting terminology); 2. economic indicators from RTSI; 3. the time variable, at different degrees of granularity.

4.1. Correlation Analysis

Correlations: Post vs. Word Level. To examine the relationship between Russian economic performance indicators and news coverage on given topics, we start out with a correlation study where a time slice is defined as a week. For each subset of the VK corpus, the strength of the relation between RTSI values and potential objects of projection is investigated by calculating Spearman’s correlation coefficients.

For this, news coverage of a country or country group at the *post* level is defined as the ratio of VK posts mentioning the country (group) at least **once** compared to the total number of posts in a given time slice. Corresponding RTSI values are calculated by summing up

the values in a given time slice. Then, normalized news coverage values are obtained by normalizing the number of posts on a given object of projection (in our case, mentions of a geopolitical entity) in a given time slice by all posts in that time slice. Economic performance indicators are computed by summing the values in a time slice.

The obtained coefficients are listed in the left part of Table 2. Here, a few significant relations emerge, such as a relatively strong positive correlation with moderate significance for the label EU AND NEIGHBORS in the state-controlled ($\rho = 0.64$) and the label CIS states in the state-independent ($\rho = 0.69$) subsets, respectively.

In the next step, the approach is refined by taking more fine-grained metrics from different points of view: First, we move from *post* to *word* level to see whether a given label is extensively brought to the reader’s attention by means of disproportionately many references compared to the total number of words used. Similarly to *post* level, the *word* level metrics is calculated by normalizing token frequency of the number of occurrences of a projection object by the total number of tokens in a given time slice. As shown in Table 2, we find that results on word level oscillate around post level findings with the exception of the label CIS, for which a significant relation can be observed for the state-controlled subset on word level that is not captured on post level. This does not entirely agree with Field et al. (2018), who found only weaker correlations that reflected the post level results when using the metric word level. We attribute our result to the impact of the post length, which may vary relatively strongly, as well as to the number of countries encompassed by a label. For reasons of clarity and space, we focus on post level results in the following, and refer to word level results in case of strong differences between the metrics.

Label	Post Level		Word Level		Post Level					
	7 days				5 days		3 days		1 day	
	CONT	FREE	CONT	FREE	CONT	FREE	CONT	FREE	CONT	FREE
Africa	-0.40	-0.29	-0.48	-0.29	-0.28	-0.35	0.04	-0.11	0.17	** -0.28
Aus+Oc.	-0.14	-0.19	0.29	-0.24	0.16	-0.20	0.05	0.23	-0.06	-0.01
China	0.00	0.55	0.05	0.29	0.09	0.33	0.30	0.01	0.09	0.08
CIS	0.50	*0.69	*0.67	0.45	*0.59	*0.6	*0.44	0.40	0.18	0.09
EU+NBS	*0.64	-0.10	0.62	-0.17	0.29	-0.25	0.16	-0.04	0.07	0.09
Korea	-0.43	-0.29	-0.45	-0.29	-0.23	-0.46	-0.15	-0.21	0.08	-0.03
Near East	-0.33	0.19	-0.24	-0.05	*-0.56	-0.25	-0.04	0.03	0.05	-0.11
NA	0.48	0.44	0.48	0.44	0.36	*0.56	0.08	0.30	0.04	0.16
Russia	-0.40	*0.69	-0.29	*0.71	-0.19	*** 0.75	-0.23	** 0.47	-0.11	*0.27
SA+Car.	0.40	0.36	0.48	0.36	*** 0.62	0.31	0.28	0.27	0.13	0.18
S+E Asia	0.38	-0.48	0.38	-0.57	0.29	-0.47	0.21	-0.37	0.07	-0.13
Syria	0.17	0.00	0.17	0.10	0.13	-0.01	-0.10	-0.14	0.00	-0.18
Ukraine	-0.19	-0.36	-0.12	-0.45	-0.06	0.13	-0.15	-0.19	0.01	-0.11
U.S.	-0.12	0.02	-0.12	0.12	-0.15	-0.06	0.06	0.07	0.04	0.18

*p<0.1; **p<0.05; ***p<0.01.

Table 2: Spearman’s rank-order correlation coefficients comparing RTSI and normalized absolute news coverage values of a given label in a time resolution of 7 days on post and word level, as well as in a time resolution of 5, 3, and 1 day(s) on post level. Columns CONT and FREE refer to state-controlled and independent subsets, respectively.

Correlations: Manipulating the Time Variable. We explore the impact of different time resolutions using time slices of five, three, and one day(s). The results, provided in Table 2, display a mixed picture with some correlation coefficients getting weaker or even disappearing (RUSSIA) when the time slice under consideration becomes smaller, while others (SOUTH AMERICA; AFRICA) only appear at five- or one-day resolutions. Finally, we narrow down the label set and further refine the relatively diverse results regarding appropriate time slices. For this, we calculate time-lagged correlation coefficients, taking into account RTSI values at time points r_{t-1} and r_{t-2} , and news coverage on post (or word level) at a time p_t (w_t), for time slices of seven and five days as well as in a daily resolution. The obtained coefficients shown in Table 3⁵ point into various directions, including a strong inverse relation between RTSI values and news coverage on the label NEAR EAST for the lag of a (working) week for *both* state-controlled and independent subsets. This is also true for the label CIS for a lag of two (working) weeks, i.e. 14 (10) days. Differences can be seen, for example, regarding the label RUSSIA, where a strong positive relation is obtained for the state-controlled subset for lags of one and two (working) weeks, which is not resembled in the data from state-independent subsets.⁶ Thus, more coarse-grained time slices seem to help capture stronger correlations and trends, which are inherent to stock market values.

⁵See supplementary material for results on word level.

⁶One could argue that a Russian news outlet naturally publishes more information on Russia itself than, for example, a Chinese news outlet. While (dis)proving this hypothesis is outside the scope of this work, we concentrate on comparing controlled and independent news outlets by highlighting differences between results.

The overall results from the correlation analysis indicate the presence of agenda-setting on foreign countries in times of economic downtrends which is in line with previous work (Field et al., 2018; Rozenas and Stukal, 2019). However, cases such as the absence of any correlation for the label Ukraine, which surprises given the rich common history, geological proximity, as well as on-going political and military situation, point to the need of further analysis to validate whether the established correlations are in fact directed.

4.2. Regression Analysis

To test the hypothesis that economic performance veritabily impacts news coverage of an object of projection, and to assess whether the correlations established in the previous section 4.1 are indeed directed, we employ regression analysis. In contrast to previous work by Field et al. (2018), who model the relation between news coverage and economic performance indicators regarding a single country, namely the U.S., we build a larger set of more complex models to explore the impact of the variable *country*, as well as the factors *state-independent* vs. *state-controlled* for the relation between news coverage and economic performance for 14 different countries and country groups. In more detail, we first fit a range of linear regression models, covering simple, multiple, and multiple linear models with interaction terms. Second, we employ a time-lagged regression model, which effectively implements the notion of Granger causality.⁷ To fit the linear models, news coverage on post level and the RTSI closing price (in rubles) are used. First, the percentage change of news coverage is calculated for each time series, thus accounting for longer trends

⁷Whenever a model is fit that is assumed to not satisfy the assumption of linearity, we do not consider it in the analysis.

Label	Post Level				5 days				1 day			
	7 days											
	r_{t-1}		r_{t-2}		r_{t-1}		r_{t-2}		r_{t-1}		r_{t-2}	
	CONT	FREE	CONT	FREE	CONT	FREE	CONT	FREE	CONT	FREE	CONT	FREE
Africa	-0.02	0.73	0.50	0.13	-0.08	-0.19	0.33	0.09	0.15	*-0.27	0.01	-0.17
Aus+Oc.	-0.05	-0.29	0.01	0.32	0.08	0.11	-0.10	0.33	0.01	0.13	0.10	0.01
China	0.26	-0.71	-0.14	-0.25	0.06	-0.13	0.11	-0.01	-0.02	0.06	-0.01	0.02
CIS	-0.52	-0.07	-0.61	** -0.80	-0.14	-0.13	** -0.70	*** -0.80	0.20	0.14	0.11	0.08
EU+NBs	0.52	-0.51	-0.54	0.05	0.34	0.30	0.42	0.46	0.13	0.09	0.14	0.11
Korea	0.29	-0.34	0.51	0.29	0.06	-0.46	0.32	0.02	0.10	-0.12	0.07	-0.01
Near East	** -0.76	0.15	0.05	-0.46	-0.41	*-0.54	-0.12	*-0.55	0.00	-0.20	0.03	-0.07
NA	*-0.64	0.32	-0.59	-0.47	-0.28	-0.39	-0.48	*** -0.82	0.02	0.18	-0.07	0.19
Russia	** 0.76	-0.12	0.42	-0.51	** 0.70	0.10	** 0.62	-0.31	0.02	*0.25	0.16	0.21
Sa+Car.	-0.05	-0.37	-0.41	-0.13	0.21	0.22	-0.39	-0.03	0.13	0.22	0.15	0.22
S+E Asia	0.57	-0.29	-0.11	0.40	*0.58	0.30	0.36	*0.59	0.18	-0.02	*0.24	0.03
Syria	0	0.22	0.07	0.12	-0.13	-0.34	0.26	0.17	-0.01	*-0.23	-0.01	-0.20
Ukraine	-0.12	0.32	0.13	0.11	0.02	-0.05	0.07	-0.17	-0.03	-0.11	0.01	-0.13
U.S.	0.60	-0.68	0.12	-0.25	0.53	0.41	0.47	0.25	0.11	0.11	*0.25	0.12

Table 3: Spearman’s rank-order correlation coefficients comparing RTSI and normalized absolute news coverage values of a given label on post level in 7-,5-, and 1-day time resolutions, using lags of 1 and 2 time slices. For example, r_{t-1} results describe the correlation of stock market values from 7 days ago with news coverage today.

of the stock market:

$$\Delta(p_t) = \left(\frac{p_t}{p_{t-1}} - 1 \right) * 100$$

where p_t refers to absolute news coverage on post level and p_{t-1} to absolute news coverage on post level by a given time slice earlier in time. Percent change values of the RTSI closing price $\Delta(r_t)$ are calculated analogously. To include information from past observations of news coverage and RTSI values, a time-lagged linear regression model is implemented:

$$\Delta(p_t) = \sum_{i=0}^m \alpha_i (\Delta(p_{t-i})) + \sum_{j=0}^n \beta_j (\Delta(r_{t-j}))$$

where $\Delta(p_t)$ refers to the percent change of news coverage, m and n indicate the amount of time looked back in days, α is the regression coefficient estimated for the time-lagged percent change of news coverage, and β is the regression coefficient estimated for the time-lagged percent change of RTSI values (Field et al., 2018). In case the regression coefficient for time lags of Δr_t is significantly different from zero, this would indicate that RTSI values *Granger-cause* news coverage. Recall that negative estimates can indicate an inverse relation between RTSI and news coverage values on a given country label from a given subset of the VK corpus, suggesting targeted distraction from economic downtrends. In contrast, positive estimates suggest possible targeted attribution of economic uptrends. Using lags of one and two, we fit a separate model for each country label in a subset. We show an overview of the results for both subsets in Table 4.

Our findings, as described in more detail in the supplementary material, can be summarized as follows. First, exploring the relationship between the RTSI and news coverage observed for a given country by fitting models for both subsets individually and together yields significant predictors. This partly underlines previous results,

for example an inverse relation for the label NEAR EAST (both subsets) and uncovering new ones, such as an inverse relation for KOREA (state-independent). However, the smaller the time slice, the weaker the coefficients.

Second, adding information on the *status* of the subset (state-independent or state-controlled) or the *country* label in form of categorical variables is not shown to be predictive of the amount of news coverage from a given country label in our setup.⁸

Third, taking into account each subset and country individually, results from the time-lagged linear regression analysis display significant findings. Among others, the strong inverse relation between RTSI values and news coverage on the NEAR EAST for lags of a working week (five and six days) are underlined once more (both subsets). The analysis also uncovers relations not observed previously, such as positive relations for news coverage on NORTH AMERICA AND MEXICO, as well as mixed relations for UKRAINE in both subsets over various time resolutions.

4.3. Qualitative Analysis.

We now turn to a qualitative investigation of news coverage on sample posts⁹ for Ukraine, whose geopolitical relationship with Russia is clearly relevant and for which the results so far display a relatively mixed picture. We identify the following degrees on the spectrum of control to independence on content level.

The state-controlled perspective includes a fair amount of communication about military incidents, relevant political figures and moves, as well as Russia’s role in the matter, for example by reporting what the Foreign Minister of Russia Sergey V. Lavrov said at the 2018 Munich Security Conference: “*Russia is more interested*

⁸An exception are daily time slices, where integrating the variable *country* seems to be more promising but not capturing too much of the data’s variance.

⁹See the supplementary material for corresponding posts.

Label	5 days				3 days				1 day				
	r_{t-1}		r_{t-2}		r_{t-1}		r_{t-2}		r_{t-1}		r_{t-2}		
	β	Adj. R^2	β	Adj. R^2	β	Adj. R^2	β	Adj. R^2	β	Adj. R^2	β	Adj. R^2	
Africa	CONT	-0.73	0.25	**1.34	0.61	-0.35	0.11	** -2.43	0.39	4.85	0.26	-14.56	0.38
	FREE	0.05	0.10	-1.40	0.14	0.09	0.43	0.18	0.41	-8.28	0.16	7.68	0.19
Aus+Oc.	CONT	0.56	0.20	***2.53	0.63	0.53	0.06	1.36	0.13	11.24	0.13	-0.97	0.25
	FREE	0.50	-0.05	0.14	0.20	1.12	0.31	*** -2.30	0.50	-2.87	0.41	3.96	0.39
China	CONT	0.93	0.06	1.06	0.04	0.38	-0.00	1.52	-0.04	0.69	0.06	-10.25	0.05
	FREE	1.30	0.24	***3.15	0.60	-0.84	0.09	-1.18	0.07	-6.32	0.13	-7.10	0.15
CIS	CONT	0.34	0.00	1.23	0.03	0.42	0.01	0.44	0.06	6.62	0.16	1.02	0.24
	FREE	0.33	0.03	0.75	0.03	-0.23	0.20	0.76	0.42	-0.01	0.11	10.66	0.28
EU+NBS	CONT	**0.64	0.34	-0.13	0.31	0.35	0.15	**0.91	0.59	9.85	0.16	0.63	0.15
	FREE	0.13	-0.04	0.43	0.23	0.18	0.31	0.18	0.28	-7.68	0.01	0.98	-0.02
Korea	CONT	0.06	0.01	-0.43	0.31	0.50	-0.04	-0.59	0.08	9.51	0.10	13.01	0.19
	FREE	-0.19	0.01	-2.62	0.26	1.15	-0.03	-1.33	0.04	-4.61	0.09	15.78	0.09
NE	CONT	-0.39	0.02	-0.11	0.09	1.29	0.05	*** -12.95	0.74	-13.91	0.02	-33.84	0.03
	FREE	*** -8.57	0.52	-0.65	0.50	0.99	-0.01	*** -11.19	0.89	-10.56	0.08	13.35	0.08
NA	CONT	-0.01	-0.04	*2.35	0.12	2.00	0.01	1.84	-0.00	5.95	0.07	15.13	0.13
	FREE	0.45	-0.03	0.86	0.00	0.11	0.45	**1.54	0.60	-2.03	0.03	*14.49	0.19
Russia	CONT	0.18	0.11	*** -0.78	0.64	0.21	0.21	-0.13	0.20	-1.85	0.02	4.48	0.06
	FREE	0.21	0.10	0.13	0.10	0.05	0.25	*0.42	0.40	-0.38	0.27	2.01	0.33
SA+Car.	CONT	0.87	0.09	-0.63	0.61	*2.31	0.34	*2.23	0.38	-7.95	0.03	6.21	-0.01
	FREE	0.22	-0.03	***3.01	0.33	1.02	0.05	-0.70	0.06	14.15	0.34	-16.31	0.41
S+E Asia	CONT	*1.33	0.14	**1.73	0.29	1.87	0.15	0.67	0.29	3.81	0.15	13.51	0.16
	FREE	0.26	-0.01	*-1.37	0.12	0.67	0.02	0.58	0.10	1.45	0.10	5.21	0.13
Syria	CONT	0.64	0.06	*1.17	0.21	1.23	0.11	*-2.71	0.28	-32.55	0.08	5.00	0.04
	FREE	1.21	0.08	2.08	0.08	0.64	-0.05	-0.43	0.04	-22.26	0.06	5.83	0.03
Ukraine	CONT	-0.24	0.03	*-0.44	0.23	-0.58	0.40	**1.19	0.59	-9.54	0.20	-0.60	0.17
	FREE	0.21	-0.03	*1.69	0.31	0.15	-0.00	0.32	-0.04	-5.53	0.02	*-38.39	0.08
U.S.	CONT	0.15	0.00	0.14	0.30	0.17	0.02	-0.39	0.03	7.84	0.08	1.70	0.08
	FREE	0.09	0.10	**0.86	0.48	-0.34	0.04	-0.61	0.17	7.18	0.05	17.90	0.07

p<0.1; *p<0.05; **p<0.01 ***p<0.001.

Table 4: Time-lagged linear regression analysis for time resolutions of 5, 3, and 1 day(s) with lags of 1 and 2 time slices (e.g., 5 or 10 days) for state-controlled and independent subsets, respectively.

in solving the domestic crisis than anyone else, assured Sergey Lavrov [... He] believes that Ukraine is a country with an enormous life potential and talented people that has been put into a state of inability to manage itself.” Concerning the Russian economy, the state-controlled media communicate that “anti-Russian sanctions hit the Ukraine economy” like an “(e)conomic boomerang”, doing Ukraine more harm than Russia and make clear that Russia “does not want to solve the Ukraine’s economic problems”. They also seem to perceive that “Ukraine only imitates to work” and communicate requests, such as “Let Ukraine pay for us”.

Regarding the state-independent media outlets, the picture is less homogeneous, as we observe a qualitative difference between the two outlets. RBC tends to report more about Ukraine and provides a perspective that is closer to the state-controlled media outlets. Examples for this include the prohibition of a Russian film due to the participation of a Russian musician from the Ukrainian black list, repetitive mentions of Ukraine’s ban of the Russian language as a subject in school and as an official language, and information about potential money laundering by the Ukrainian president. In contrast, Meduza does not cover the topic Ukraine much and if so, they tend to focus on more positive events, such as released captives from the Donetsk and Luhansk Oblasts¹⁰. However, they also touch upon topics such

¹⁰Namings such as *Donetsk* and *Luhansk People’s Republic* refer to the regions as breakaway states from Ukraine as of April, 2014.

as the closing of “schools due to gas shortages” and few political events, from both Russian and Ukrainian points of view.

The observation of RBC as more state-controlled-like outlet, if extended to other countries, offers itself as a potential explanation of the low significance of the status predictor. If more data were available (recall that the state-independent outlets are less represented in VK) the outlet could be used as a predictor.

5. Conclusion

The experiments presented in this paper provide a novel perspective on agenda-setting in news on Russian social media: broader than previous work, supported by a thorough exploration of different aggregation options, as well as a robust statistical analysis and qualitative inspection of a selection of relevant posts. Our results show that there are indications for the use of targeted distraction as a strategy of manipulation in the VK corpus. While we find cases where state-controlled and state-independent subsets cover news on the same topics, we also observe a range of instances revealing differences regarding selected topics, leaving us with a mixed picture so far. The natural follow-up step in this research agenda is integrating the question of *what* is reported in the media (agenda-setting) with that of *how* certain topics are represented: current work is precisely targeting this, adopting methods for the computational detection of framing in the news (Liu et al., 2019; Khanezhzar et al., 2019; Akyürek et al., 2020).

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Appendix

6.1. Collapsing Named Entities.

africa: èfiop, afrik, nigeri, južno-afrikanskaja respublika, juar, alžir, angol, gvine; **australia_oceania:** tong, zeland, avstral; **china:** gonkong, kita, juan', knr; **cis:** moldav, armen, belorus, kirgiz, uzbekist, azerbajdžan, turkmen, kazakh, tadžik, sng, armjan; **eu_and_neighbors:** evrosojuz, švejar, alban, pribaltijsk, finljand, finsk, finn, fink, evrop, češsk, litv, katalon, franc, irland, severnaja makedonija, latyšsk, litovsk, german, ispan, dani, lihtenštejn, frg, niderland, golland, portugugal, brit, švec, nemeč, veng, sloven, greci, šved, ljuksemburg, evrope, federativnaja respublika germanija, norve, pol', bel'g, angli, avstr, serb, grečeskij, ital, bolgar, čekhi, veliko, černogori, gdr, latvi, èston, khorvat, mal't, slovak, kipi; **korea:** kndr, kore, phen'jan; **near-east:** makedon, egipet, islamskoe gosudarstvo, kurd, turec, iran, saudovsk, turc, palestin, ig, izrail, irak, katar, iordan, livi, ankar, egipet, jemen; **north_america:** meksik, kanad; **russia:** jakut, sovetusk, sssr, dagestan, čečen, čečn, rf, rus, krym, rossijskaja federacija, ross; **south_america_carib** argentin, brazil, peru, gaiti, latinsk, kub, èkvador, čili, venesuèl; **south_and_east_asia:** m'janm, pakistan, tajvan, indi, thailand, afgan, papua, japon, šri-lank, azi, singal, mongol, mal'div, gruzi, zapadnaja novaja gvineja; **syria:** guta, vostočnoj gute, siri; **ukraine:** ukrain, donbass; **usa:** vašington, amerik, štaty, sša, gavaj, Guantanamo.

6.2. Country (Group) Label Mapping

A list of country (group) labels is provided in Fig. 1, which are described in more detail in the following:

- The label **Africa** denotes all mentions referring to countries on the African continent which are not considered to be part of the label **Near East**.
- The label **China** incorporates Hongkong.
- The label **EU and Neighbors** denotes all EU member countries (Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Serbia, Slovakia, Slovenia, Spain, Sweden) and the remaining EFTA countries Iceland, Liechtenstein, and Norway as well as Switzerland, which is well-connected to the EU by bilateral treaties. Andorra and San Marino, that are integrated by a custom union, are also encompassed. In addition, EU candidates like Montenegro, Serbia, North Macedonia and Albania are considered part of this label.
- The EU candidate Turkey is a border case. In the context of this work, Turkey is not considered part of the EU but is included in the label **Near East**. This reflects the Russian perspective on Turkey at the time of the data collection.
- The label **Korea** encompasses both North and South Korea.
- The label **Russia** includes mentions of Crimea. This reflects the Russian perspective on the topic Crimea, which is recognized (by Russia at least) as a part of the country since March 2014. We consider this true for both state-controlled and independent media outlets.

- The label **CIS** incorporates all members of the Commonwealth of Independent States (CIS). Current member states of the CIS include Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Moldova, Tajikistan, and Uzbekistan. Turkmenistan is also included in the label, being a founding as well as an associate state since 2005. Russia is also part of the CIS but handled separately.¹¹
- Due to ongoing political conflicts and a generally special status among international and national associations at the time of the data collection, **Ukraine** and **Syria** are considered as individual labels and analyzed accordingly.
- The label **U.S.** includes all parts of the United States.
- The label **North America** involves Canada and Mexico. It does not encompass mentions to the U.S.
- The label **South America and the Caribbeans** groups all countries on the continent South America as well as all Caribbean Islands.
- The label **South and East Asia** involves all Central, Middle, and Eastern Asian countries that are not encompassed in another label.
- Mentions referring to states no longer existing, such as East Germany (GDR), are collapsed into the country group label they either officially belong to or are generally associated with today. Thus, references to the GDR are collapsed into the label **EU and Neighbors**, while mentions referring to the Soviet Union are merged into **Russia**.
- Non-country NER results that are extracted as a country reference which clearly point to a country such as the city Pyongyang are included in the corresponding country label.
- The non-country term "zapad" (*the West*) is not incorporated in any particular label. In the given context, it is used as a reference to the Western world, civilization, and culture that, from a Russian perspective, can encompass at least Western Europe, the U.S., and Canada. It possibly also refers to countries such as Australia, New Zealand, South Africa, Israel, Japan, and South Korea. Thus, corresponding mentions do not concern a single label to which they could be unambiguously assigned to.
- Mentions denoting non-stabilized regions and stabilized regimes which might or might not be recognized as states by other countries such as Abkhazia or South Ossetia have been included within a label STATES WITH LIMITED RECOGNITION. However, the number of posts encompassed by this label is relatively small and does not or only barely satisfy the assumption of a normal distribution or linearity more often than not. Hence, references and corresponding results are not reported.

6.3. VK Corpus Statistics.

Table 5 displays the VK statistics *after* preprocessing.

	CONTROL	FREE	TOTAL
Tokens	253,646	96,371	350,017
Types	39,334	23,541	50,890
Posts	10,635	3,701	14,354
Avg. # of posts/day	204.5	71.5	276
Avg. # of tokens/posts	23	25	24

Table 5: VK corpus statistics after preprocessing.

¹¹Note that Russia is encoded with a separate label. However, Russia is still a member of the CIS and mentions of CIS are implicitly also referring to Russia to a certain extent.

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