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AGENDA DIVERGENCE IN A DEVELOPING CONFLICT: A QUANTITATIVE EVIDENCE FROM A UKRAINIAN AND A RUSSIAN TV NEWSFEEDS[3]

Although conflict representation in media has been widely studied, few attempts have been made to perform large-scale comparisons of agendas in the media of conflicting parties, especially for armed country-level confrontations. In this paper, we introduce quantitative evidence of agenda divergence between the media of conflicting parties in the course of the Ukrainian crisis 2013-2014. Using 45,000 messages from the online newsfeeds of a Russian and a Ukrainian TV channels, we perform topic modelling coupled with qualitative analysis to reveal crisis-related topics, assess their salience and map evolution of attention of both channels to each of those topics. We find that the two channels produce fundamentally different agenda sequences: in particular, while the Russian channel pays little attention to confrontation between the Ukrainian government and the opposition before the regime change, the Ukrainian channel is less inclined to cover armed violence in East Ukraine and refugees after the regime change.

JEL Classification: Z.

Keywords: news, agenda building, conflict coverage, topic modelling, Ukrainian crisis.

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1. Introduction

Conflict representation is an established topic in comparative media studies. It has become almost universal knowledge that media of conflicting parties align with the interests of those parties and thus demonstrate divergent, often opposite framings of the same events (Bennett, 1990; Hertog, 2000; Nossek, 2004). Less attention has been paid to news agendas during conflicts, especially large-scale country-level confrontations that risk to last in time. When populations of conflicting societies cease to share not only a common understanding of the same events but even the common awareness of them or their importance, this may have a much more profound effect on the conflict development (Jakobsen, 2000; Norris et al., 2003; Bennett et al., 2007).

One of the most explicit examples of this process is the recent Ukrainian crisis that started in 2014. Once parts of the common Soviet and early-post Soviet media environment, Russian and Ukrainian audiences, since the start of the conflict, have been rapidly moving away from each other regarding their media diets. Unavailability of Ukrainian TV in Russia has been increasingly supplemented by the mirror policies of the Ukrainian government that gradually shut down all Russian TV channels in Ukraine. In 2017, Ukraine's decision to ban *VKontakte*, the leading social network in the Post-Soviet space owned by a Russian business, has put a severe limitation to informal communication within families and friendship communities that might have a soothing effect on the situation. However, even before that, families and friends were reporting the deliberate reduction of their cross-border communication to strictly private issues, such as Birthdays and child health, as they were increasingly unable to carry on peaceful dialogues on political matters (Szostek, 2017).

In this paper, we introduce quantitative evidence of agenda divergence between the media of conflicting parties using data from the online newsfeeds of the two official TV channels: channel 1 from Russia and Channel 5 from Ukraine. Until recently, it was a challenge to study media agendas and their change on a large scale, as the only method to do so was manual content analysis, that, furthermore, is prone to subjectivity. Benefitting from the new techniques of automatic text analysis, we use an algorithm of topic modelling that lets us to define an agenda objectively, through a loose set of the most typical words, and to perform co-clustering of both most probable words and texts without any prior human preconceptions. With this approach, we not only retrieve media agendas from two large collections of news texts but also measure their salience and quantitatively assess their distribution over channels at different periods of the conflict. We demonstrate quantitatively that the difference between the two channels in the salience of crisis-related topics grows with time. Additional qualitative analysis of top texts in each relevant topic helps reveal differences in framing.

2. Agendas, frames and their automatic detection

Most broadly, media agendas may be defined as issues or topics, or sets of those, covered by media (Shoemaker & Reese, 2014, p. 5). An agenda-setting function of media, as it was originally formulated (McCombs & Shaw, 1972), refers to the ability of media to bring certain topics to the attention of audiences, perhaps at the expense of other topics, and to influence audiences' knowledge about those topics, as well as publics' opinions about their relative importance. A related concept of media (news) frame whose development is comprehensively described by Scheufele (1999) is, most generally, defined as a way in which meaning is ascribed by a news story to a given agenda point. It may imply different mechanisms from selective coverage of agenda's attributes to direct moral judgements. Framing effect of media is thus defined as the ability of media to influence audiences' interpretations of agendas. A similar but more narrow concept of priming effect – an ability of media to influence criteria by which the audiences judge public figures – was introduced by Iyengar & Kinder (1986). In one of his later works, an author of agenda-setting theory (McCombs, 2005) offers to consider framing and priming as second-order, or attribute agenda-setting, as both concepts in fact deal with the ability of media to influence audiences' vision of salience of certain agenda's features. This approach is, in turn, criticised by Scheufele (2000).

As a frame is related to selective attention to agendas' attributes, it should be expected to be closely connected to the concept of media bias, however, usually, the latter is studied in a separate stream of research (Castro-Herrero et al. 2016; Budak, Goel, & Rao, 2016; Ji & Liu, 2017). While framing research aims at establishing the link between media representations and public opinion, media bias research seeks to compare media representations with "reality", or at least with other available representations. Despite this separation, the concept of bias, as it can be seen from its various definitions summarised by Groeling (2013), is in fact very close to that of a frame, or a second-order agenda. A narrower concept of political or party slant, also prevalent in the studies of media texts, refers to biases specific for political domain (Lin, Bagrow, & Lazer, 2011).

In all times, it has been difficult to quantify either agendas, frames, or biases and to measure them objectively – that is, to produce such a measurement procedure which, when replicated by other humans on the same data, would yield the same categorisation. Recent developments of computer science approaches have given promising results for solving this problem. Comprehensive overviews of automated approaches to text analysis for social scientists are provided in (Grimmer &

Stewart, 2013) who focus on political science tasks and in (Günther & Quandt, 2016) interested in journalism and media studies tasks. The former authors illustrate an explanation of different methods with a variety of research goals, such as classification of political texts into topical categories, known or unknown beforehand, extraction of political slants from texts and placement of text characters in political spectra. Broadly speaking, it is possible to extract unknown categories with unsupervised machine learning (UML) techniques, akin to cluster analysis, while those that are known beforehand are better to be searched for with supervised machine learning approaches (SML) that demand algorithm tuning and validation on a collection of texts whose categories are already marked up.

Other researchers go further by applying those methods to specific research goals. Flaounas et al. (2013) use UML to obtain topical structures of media text collections and combine those with other data to determine topic popularity, as well as topical differences between various news sources. Likewise, Koltsova & Koltcov (2013) use UML to extract topical structure from the texts of popular bloggers and trace topical change in a pre-election period, while Nagorny & Koltsova (2017) apply UML to extract topics from regional news and offer approaches to measure topic popularity and likability with the data from readers' comments and likes, respectively. In all cases, topic labels are close in essence to agenda labels used in the original work of McCombs & Shaw (1972). All these studies use topic modelling algorithms to detect topics, while Kim et al. (2014) go still further and suggest to measure the agenda-setting effect of thus detected topics with the data from news sharing by the respective audience.

Likewise, some other scholars directly address the agenda-setting effect with big data approaches, however using keyword search for issue detection. Thus, a group of researchers that includes both McCombs and Shaw (Vargo et al. 2014) investigated the relation between agendas of Obama and Romney supporting individual Twitter users, on the one hand, and agendas of media organisations' Twitter accounts, on the other. Neuman et al. (2014) studied the mutual influence of agendas in social media and in regular media with time-series analysis. A limitation of keyword approach, apart from it being able to detect only pre-known issues, is that agendas, as they are defined in the original work, could not be adequately captured with a set of terms. Agendas, if they are to reflect phenomena of public life, are relatively broad and often are de facto described by word sets differing from those that any expert might think of; these word sets are instead something to be inferred from texts than pre-define.

For those who seek to infer pre-known issues, supervised machine learning gives more possibilities than keyword search, and in fact, it has been already used for detection of both media agendas and frames. Scharkow (2011) trains a number of SML algorithms to detect broad topics in German online news and examines the influence of various text processing techniques on the quality of modelling. Burscher et al. (2015) do similar work to detect pre-defined social policy issues in Dutch news. In an earlier work (Burscher et al. 2014) the authors apply SML to detect what they call the four generic news frames - conflict frame, the economic consequences frame, the human-interest frame and the morality frame. In all these cases, human coders are asked whether they can see specific topics in given texts, and after that, an algorithm learn to recognise similar texts.

In this research, given our goals, we opt for topic modelling as a method UML that is outlined in more detail further below.

3. Coverage of war and conflict in media

Conflict in social science may be broadly defined as a process in which individuals, groups or countries make active steps towards an outcome that the contending parties are not willing to provide (Rubin, Pruitt, & Kim, 1994, p.5). A military conflict or war is thus a most destructive type or phase of broader social conflicts (Allen & Seaton 1999 p. 12-19). Although literature studying media coverage of a conflict, and especially armed conflict, is vast, there is an apparent lack of rigorous empirical comparisons of coverage of the same conflict by media associated with conflicting parties. Quite a number of books is devoted to theorising about the role of media in conflicts and wars providing a multitude of illustrative material (Thussu & Freedman, 2003; Seib, 2006; Mortensen, 2015). Many of them broaden our understanding of the issue; however, they do not aim at inferring testable knowledge.

Empirical research is most often focused on a single conflict (Greenwood & Jenkins, 2015) and is usually done with qualitative approach (Kalb & Saivetz, 2007), or quantitative manual approach (Zollmann, 2015). Some studies comprise either coverage of two-three conflicts by the media of some country (Ben-Yehuda et al. 2013), or coverage of a single conflict by the media of a few countries (Pantti, 2013), none of which are usually direct conflict parties. This stream of literature in sum argues that media usually focus on the active phases of conflict, emphasise violence and suffering, and de-emphasise conflict resolution and post-conflict recovery. Some notable exceptions from the case-centred research include Baum & Zhukov (2015) who study coverage of the Libyan conflict in the media of 113 countries. They infer status-quo bias and revisionist bias in the media non-democratic and democratic countries, respectively, from the amount of coverage of different types of events.

In line with this semi-automatic approach, some studies have started to use SML to study media coverage of conflicts and crises. Thus, Montiel et al. (2014) study a China-Philippines maritime dispute and train a classifier that successfully predicts whether a given news item belongs to a Chinese or a Philippine media outlet. They use qualitative analysis to determine the differences in content that let the algorithm recognise Chinese and Philippine media as different classes. De Fortuny et al. (2012) investigate the evolution of coverage of a prolonged political crisis in Belgium and find significant biases against some political parties both regarding amount and polarity. However, to our knowledge, none of the ML-oriented studies of conflict coverage directly relates their results to agenda building or agenda setting theories which hinder the conceptual depth of these works. On the other hand, works that study conflict coverage as an agenda-setting process – e.g. 2008 Russian-Georgian conflict coverage in the US press (Bayulgen & Arbatli 2013) – do not apply any automatic techniques which may limit their scale and objectivity.

Works on Ukrainian political conflicts share many of those limitations. In a relatively early work, Baysha & Hallahan (2004) use manual content analysis to study framing of the 2000-2001 crisis by various Ukrainian media. They find that already at that time the country's media were highly politicised, manipulative and polarized – either in favour of the incumbent or the opposition. The 2014 crisis has received much more attention from researchers. Nygren et al. (2016) hand-code 1875 news items from the Russian, Ukrainian, Polish and Swedish media and find substantial differences in both the salience of news agendas and framing of particular topics. The latter looks particularly pronounced in the coverage of the armed conflict in Eastern Ukraine where blame attribution diverges grammatically and finds itself expressed in either accusative or supportive nominations of the conflict participants (from people's militia to terrorists) and the event itself (from war to anti-terrorist operation).

Makhortyh & Sydorova (2017) hand-code 1518 images from a pro-government and pro-separatist pages in VKontakte social networking site from summer 2014. They find that while the latter emphasised destruction and death, the former featured glossy pictures of Ukrainian weapons. Neither of these works performs any statistical analysis or large-scale automatic data analysis. Karamshuk et al. (2016), on the contrary, use a significant amount of data and sophisticated techniques, but they aim at the development of a methodology rather than at obtaining empirical conclusions. While seeking to determine political slant in the news about Ukrainian crisis, they, in fact, train a classifier to predict whether a message belongs to a given news source given manually marked data with sources coded in three classes (pro-Ukrainian, pro-Russian and Russian independent). Watanabe (2017) does aim at a rigorous empirical result and seeks to establish pro-government bias in the vast collection of English-language news of the Russian ITAR-TASS news agency about the Ukrainian crisis. However, he measures pro-Russian slant with a number of negative words occurring close to the words "democracy" and "sovereignty" in texts about particular crisis events. Sentiment words are usually not enough to detect political alignment; instead, they help determine general sentiment that can include grief or fear at the negative end. Thus, to the best of our knowledge, there are no studies that would perform a large-scale comparison of agendas of the media belonging to the conflicting parties or trace their evolution as the conflict evolves.

4. Background of The Ukrainian Crisis

The entire storyline of the Ukrainian crisis is so highly debated that making a mere list of its key events and participants turns out to be nearly impossible without having it to contradict the vision of at least one of the conflicting parties. A brief overview that follows, most probably, does not avoid this trap either, but may hopefully provide a general idea of the conflict background.

The Ukrainian crisis of 2013—2014 developed from the longstanding internal conflict between East and West-oriented groups of influence inside Ukraine, as well as interests of some other states, including Russia. Historically, Ukraine has visible regional divisions in language use (Russian in the East and South vs Ukrainian in the centre and the West), as well as cultural and religious affiliations (several Orthodox jurisdictions vs Greek Catholic religion). This fragmentation manifests itself in voting, TV consumption and more importantly in national identity definitions (Ivanov, 2016). Conventionally, they may be divided into three groups: 1) those that see Ukraine as a part of Europe completely different from Russia; 2) those that emphasize closeness with Russia and distinctiveness from Europe; 3) and finally those that see Ukraine as culturally close to Russia but still distinct enough to be a part of Europe.

As post-Soviet Ukrainian elite has also been fragmented along these lines, the recent history of Ukraine has been marked by a series of political crises that – not without competing external pressures – have been bringing either East or West-oriented groups to power (Kubicek, 2000; Feklyunina, 2016). In 2013 the presidential position was occupied by Viktor Yanukovych, an East-oriented and conventionally a pro-Russian leader. He had won the presidential race over the former Ukraine's prime minister and one of the leaders of the 2004 pro-Western Orange revolution Julia Timoshenko, who under his rule was put in prison.

Despite Yanukovych's pro-Russian stance, his team was actively working towards signing an Association Agreement (AA) and Deep and Comprehensive Free Trade Agreement (DCFTA) with the European Union. This agreement was to open Ukrainian and European markets to each other, but it simultaneously meant that Ukraine had to stop all similar agreements with the Russian-led Customs Union. It thus was to become a crucial step in dragging Ukraine from Russia's sphere of influence to that of the European Union and, more broadly, the "West". Also, from some point in time EU negotiators had put a condition of Timoshenko’s release from jail for signing DCFTA, which would have posed a great political risk for Yanukovych. In November 2013, after failed negotiations on Timoshenko and consultations with Russia, Yanukovych’s government abruptly suspended preparation to signing DCFTA just a week before the planned date. This move immediately took thousands of Ukrainians to the streets of Kiev to protest the move.

Consequent increasingly violent waves of demonstrations demanding closer European integration and resignation of the Ukrainian president and the government were named Euromaidan.[4] According to the Russian side, EU and USA representatives took an active part in organising the movement. Tensions between the government and the protesters grew, with regional government buildings being forcefully occupied especially in the Western regions, and peaked on February 19, 2014, when 88 people were killed and hundreds more wounded allegedly by security forces in the centre of Kyiv. Two days after the clashing, the president and the opposition leaders signed a settlement agreement under terms of early presidential elections and constitution change shifting power from president to parliament. However, as, according to Yanukovych, his cortege was attacked by armed people, he had to flee the country with the help of the Russian security forces (“Putin: Russia helped Yanukovych to flee Ukraine,” 2014).

Shortly after that, a new wave of protest began in South-Eastern regions of the country. Demanding greater autonomy from Ukraine and closer ties with Russia, protesters were immediately recognized as a separatist threat by the new Kyiv government. Most prominent protests took place on the Crimean Peninsula where the Russian navy had been stationed since the Soviet times. These circumstances led Crimea – with the help of the Russian military – to swift seceding from Ukraine and joining the Russian Federation which immediately resulted in painful international sanctions against Russia (“Putin admits Russian military presence in Ukraine for first time,” 2015). In other Eastern regions, anti-Euromaidan rallies clashed with Euromaidan supporters. While in some of them pro-Russian protest failed, in two regions ‘self-defence forces’ (*opolchenie*) stormed and occupied government buildings. Eventually, protesters managed to establish – allegedly with the help from Russia – two proto-states along Ukraine’s eastern border: ‘Donetsk People's Republic’ and ‘Luhansk People's Republic.’

[4] 'Maidan' in Ukrainian means market square. The square in central Kiev where the protests took place is called Maidan Nezalezhnosti (literally: Independence Square) or simply Maidan.

The conflict in Eastern Ukraine quickly escalated to the point of civil war when Kyiv declared anti-terrorist operation and deployed military forces against pro-Russian militias ("The Ukraine Crisis Timeline," n.d.). From April to August 2014 heavy fightings produced thousands of causalities of the military as well as civilians with one of the most infamous being the downing of Malaysian Airlines flight MH17 killing almost three hundred people. Although the rebels were clearly losing before mid-August, after the change of their leadership in late August, their armed actions were a sudden success. According to the Ukrainian side, between 22 and 25 August, Russian artillery, personnel, and what Russia called a "humanitarian convoy" crossed the border and joined the rebels who, as a result, regained much of the territory they had lost before. A deal to establish a ceasefire, called the Minsk Protocol, was signed on 5 September 2014. This deal did not end the conflict, but it terminated its active phase studied in this research.

5. Data and Methods

To compare conflict coverage in Russian and Ukrainian media, we chose television as still the most influential type of media in both countries (TV reach in Russia and Ukraine was 98.4% and 96.8% in 2014, respectively, as compared to 70.2% and 50.9% of internet penetration (BBG, 2014a; BBG, 2014b)). The choice of Russian channel 1 was evident as it both had the highest reach (98%) and rating (13.3%) (Brand Media, 2017) and has always been positioned as the country's main channel and the official mouthpiece of its government. As the Ukrainian media market has been very fragmented, the choice of a Ukrainian channel has been much more difficult. When the government changed in the middle of the crisis, so did the relation of politicised channels to the current regime; therefore, it was impossible to pick up a channel that was "pro-government" during the entire period. We finally opted for Channel 5 that was associated with the post-Yanukovych government and owned by the new president Pyotro Poroshenko (Channel 5, 2003), as presumably the most contrastive case. The limitation of this choice is that Channel 5 has never been a leader either in terms of reach or rating (Industrial Television Committee, 2014); however, it has been always positioned as the main news channel in Ukraine.

To capture news coverage of the major events of the Ukrainian crisis we chose the period of 53 weeks from September 2, 2013, to September 7, 2014. As it can be seen from the crisis timeline, this period starts eleven weeks before the crisis to provide a sample of non-crisis coverage. It then embraces all the major crisis events and terminates shortly after the conventional end of the active phase of the conflict that came with the Minsk ceasefire protocol.

Selected channels have official websites: Channel 1 publishes full transcripts; Channel 5 provides access to shortened versions of the news. We parsed these texts which resulted in the collection of 44,989 news items with 20,025 belonging to the Channel 5 and 24,964 to Channel 1. To use topic modelling effectively, all texts had to be in the same language, otherwise, the algorithm would have clustered each language to its cluster. We used automatic translation provided by Yandex API to translate news items of Channel 5 into Russian. The quality of translation was checked on a selective basis; as Russian and Ukrainian languages are very similar, automatic translation performed well. The collection was lemmatised with MyStem software (Segalovich, 2003).

To infer topics, we used an UML approach known as topic modelling: by clustering simultaneously words and texts (based on word co-occurrence in texts) it provides, for each topic, (a) a list of most probable words that allows understanding the content of this topic without reading texts, and (b) a list of most probable texts that can thus be easily sampled for manual analysis. The most common topic modelling algorithm is known as Latent Dirichlet Allocation (LDA) and was introduced by Blei (2003); we used a version of LDA with collapsed Gibbs sampling implemented in R (Chang, 2015) to model all texts of Channels 1 and 5 jointly.

One major limitation of LDA is reproducibility of results. The algorithm has stochastic nature meaning that each run on the same data with the same parameters would yield different topic solutions. Koltsov et al. (2014) suggest a strategy to address this limitation and find stable topics. First, obtain five topic solutions with the same parameters for the document collection. Then, for each topic from the first solution find the closest equivalents in each of the remaining solutions by computing the Kullback-Leibler distance (KL). Topics will be considered stable if their similarity exceeds 90% threshold among three or more equivalents.

We thus fit five topic models for 100 topics with the number of topics chosen based on interpretability and analytic utility as suggested by Blei & Lafferty (2009). Then, we identified stable topics as discussed above and averaged their probabilities in each text across all topic solutions. These probabilities are commonly used as proxies for topic salience in a given text or a group of texts. Then each topic was assigned a label based on its top words and reading of the top documents; the topics were manually divided into crisis-related and other topics.

To get a view of the coverage *dynamics*, the probabilities of each topic were aggregated by week based on news timestamps. This resulted in a time series of 53 weeks, however, three weeks were excluded from the analysis: the last week because of technical errors with data collection; New Year week for absence of news as it distorted data on differences between the TV channels;

and week from February 10 to February 16 as Channel 5 had no news during that week. It should be noted that absence of news on Channel 5 right before the regime change surely has a great political meaning; however, we excluded this week as an outlier because it skewed statistical trends.

For each week, topic probabilities were also aggregated by channel. For each topic, we estimated the weekly divergence between the Russian and the Ukrainian channels by calculating Kullback-Leibler (KL) distance between their topic distributions over weeks. Absolute differences between saliences of topics correlate with the saliences themselves (i.e. the bigger is the topic, the more its volume differs between the channels). KL accounts for this effect and shows the dynamics of volume-independent divergence.

Guided by the results of topic modelling, texts were ranked by their probabilities and thus sampled for further qualitative analysis: 25 top texts in each topic from each channel that formed 15 pairs of sets representing 15 crisis-related topics. In addition, in each of such sets, we calculated absolute and relative word frequencies, the latter aimed at revealing words specific for the texts within a given topic on one of the channels but not on the other.

6. Evolution of Crisis Topics Salience

Figures 1 and 2 present general distribution of crisis-related topics between the Russian and the Ukrainian channels. Before interpreting them, it is important to make two notes. First, since topic modelling allows overlapping membership of texts in topics, crisis-related content may partially appear quite high in the lists of texts sorted by prevalence in non-crisis topics. Thus, *health & first aid* contains some proportion of news on injuries received at war on Channel 5, and both topics related to the Russian and the Ukrainian parliaments touch some conflict-related legislation on both Channels. However, only topics centred specifically around the crisis were marked as such.

Second, topics have been labelled based on top 25 words and top 50 texts (25 from each channel); therefore, the labels reflect only this content in the most general way. Sometimes topics are in fact dominated by a certain sub-topic or its aspect, especially when they are examined on a weekly basis – that is, beyond top content. Thus, *Urban roads & transport* is almost exclusively about Moscow and is virtually absent from Channel 5. *Elections* topic is dominated by various local elections in Ukraine in 2013 on Channel 5 and by the Presidential Ukrainian elections in 2014 covered by Channel 1 but carefully avoided by Poroshenko's channel. Some topics are broader than the event that dominates them – for instance, *MH17 plane shootdown* is merged with other plane crashes, and therefore it appears before the MH17 event actually happened.

From Fig. 1 we can see that crisis-related topics hold high positions among all topics taking about 35% of total salience of 49 stable topics examined. They account for 45% of salience on Channel 5, and for 27% on Channel 1. This is understandable as the crisis takes place in the country where Channel 5 broadcasts. At the same time, the overall topic repertoire of Channel 1 is broader – in particular, it includes culinary and culture sections which Channel 5 does not feature at all. Against this background, a quarter of attention to the crisis in another country is an enormous amount.

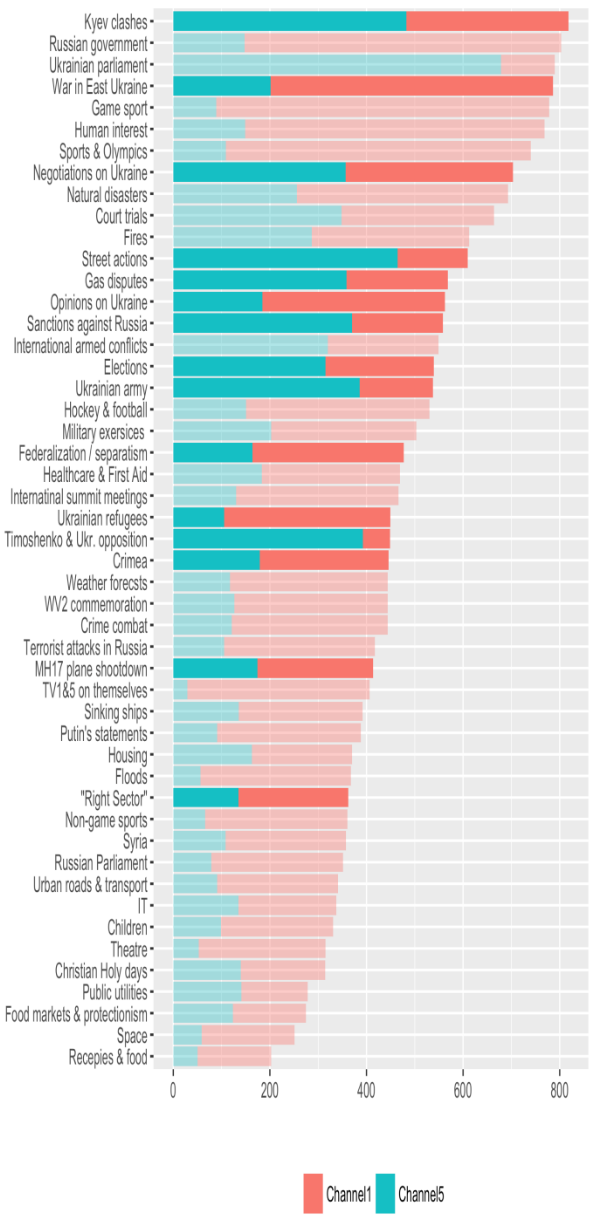

Fig. 1. Topic salience. Red: Channel 1, green: Channel 5; bright: crisis-related topics; pale: other topics; x-axis: sum of probabilities of texts in a topic, range (0; n), where n=number of texts in collection.

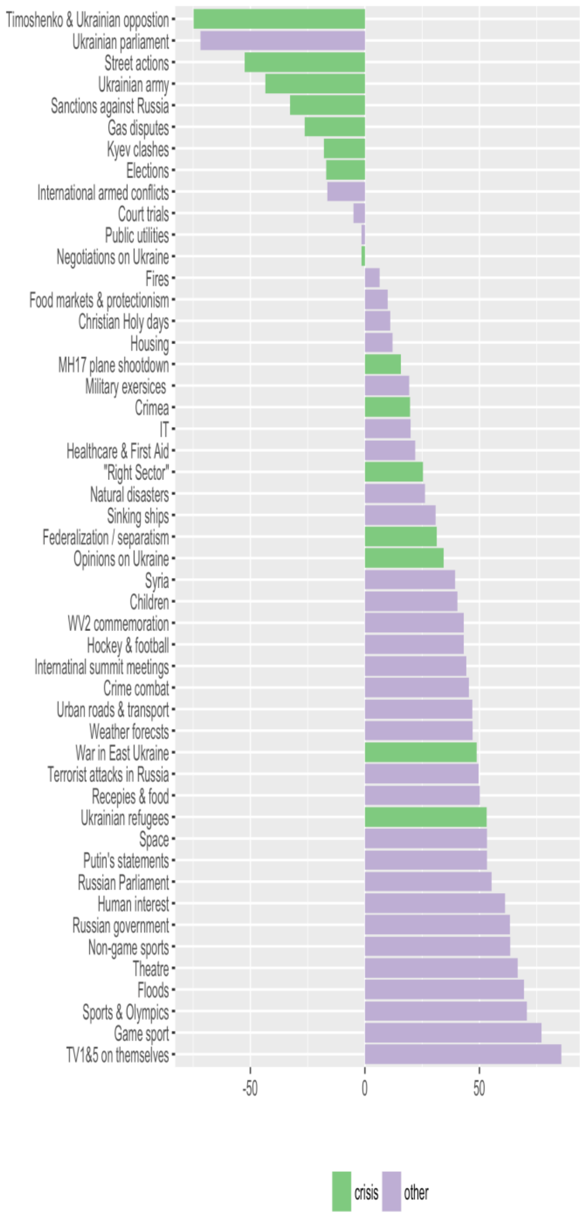

Fig 2. Differences between channels in topic salience, % of topics' overall saliences. Green: crisis-related topics; purple: other topics. Left to y-axis: topics prevailing on Channel 5; right to y-axis: topics prevailing on Channel 1.

When represented on a time scale of weeks (Fig. 3), development of crisis topics salience falls into two distinct periods divided by Kyiv shootings after which the graphs of Channels 1 and 5 intersect for the first time. Before that, the overall salience of crisis topics is clearly smaller, and the Russian channel pays less attention to the conflict than the Ukrainian channel, thus finding relatively little interest in the disputes over Timoshenko release and DCFTA preparation suspension. Paradoxically, after shootings and especially after Crimea secession Channel 1 pays more attention to the Ukrainian crisis than a channel within the country in crisis. This phenomenon of excessive coverage of Ukraine at the expense of internal Russia's issues has been commented on by some Russian TV critics; as one of them has explained, this happens "because it finds viewers' support, aligns with the government's interests and through all these imperial conquest stories allows to avoid problems within [this] country and to show the viewers a strong government" (Borodina, 2014). While some of these statements may be disputable, high ratings of Russian news of that time have been well documented (BBG, 2014). It should also be noted that overall salience of all stable topics on Channel 5 constitutes roughly 64% of that of Channel 1; controlled for this, the salience of crisis-related topics on Channels 1 and 5 is approximately the same in the second period. More details about weekly distributions of topic salience may be found in Appendix 1.

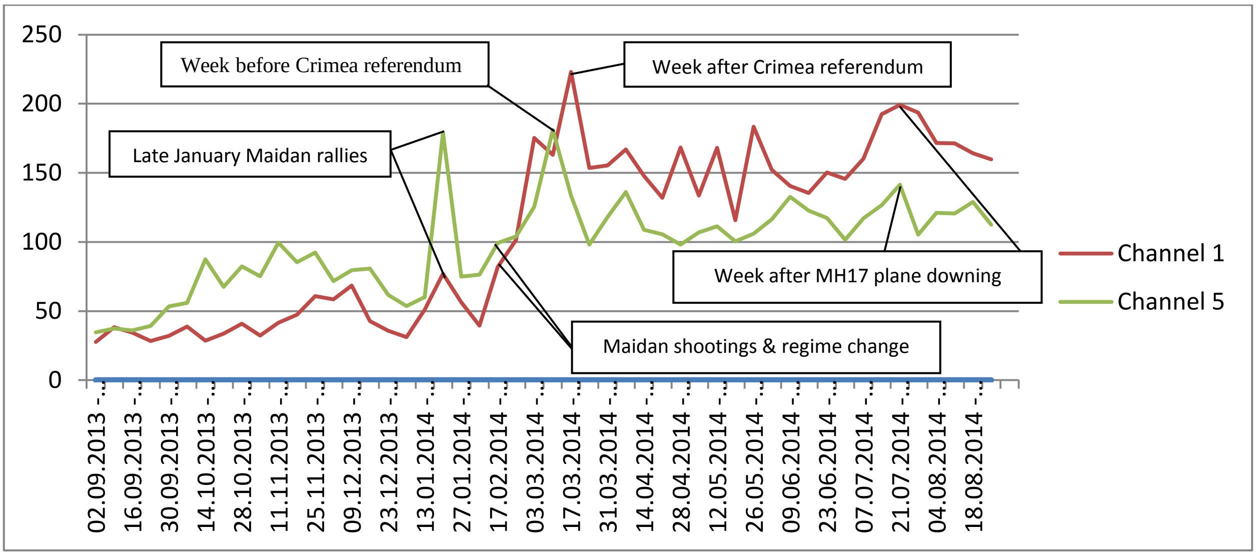

Fig. 3. The total salience of all crisis-related topics over time. X-axis: weeks; Y-axis: sum of probabilities of topics in texts, range = (0; n), where n – total number of texts. Green: Channel 1; brown: Channel 5.

Nevertheless, differences in the salience of specific crisis-related topics between the two channels are dramatic, even when controlled for the absolute weight of each topic (Fig. 2). Here, the differences have been calculated as the percentage of the total salience of each topic. Bars to the left of the y-axis indicate differences in favour of Channel 5, while to the right are those pointing at differences in favour of Channel 1. We can see that some topics are in fact channel-specific. Thus, the Russian channel is more inclined to raise the problem of refugees from the Ukrainian East and to cover the Russia's success of Crimea acquisition. It also has to spend more effort to promote its version of MH17 downing to its audience. Finally, it pays more attention to the radical anti-Yanukovich political group 'Right Sector', presumably in order to present the entire anti-Yanukovich movement as radical. On the contrary, Channel 5 focuses much more on sanctions against Russia as a very painful issue for the Russian government. Naturally, the violent clashes in Kyiv and other cities gain more of its attention than that of Channel 1. It also has to focus on the Russia-Ukraine gas pricing dispute since the absence of gas in Ukraine in winter means no heating for a large number of common people. *War in East Ukraine, Federalization / separatism, Ukrainian army, Street Actions, Kyiv clashes* and *Timoshenko & Ukrainian opposition* topics will be analyzed in more detail further below. Unfortunately, we cannot estimate the statistical significance of the difference between the two channels as the distribution of probabilities of most topics over texts is far from normal (most often it is power-law). It is, however, clear that *Negotiations* to find solutions to the Ukrainian situation – the most "peaceful" crisis-related topic and one of the most salient among all – is found equally important by both sides.

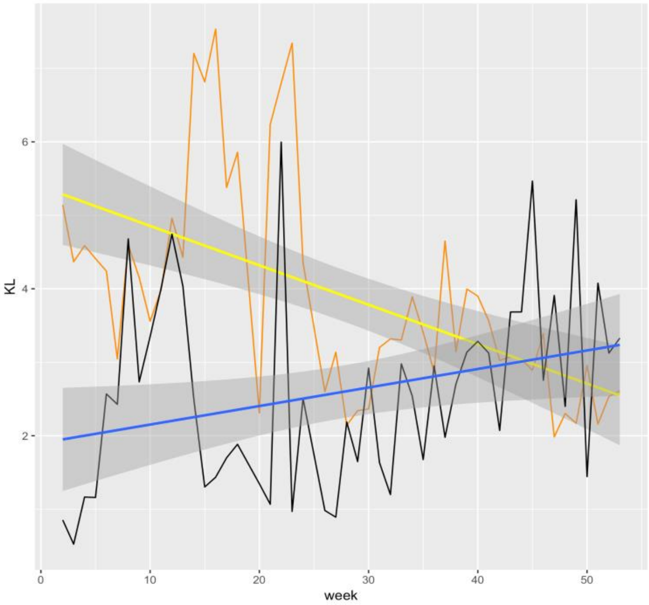

Fig. 4. Dynamics of differences in topic salience between Channels 1 & 5 with a linear approximation. X-axis: weeks; Y-axis: KL divergence. Black: crisis topics; blue: crisis topics approximation; orange: other topics; yellow: other topics approximation.

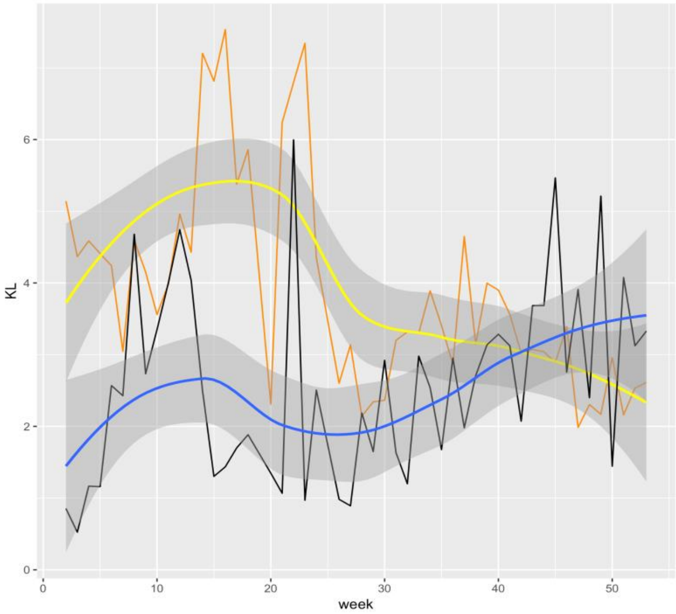

Fig. 5. Dynamics of differences in topic salience between Channels 1 & 5 with LOESS approximation. X-axis: weeks; Y-axis: KL divergence. Black: crisis topics; blue: crisis topics approximation; orange: other topics; yellow: other topics approximation.

Figures 4 and 5 map the week-by-week development of differences in the overall salience of crisis-related topics (black) and other topics (orange) between Channel 1 and Channel 5. As we can see, weekly differences are very volatile. In fig.4 we approximate the respective graphs with linear functions which is imprecise but shows the general descending trend in non-crisis topic differences and the ascending trend in crisis topic differences. As said before, KL divergence metric compensates for varying saliences of individual topics, so the rise of difference between crisis-related topics is not due to the growth of their salience. We thus can see that both the salience of non-crisis topics and the difference between them shrinks as the conflict develops, and they get substituted with politicised topics in both channels. This substitution is consistent with our earlier findings related to the topical structure of the Russian blogosphere in Russian electoral cycle 2011-2012 (Koltsova & Koltcov 2013), however, the growth of differences between crisis topics with time is a new finding.

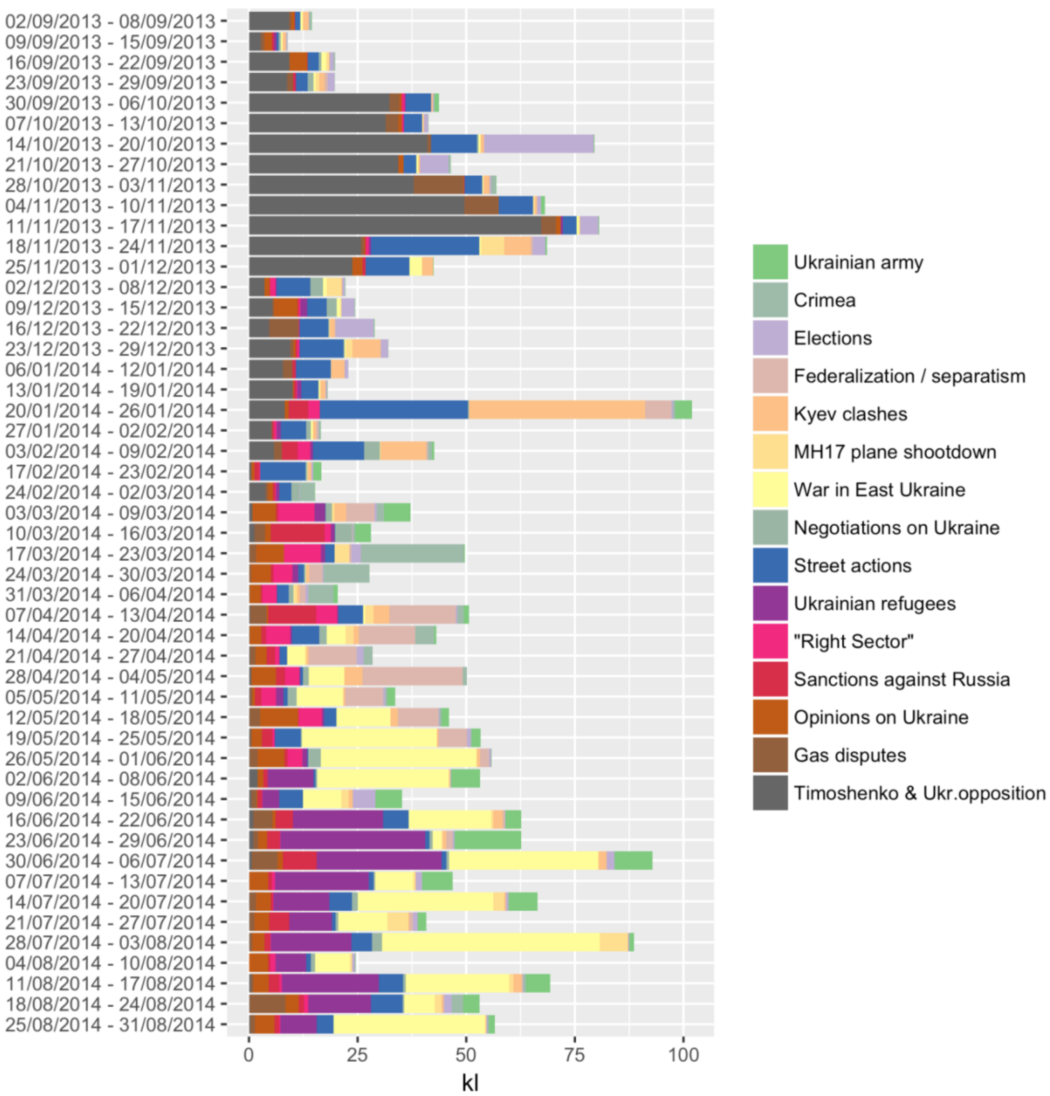

Fig. 6. Weekly differences between Channels 1 & 5 by topic. X-axis: cumulative KL divergence for all crisis topics; colour areas within bars show KL values for individual topics; Y-axis: weeks.

Fig. 5 where we approximate the graphs with LOESS function reveals non-linear trends in the development of differences. In crisis-related topics, we can see two waves reflecting difference growth periods: the first spans October-November 2013, the period of the most intense disputes on Timoshenko and DCFTA; the second and the bigger one starts roughly from May 2014, with the launch of the active military campaign in East Ukraine. A closer look at weekly differences distribution over individual topics (Fig. 6), coupled with qualitative text analysis sheds light on the details of those differences.

6.1. Evolution of Crisis Topics Content and Political Slant

On October 3, 2013, members of the European Parliament's monitoring mission on human rights Kwasniewski and Cox asked Yanukovych to pardon Timoshenko as she was said to need urgent treatment in Europe, after which many European officials confirmed that this was a condition for signing DCFTA. Until late November, Timoshenko’s health seemed to be one of the most important problems in Ukraine, judged by the amount of attention paid to it by Channel 5, while Channel 1 is virtually silent. This topic evolved in parallel with a smaller topic of *Street actions*. This latter is distinct from *Kyiv clashes* as it includes peaceful actions only, while *Kyiv clashes* embrace violent protests – mostly in Kyiv, but also outside it. As it can be seen, before 2014 the violent topic is modestly represented along with *Street actions*.

Since mid-November, *Street actions* topic grows on Channel 5 that features stories about rallies for European integration and against refusal from DCFTA. It also pays attention to pro-Yanukovych protests, though more than once it mentions that some participants admitted they were participating for money. In the first half of December, the salience of *Kyiv clashes* exceeds *Street actions* on both channels, however, while on Channel 5 the difference is twofold, on Channel 1 it is one level of magnitude. That is, the Russian channel is much more inclined to cover December rallies as violent. It depicts protesters capturing administrative buildings, blocking streets and using Molotov cocktails against riot police, while the latter is then portrayed dissembling barricades and unblocking streets. Channel 5 emphasises that protesters were blocking the work of the parliament demanding resignation of the government and that some government members condemned brutal police actions.

Next, *Kyiv clashes* peaks dramatically on Channel 5 accompanied by a smaller peak in *Street actions* in late January 2014 when the parliament passed a restrictive anti-protest law that led to mass street protests throughout Ukraine and the first victims. Channel 1 pays very modest attention to this event: the difference between the to channels for *Kyiv clashes* is threefold, and for *Street actions* – 30-fold.

It is most surprising that the week 17-23 February 2014 that embraces major clashes in Kyiv and the fall of Yanukovych's government produces neither the highest salience scores nor the biggest difference in salience between the channels. The latter phenomenon could have been caused by the fact that this event was of equal importance for both countries. Relatively low salience might be explained by a unique vocabulary of low-frequency words used to describe the regime change events which did not let this issue to form a stable topic. The most salient topic of the week, *Kyiv clashes*, covers street violence but not the political transition. This might be considered a limitation of the topic modelling approach. In addition, both channels might be hesitant about choice of coverage in this very unstable period. When the stakes were as high as regime change, the defeat of the opposition might mean the loss of all resources for the channel 5 owner as the main sponsor of Maidan protest. Also, regime change in Ukraine – perhaps, not occasionally – coincided with Winter Olympics held in Russia. It had been anticipated as a very important promotion event for the Russian government who had hoped to finally establish an international image of Russia as a "civilised" country with rich culture and high-quality service. The events that followed ruined these plans but before the Olympics ended Russian government demonstrated no reaction on Ukraine's situation. In any case, during that week, many news from Maidan on both channels were relatively neutrally formulated, and neutral nominations of participants prevailed although some polarisation was also apparent. Both channels featured "protesters" seizing buildings, but Channel 1 also mentioned use of guns by "radicals", while Channel 5 portrayed enforcers leaving their positions "in panic" by the end of the week.

Right after the regime change, both channels go on with the *Street actions* topic without big difference in salience, however, they cover different actions in very different ways. Channel 1 emphasizes within-Russia rallies in support of the Russian-speaking people in Ukraine. Channel 5 starts from world protests against Russian military interference in Ukraine, but quickly comes to cover a large variety of actions: for Ukrainian unity, pro-Russian protests, Russian rallies against the war and "for the war and Putin". Trying to differentiate between "genuine" pro-Russian protesters and provocateurs, the channel uses a very diverse vocabulary: while sometimes protests against Kyiv are termed peaceful, in other cases actions are said to be organised by pro-Russian henchmen, rusohpils and separatists.

Very soon, the leadership in salience goes to *Crimea*, but the difference in salience between the channels becomes large only in the week of the referendum and Russia's presidential decree and parliament voting to accept Crimea. This topic is the one that radically polarises the discourses of the two channels. While on Channel 1 words that score high in relative frequency are those related to "normal" voting process (voter, voting, poll station, city council), on Channel 5, the most frequent word is "illegitimate". In the week of the referendum, such nominations as occupation and annexation are the most commonly used as well.

Simultaneously, *Street actions*, a predominantly Channel 5 topic, shrinks and gets supplemented with *Federalization / Separatism* topic which is predominantly of Channel 1. From its title, it is not difficult to understand the main nominations the two channels applied to the processes that were emerging in Eastern Ukraine in March – April 2014. The amount of attention paid by the two channels to these processes reflects the level of support to them from the respective governments. Although texts of both channels have much vocabulary in common, their political stances are clearly the opposite. Channel 1 describes rallies for referendums and against “Kyiv henchmen” in Donetsk and Luhansk regions, preparation of those referendums and the announcement of the creation of republics in both regions by "people's governors". Channel 5 calls the latter "self-proclaimed governors" and "impostors" claiming that true governors are trying to solve the conflict by fighting terrorists but listening to protestors, while; the republics are said to be proclaimed by separatists.

From mid-April, when the anti-terrorist operation was announced by the Ukrainian government, *War in East Ukraine* emerges as the dominant topic in which, surprisingly, Channel 1 clearly prevails. This would be hard to explain if this topic was not paralleled by the predominantly Channel 5 topic of *Ukrainian army*. While *War in East Ukraine* depicts battles, destruction and human casualties, *Ukrainian army* topic allows Channel 5 to partially shift its attention to military supplies, logistics and recruitment. Admitting lack of all kinds of resources, Channel 5 emphasises the contribution of volunteers – both those who volunteer for military service and those who donate to the army. Many stories describe how heroes returning from the East are warmly met at home, but funerals and protest actions for more intensive rotation also find their way to the Channel 5 news. Channel 1, when it pays attention to the topic, emphasises mothers' protests against conscription, desertion and escapes across the Russian border, soldiers abandoned by their commanders on the front line and military losses.

These differences are relatively small compared to the *War in East Ukraine*. While in *Federalization / Separatism* topic polarised nominations were already widely used, in *War in East Ukraine* the lists of channel-specific words are manifestly led by *militiaman* in Channel 1 and *terrorist* in Channel 5. On Channel 1, the topic starts earlier shown as battles between Ukrainian enforcers/army and the militiamen. As the latter retreat, the Channel emphasises casualties among civilians, excessive shelling and destruction blaming the Ukrainian forces. Channel 5 starts the story as an anti-terrorist operation, then shifting to reporting full-scale battles against terrorists and separatists who are said to suffer much greater losses than the Ukrainian army. When in late August situation changes, Channel 5 starts paying much more attention to shelling and civilian casualties, attributing them to the other side.

Meanwhile, the most dramatic event of late August was the so-called Ilovaisk cauldron when Ukrainian troops got encircled near the town of Ilovaisk by the overwhelming (allegedly Russian) military forces and suffered heavy losses of more than 1000 people during the retreat. In the course of the respective week, Channel 5 mentions Ilovaisk in six texts out of 357: once with a short message about Red Cross volunteers who returned safely after having being shelled near Ilovaisk. Another time Channel 5 reports a protest action demanding "unblocking" of the military under Ilovaisk and resignation of Ukraine's defence minister. The rest are brief references to Ilovaisk among other towns of the East. Meanwhile, Channel 1 lavishly reports Ilovaisk mentioning it in 30 messages out of 446.

Tracing the evolution of vocabulary in topics related to street activity, from the *Street actions* (Autumn-Spring) through *Kyiv clashes* (Winter-Spring) to *Federalization / Separatism* (Spring) to *Ukrainian Army* and *War in East Ukraine* (Summer) we can see that the first is the most peaceful. *Kyiv clashes* contains a lot of words referring to violent actions (such as barricades, Molotov cocktails, and fire), but neutral nominations of participants still prevail over politicized ones. Next, *Federalization / Separatism* uses overwhelmingly polarized nominations – from supporters of federalization to separatists and terrorists. Finally, the vision of Summer events by the two channels becomes so different that it falls into two very distinct topics. Channel 1 features *War in East Ukraine* 3.8 times more intensively than it talks of the *Ukrainian army*; for Channel 5, paradoxically, *Ukrainian army* is twice as more important as *War in East Ukraine*. Channel 5 thus in a way substitutes description of military actions with more trivial issues of army logistics, while Channel 1 readily depicts suffering and horror.

7. Conclusion

In this paper, tracing crisis-related agenda sequences of the Ukrainian and the Russian TV channels we find that they are fundamentally different. This difference is relatively high before Channel 1 starts paying significant attention to the crisis, but after a brief decrease in early 2014 the difference only grows. For the audience of Channel 5, the crisis starts with the issue of release of

Ukraine's prominent opposition leader, develops through DCFTA suspension leading to protests, anti-protest legislation, and results in regime change. For the audience of Channel 1, largely unmotivated street violence quickly leads to unexpected regime change. Although the regime change itself gets similar amount of attention from both channel, the following Crimea events become a turning point for further agenda divergence into two different streams of issues.

We also show that agendas' salience and evolution can be assessed quantitatively and relatively unbiased evidence may be obtained on issues prone for subjectivity, such as conflict coverage by conflicting parties. The approach shows well agenda preferences of different news sources that have political meaning. One of the limitations of the applied quantitative approach is its inability to detect political alignment within agendas as it usually puts together messages on the same issue, but with different positions. One way to overcome this limitation is to combine it with qualitative text analysis which is made much easier by the use of topic modelling as preliminary text filter. This combination provides both profoundness of qualitative studies and the scale of quantitative research.

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Appendix 1. Topic Salience by Week

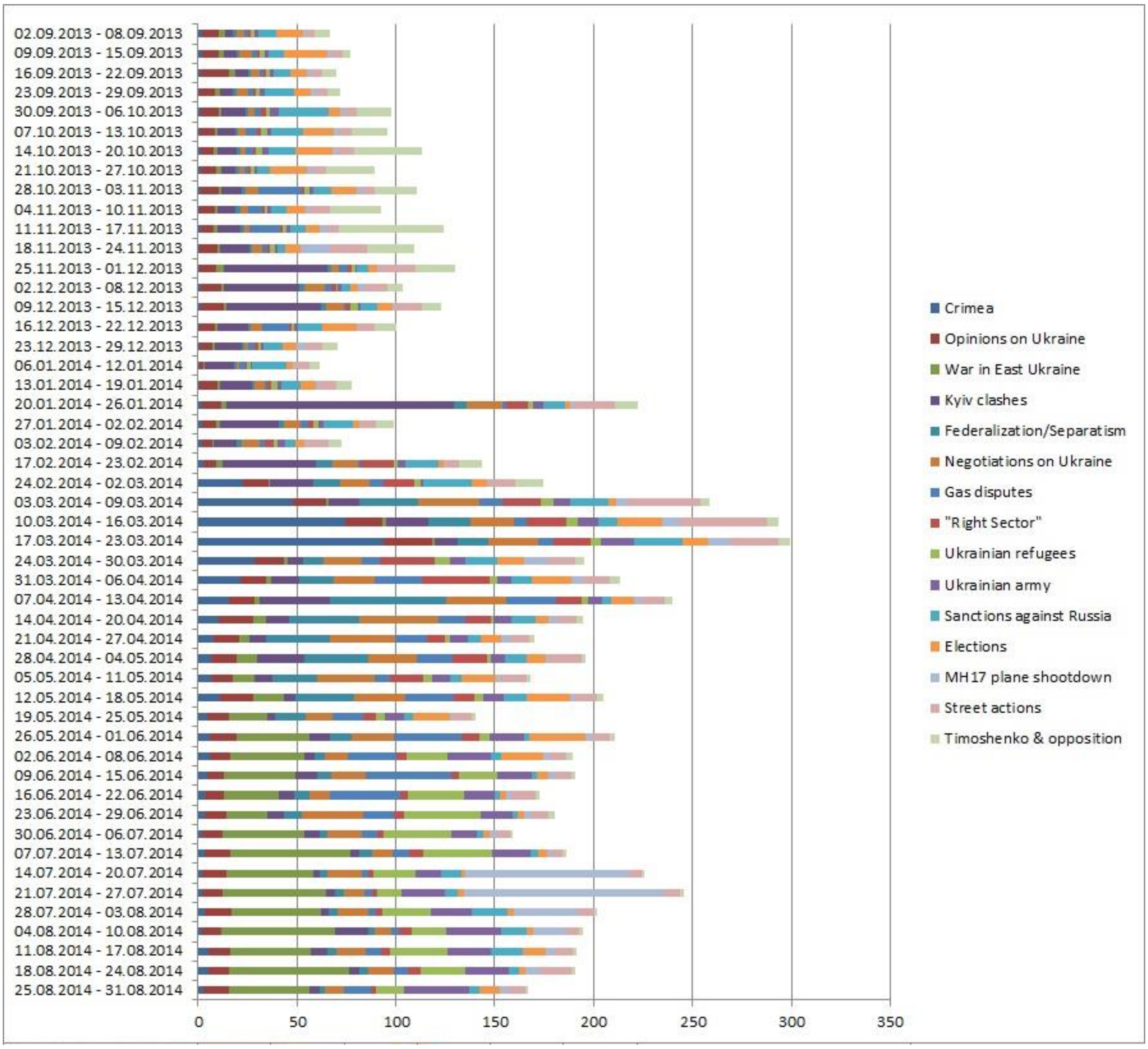

Fig. 7. Weekly topic salience. X-axis: cumulative topic salience for all crisis topics; colour areas within bars show topic salience for individual topics; Y-axis: weeks.

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