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Public sentiment towards economic sanctions in the Russia-Ukraine war

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Abstract

This paper introduces novel data on public sentiment towards economic sanctions based on nearly one million social media posts in 109 countries during the Russia-Ukraine war by using machine learning. We show the geographical heterogeneity between government stances and public sentiment. Finally, political regimes, trading relationships, and political instability could predict how people perceived this inhumane war.

JEL Classification: F51; H77

Keywords: democracy; public sentiment; Russia-Ukraine.

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1. Introduction

The Russian invasion of Ukraine has been condemned as an unprovoked act of war. While the Western propaganda has been full of criticism and statement against this war, some countries, particularly the Russian alliances, follow the Putin's government's narrative to describe this war as the '*special military operation*'. Hence, information about this war might be diverged in a variety of independent sources, which are more likely to form the heterogeneous beliefs from the public. Although the public sentiment lies on the centric literature of economics such as domestic violence (Amarasinghe, 2022), political views (Bursztyn et al., 2020), etc., an understanding of the information-gathering behaviour by individuals about Russia-Ukraine war, particularly in the era of Internet, has not been answered yet. Given the growing momentum of literature in quantifying the sentiment based on newspapers (Aguilar et al., 2021) and books (Saltzman & Yung, 2018), our study sheds a new light on textual analysis approach by using social media posts regarding the recent war.

To address this gap in the literature, this paper analyses the public sentiment of Russia-Ukraine war by using nearly one million Facebook posts from 109 countries with the combination of four cutting-edge textual analysis approaches (See Appendix A1). Additionally, we construct the novel index to capture whether and how people's attitudes are aligned with their government votes in United Nations. Lastly, the country public sentiment can be explained by the trading intensity of Russia and political regimes and political views while the new index could explain from 63-72% of the government votes in the United Nation after controlling macroeconomic determinants.

2. Data and index construction

This study collects the big data from Facebook through the CrowdTangle to investigate social media discourses related to the Russia-Ukraine war. These posts were collected from February 1 to March 31, covering the most intensive period of the conflict starting from 24 February. In total, 877,691 public Facebook posts relating to the Russia-Ukraine conflicts were collected, and more than 580 million interactions (e.g., likes, love, shares, comments) were recorded. The texts were used as inputs in this study to extract semantic insights related to the Ukraine-Russia conflicts. There are five main sequential steps to perform the text analyses for public posts from Facebook: (i) cleaning text; (ii) translating text into English; (iii) tokenizing, cleaning text, and removing stop-words; (iv) constructing frequency and network analysis of terms and bigrams; and (iv) constructing the public sentiment by using the BERT, TF-IDF, Flair, and Vader models⁵. The weighted average sentiment scores (based on the number of interactions of each post) for each country from these four models were used as the final score for the public sentiment to define if this text reflects positive or negative sentiment. In all four machine-learning approaches in Appendix A1, they produce a metric to represent the likelihood of positive sentiment. For example, Vader and Flair use range from -1 to 1 (negative to positive); BERT and TF-IDF use range from 0 to 1 (negative to positive). To be consistent, we transform all the metrics into the same scale from 0 to 1. Accordingly, if the score is larger than 0.5, we indicate it as positive; and if it is less 0.5, it is negative.

3. Results

3.1. Public sentiment towards sanctions about the Russia-Ukraine war

From the most frequently occurring terms, a few common themes were extracted. We constructed six themes and their rank according to their occurrence, including (1) key stakeholders, (2) military operations, (3) perception of conflict, (4) humanitarian concerns, (5) sanctions and economic impacts, and (6) media

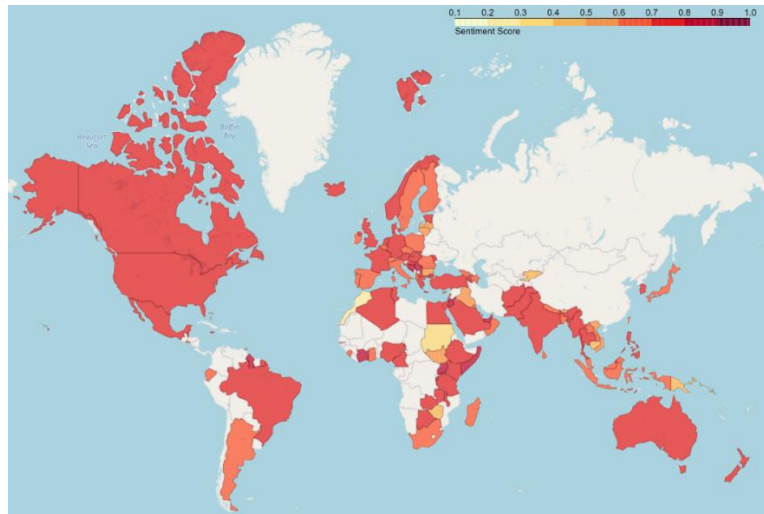
⁵ The details can be found at Appendix A1.

channels⁶. Accordingly, people are more likely to use the stakeholders related to the wars (e.g., the politicians, country's names, and the relevant organizations). Concomitantly, Figure 1 depicts the network of 10,000 most occurred bigrams and their modularity by using approach proposed by Blondel et al. (2008). As a result, the most popular themes are still key political leaders and organizations, military operations, global attempts to stop the war using sanctions and diplomatic channels, humanitarian concerns, energy and oil prices, and the roles of the media in the war. Although economic sanction is the topical title on many newspaper and propaganda campaigns, little is known about public sentiments. There are around 64,000 posts in the sample that were used to extract public sentiment on this area. Excluding countries with fewer than 50 interactions, public sentiment scores in 109 countries were calculated and are presented in Figure 2.

Figure 1. Bigram network analysis

The sentiment score map in Figure 2 shows public support for sanctions against Russia in most countries in our sample (109 countries with an average score of public sentiment of 0.68). However, when considering the strengths of support, there is clear fragmentation in public sentiments between countries with different positions in the geopolitical world. The public in Western countries such as European countries, the United States, Canada, Australia, and New Zealand strongly support the sanctions, with an average score of public sentiment of about 0.71. Nevertheless, the public in some countries that have a geographical position close to the Russian public, such as Lithuania, Latvia, and Bulgaria, seem to be divided and only show marginal support for sanctions against Russia (sentiment score above 0.50 but below 0.60). The public in key countries in Central and South America, such as Mexico, Ecuador, Brazil, and Argentina, also show high consensus and strongly support the sanctions. However, diverse public sentiments about sanctions against Russia could be observed in Asian and African countries. Cambodia, Kyrgyzstan, Zimbabwe, Sudan, and Morocco are against sanctions (sentiment score below 0.50) while South Sudan, Bhutan, Iraq, and Vietnam marginally support the sanctions. We used votes on the condemnation of Russia's decision to go to war with Ukraine at the United Nations as a proxy for government stances on the Russia-Ukraine war. In addition, we classified the public sentiment and the government vote to the condemnation against Russia as 9 key categories (Figure 3). Specifically, Asian, and African countries show clearer divergences between

government stances and public sentiments. In Asia, Iraq, India, Pakistan, Bangladesh, Vietnam, Laos, Cambodia, and Myanmar are countries where public sentiments and governments' stances are unaligned. Similarly, several countries in Africa have this divergence between governments and the public, such as Algeria, Cameroon, South Sudan, Ethiopia, Uganda, Rwanda, Tanzania, South Africa, and Madagascar. Only the public in Morocco, Kyrgyzstan, Sudan, and Zimbabwe agreed with their government's stance on Russia-Ukraine⁷.



Notes: The brightness or darkness present the negative and positive sentiment towards economic sanctions against Russia. Countries in white colour are not included in the sentiment sample because Facebook is censored in the countries, or too few posts on the issue of sanctions are discussed. Russia and Ukraine were excluded to avoid biases.

Figure 2. Public sentiment score of 109 countries on sanctions against Russia

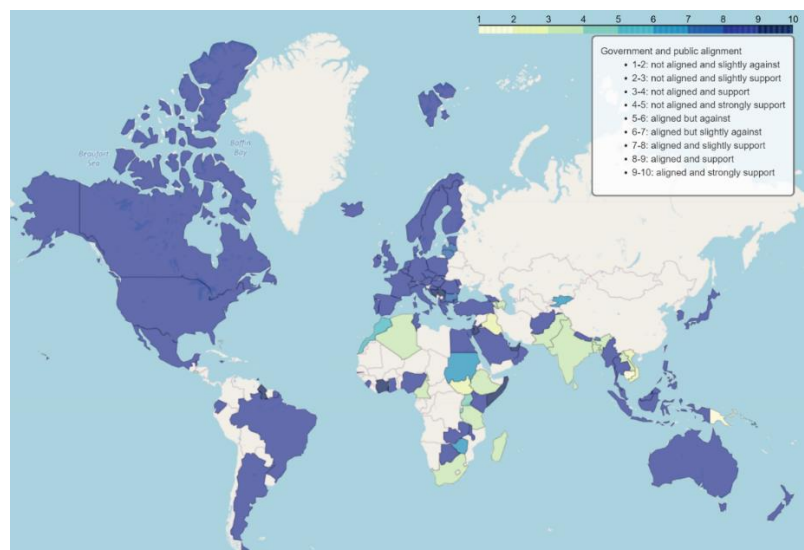


Figure 3. Government and public alignment map on sanctions against Russia matters

⁷ Our public sentiment index data can be found at Appendix A3.

3.2. Determinants and predictive power of public sentiment of the Russia-Ukraine war

The first three columns in Table 1 show that democratic countries have higher supporting sentiment towards economic sanctions against Russian by 10.8-13.3% in comparison with the authoritarian group. This effect is also found in flawed democratic countries; however, the magnitudes are weaker. As regard to international trading activities, people from countries where Russia heavily relies on to export its products are more likely to express the support towards sanctions against Russian invasion. In contrast, those from countries heavily depending on Russia to export their products seem to disagree with the imposed sanctions. Overall, the trading relationship with Russia plays an important role to shape human sentiment about the war, illustrated by two significant coefficients at 1% significance level. Intriguingly, after controlling economic condition, countries under political stability tend to show the higher public sentiment against the Russian war. Compared to the North America, there is a significantly higher positive sentiment towards economic sanctions in South America.

Table 1. Political regime and public sentiment in the Russia-Ukraine war

| | (1) Public sentiment | (2) Public sentiment | (3) Public sentiment | (4) Government Decision | (5) Government Decision | (6) Government Decision |
|-----------------------|----------------------------|----------------------------|----------------------------|-------------------------------|-------------------------------|-------------------------------|
| <i>Base group:</i> | | | | | | |
| <i>Authoritarian</i> | | | | | | |
| Full Democracy | | 0.133*** (0.044) | 0.108*** (0.033) | | | |
| Flawed Democracy | | 0.073** (0.036) | 0.075*** (0.026) | | | |
| Hybrid Regime | | 0.033 (0.056) | 0.037 (0.050) | | | |
| Public sentiment | | | | | 0.720*** (0.026) | 0.630*** (0.183) |
| Import from RUS | | | 0.001*** (0.0001) | | | 0.001 (0.002) |
| Export to RUS | | | -0.001*** (0.0001) | | | -0.001 (0.002) |
| Political Instability | -0.047** (0.019) | -0.054** (0.021) | -0.053** (0.020) | -0.008 (0.059) | 0.017 (0.042) | 0.016 (0.053) |
| Trust to Politician | -0.0001 (0.0001) | 0.0001 (0.0001) | -0.0001 (0.0001) | 0.0001 (0.002) | -0.0001 (0.002) | 0.0001 (0.002) |
| Free expression | | | | 0.249*** (0.050) | 0.254*** (0.033) | 0.261*** (0.034) |
| Rule of Law | | | | 0.146** (0.065) | 0.077 (0.123) | 0.054 (0.168) |
| Consensus on Goals | | | | -0.081 (0.070) | -0.095* (0.055) | -0.099* (0.059) |
| Gov Effectiveness | | | | -0.148 (0.213) | -0.134 (0.206) | -0.081 (0.287) |
| Aged65older | -0.002 (0.001) | -0.005*** (0.002) | -0.003 (0.002) | 0.001 (0.012) | 0.004 (0.008) | 0.004 (0.007) |

| | | | | | | |
|-----------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| GDP per capita | 0.002** (0.001) | 0.003** (0.001) | 0.002* (0.001) | 0.021*** (0.002) | 0.015*** (0.004) | 0.014*** (0.004) |
| Years of Schooling | -0.002 (0.006) | -0.005 (0.010) | -0.004 (0.009) | 0.010 (0.015) | 0.028 (0.018) | 0.024 (0.027) |
| <i>Base group:</i> | | | | | | |
| <i>North America</i> | | | | | | |
| Asia | -0.001 (0.021) | 0.003 (0.020) | -0.014 (0.020) | | | |
| Africa | -0.010 (0.036) | 0.007 (0.036) | -0.030 (0.035) | | | |
| Europe | 0.036 (0.023) | 0.040* (0.023) | 0.030 (0.022) | | | |
| Oceania | 0.085* (0.044) | 0.064 (0.058) | 0.084 (0.057) | | | |
| South America | 0.042* (0.023) | 0.038* (0.019) | 0.042** (0.017) | | | |
| Constant | 0.677*** (0.086) | 0.646*** (0.119) | 0.765*** (0.124) | | | |
| <i>N</i> | 79 | 78 | 78 | 55 | 55 | 55 |
| <i>Pseudo R²</i> | | | | 0.421 | 0.447 | 0.519 |

Notes: Columns (1), (2), (3) are summarizes robust weighted Tobit regression models while columns (4), (5), and (6) show the marginal effects of Logit regressions. The summary of variables description in terms of definition and statistics can be found in Appendix 4. Robust standard errors in parentheses: *p< 0.10, **p< 0.05, ***p< 0.01.

The columns (4), (5), and (6) show the predictive power of public sentiment on the government decision. The marginal change in public sentiment is associated with average changes of 0.63% to 0.72% in the odd of government choosing to fight against the Russian invasion through economic sanctions at 1% significance level. Regarding the free expression, these coefficients indicate that when citizens have marginally more chance to express their opinion and be listened by government, the probabilities of choosing to condemn Russian by their governments increase by average 0.25 percentage point at 1% significance level. Lastly, countries with higher levels of GDP per capita could predict both public sentiment and government decision at 1% significance level. However, education, proxied by years of schooling, does not matter to the public sentiment as well as government votes in the United Nations.

4. Conclusion

This paper provides the novel index about the public sentiment and its determinant and predictive power of Russia-Ukraine war. It expands the boundaries of an understanding between government and the public on the global scale in the new context.

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Appendix A1.1. Methodologies and sentiment score constructions

The Vader model (Valence Aware Dictionary for Sentiment Reasoning) creates and experimentally validates a gold-standard collection of lexical features (more than 7,000 items) together with their associated sentiment intensity measures that are uniquely attuned to sentiment in microblog-like situations (Hutto and Gilbert 2014). It then combines these lexical characteristics with an examination of five generic principles that include grammatical and syntactical patterns for expressing and highlighting sentiment intensity. The Vader model has been widely applied in social media contexts for sentiment extraction (Borg and Boldt 2020; Alaei, Becken, and Stantic 2019).

TF-IDF model (term frequency-inverse document frequency (TF-IDF) model is a statistical model that uses vectorization techniques and statistical analysis to capture the relationships between labels and document features, such as individual words and phrases (n-grams). In this study, the p-score for feature selection was set to 0.9. The TF-IDF model in this study is trained using the labeled 'Sentiment140' data from Stanford University (Go et al. 2009), which contained 1.6 million tweets with logistic regression classifier. The results were comprehensive, and the performance evaluations demonstrated promising results for the TF-IDF with an AUC metric of 87,5% (see Figure A1.1). The trained TF-IDF models were then used to predict the sentiment score of clean texts from public Facebook posts in the sample. In this study, the logistic classifier is used with the trained TF-IDF models to predict the sentiment score (from 0 as maximum negative to 1 as maximum positive).

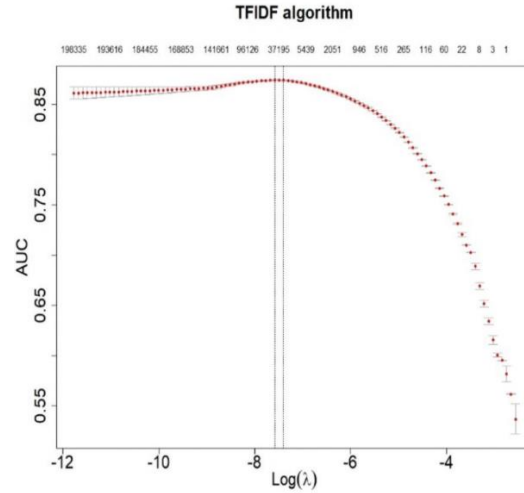


Figure A.1.1. Area under Curve metrics with different settings in TF-IDF training for sentiment analysis

BERT and Flair are deep learning models that have been pre-trained. Each model is unique in its own manner. The Flair model has a robust library that enables users to manipulate and mix various words and document embeddings. It can assess and convey text sentiments based on the corpus. In comparison to other natural language processing tools, Flair's sentiment classifier is built on a character-level LSTM neural network that makes predictions using letter and word sequences. Although it is based on a corpus, it may also be used to predict sentiment for out-of-vocabulary words, including typos. In this study, we used the pre-trained "Mix-Distillbert" Flair model for sentiment analysis.

BERT (Bidirectional Encoder Representations from Transformers) (BERT) for language understanding was developed by Devlin et al. (2019) in Google A.I. Language and is currently a state-of-the-art language processing model. The authors trained BERT using English Wikipedia (2,500 million words) and Books Corpus (800 million words), enabling the model to gain a deeper understanding of the language and to learn

variability in data patterns while also performing effectively on a variety of NLP tasks. There are two general pre-trained BERT models: the BERT-base model is a 12-layer, 768-hidden, 12-heads neural network with 110M parameters, whereas the BERT-large model is a 24-layer, 1024-hidden, 16-heads neural network with 340M parameters. In this study, we used a pre-trained BERT-based model and fine-tuned it for sentiment analysis using 100,000 labeled movie reviews from the IMDB website. The fine-tuned model still retains its edges with very high accuracy metrics (training accuracy of approximately 93.78% and validation accuracy of approximately 85%), as shown in Figure A1.2.

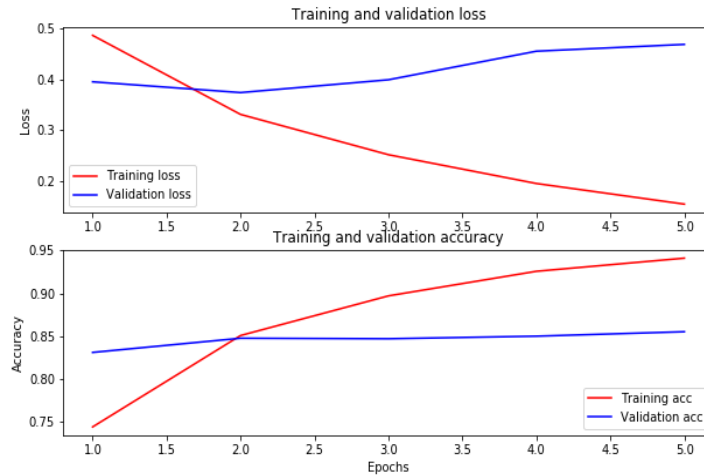


Figure A1.2. Training and Validation accuracy of fine-tuned BERT-base model for sentiment analysis

In this study, Vader's and Flair's sentiment scores, which range from -1 (maximum negative) to 1 (maximum positive), are normalized into a scale from 0 (maximum negative) to 1 (maximum positive) to foster the comparison with the sentiment scores from BERT and TF-IDF models. Next, the sentiment score for each Facebook public post is calculated using the average value of sentiment scores from the four models for that post. To represent the sentiment score for a country, we first select only public posts from that country. Then, the weighted average value of sentiment scores of all these posts from a country is calculated (weight is each post's total interactions such as like, share, loved).

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Appendix A2. Main themes extractions from frequency analysis

Figure A2.1. represents the most common terms and phrases in all public posts on Facebook related to the Russia-Ukraine conflict in 2022. The lists exclude the top five occurred terms and phrases, such as Russia, Ukraine, Russian, Ukrainian, and war, which are expected to appear in most posts by default. From the most frequently occurring terms, several common themes were extracted. Table A2.1. summarizes the most common themes and their rank according to their occurrence, including (1) key stakeholders, (2) military operations, (3) perception of conflict, (4) humanitarian concerns, (5) sanctions and economic impacts, and (6) media channels.

The first and most obvious theme concerns the key leaders and organizations involved in the conflict. This “key stakeholders” theme is also the topmost mentioned theme in public posts. “Putin” is the most mentioned term reflecting the key roles of the Russian president in the development of the conflict. “Biden,” “NATO,” “European countries” or “Ukraine president” appear to be the counterparts in this conversation. Other countries mentioned in the most occurred terms are “China,” “India,” “Czech Republic,” “United Kingdom,” “Poland,” and “South Africa”. Although military conflicts have occurred only in the Ukraine territories, battles on social media fronts have escalated and spilled over the world to include the most powerful players on the geopolitical stage. “United Nations,” “Security Council” or “global,” “international” are also mentioned as the top terms and phrases to emphasize the global scale of the conflict.

The second popular theme concerns military operations and conflict situations. Popular terms in this theme discussed the progression of conflicts relating to military actions, deployments of armed forces, and territory controls. A topic in this theme creates a special global concern regarding the intervention of nuclear weapons during military conflict.

The third theme shows the “perception of conflict” from the social media users’ perspective. The most common term to describe the conflict between Russia and Ukraine is “war” reflecting the fierce military actions between the two countries. The second most popular term describes the situation as invasion, “invasion” showing that a large portion of social media users views the military conflict in Ukraine as unjustified and violating “international law”.

The fourth theme is about “humanitarian concerns” for Ukraine people during the conflict. As the war has extended for nearly two months, millions of Ukraine people have been badly affected by losing their homes, friends, family members, and even their lives. To respond to this crisis, “peace talks” are the key solutions mentioned on social media.

“Sanctions and economic impacts” is the next main theme occurring on social media during the Russia – Ukraine war. Numerous economic sanctions from governments worldwide have been implemented to stop Russia’s aggression toward Ukraine. There are concerns regarding the economic “growth rate” resulting from these sanctions. In particular, the volatility of oil prices and the dependence of European countries on Russian gas are discussed.

Finally, the current Russia-Ukraine war is one of the first military conflicts in which mainstream media and social media have become critical fronts. Most of the main developments from the war have been “live updated,” discussed, and shared on “social media” social media’. In addition, real engagements on battlefields could be widely found in video sharing and streaming services such as YouTube.

Table A2.1. Key themes discussed in Facebook public posts and their ranking in occurrences

| Themes | Terms or Bigrams | Ranking in occurrences | Total number of occurrences |
|---|---|------------------------|-----------------------------|
| Key stakeholders | “putin”, “president”, “nato”, “biden”, “Joe”, “country”, “united”, “europe”, “countries”, “vladimir”, “moscow”, “kyiv”, “government”, “european”, “minister”, “china”, “india”, “poland”, “western”, “international”, “global”, “president biden”, “united nations”, “european union”, “russian federation”, “security council”, “Biden administration”, “soviet union”, “United Kingdom”, “Czech Republic”, “South Africa”, “foreign”, “foreign policy”, “foreign affairs” | 1 | 1,615,500 |
| Military operations and situations | “forces”, “military”, “time”, “troops”, “attack”, “border”, “nuclear”, “weapons”, “eastern”, “west”, “armed forces”, “russian army”, “ukraine borders”, “nuclear weapons”, “nuclear power”, “russian soldiers”, “national security”, “security”, “day”, “city”, “week” | 2 | 767,278 |
| Perceptions on the conflicts | “invasion”, “conflict”, “crisis”, “invade ukraine”, “military operation”, “ukraine invasion”, “invaded ukraine”, “russian invaded”, “russia’s invasion”, “invades ukraine”, “invading ukraine”, “russian aggression”, “international law” | 3 | 359,801 |
| Humanitarian concerns | “people”, “support”, “talks”, “peace”, “human rights”, “peace talks”, “ukrainian people”, “immaculate heart” | 4 | 288,395 |
| Sanctions and economic impacts | “sanctions”, “oil”, “prices”, “gas”, “growth rate”, “oil prices”, “russian oil”, “gas prices”, “Nord stream”, “natural gas” | 5 | 251,037 |
| Media channels | “news”, “live”, “media”, “social media”, “live updates”, “www.youtube.com watch” | 6 | 212,665 |

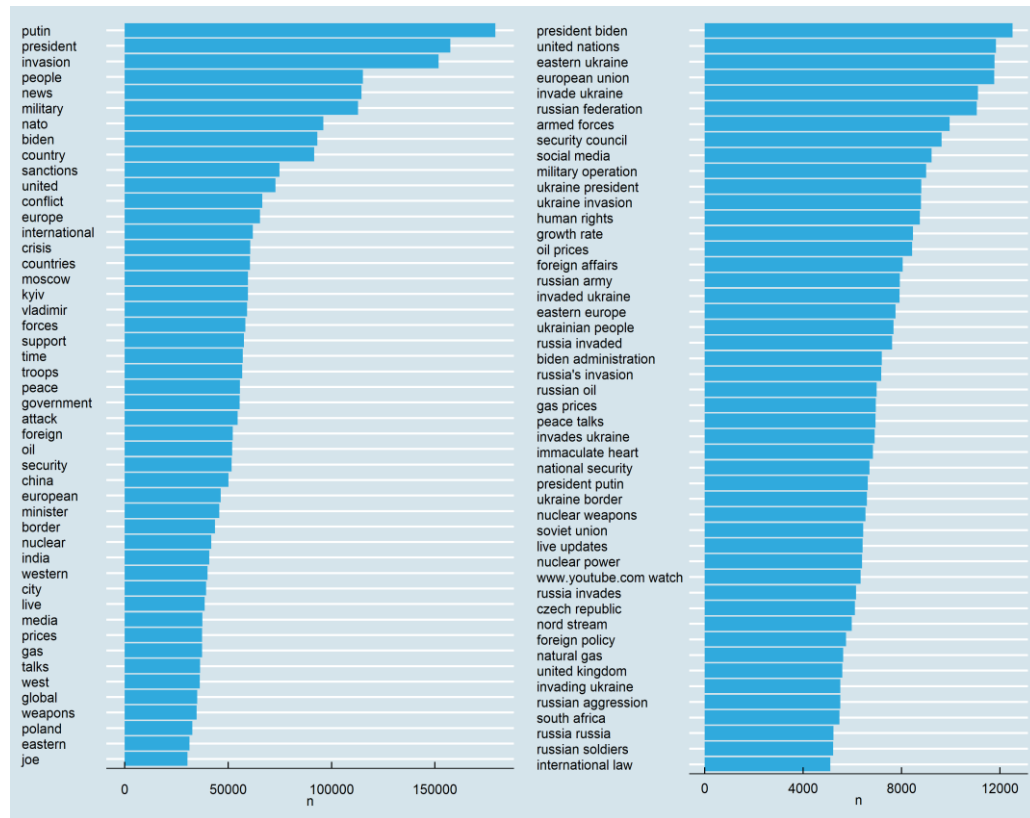


Figure A2.1. The most occurred terms and bigrams with their number of occurrences

Appendix A3. Government and public alignment illustration

Table A3.1. Public sentiment score, vote on condemnation, and government-public alignment

| COUNTRY | ISO CODE | SENTIMENT SCORE | VOTE ON CONDEMNATION | GOVERNMENT AND PUBLIC ALIGNMENT |
|------------------------|----------|-----------------|-----------------------|----------------------------------|
| AFGHANISTAN | AFG | 0.7003 | Support | aligned and support |
| ALBANIA | ALB | 0.6204 | Support | aligned and support |
| ALGERIA | DZA | 0.7266 | abstained or not vote | not aligned and support |
| ARGENTINA | ARG | 0.6623 | Support | aligned and support |
| ARMENIA | ARM | 0.7293 | abstained or not vote | not aligned and support |
| AUSTRALIA | AUS | 0.7544 | Support | aligned and support |
| AUSTRIA | AUT | 0.7522 | Support | aligned and support |
| AZERBAIJAN | AZE | 0.6293 | abstained or not vote | not aligned and support |
| BAHAMAS | BHS | 0.4790 | Support | not aligned and slightly against |
| BANGLADESH | BGD | 0.6902 | abstained or not vote | not aligned and support |
| BELGIUM | BEL | 0.6473 | Support | aligned and support |
| BELIZE | BLZ | 0.7862 | Support | aligned and support |
| BHUTAN | BTN | 0.5688 | Support | aligned and slightly support |
| BOSNIA AND HERZEGOVINA | BIH | 0.8369 | Support | aligned and strongly support |
| BOTSWANA | BWA | 0.7862 | Support | aligned and support |
| BRAZIL | BRA | 0.7338 | Support | aligned and support |
| BRUNEI | BRN | 0.8505 | Support | aligned and strongly support |
| BULGARIA | BGR | 0.5713 | Support | aligned and slightly support |
| BURUNDI | BDI | 0.8212 | abstained or not vote | not aligned and strongly support |
| CAMBODIA | KHM | 0.4985 | Support | not aligned and slightly against |
| CAMEROON | CMR | 0.7480 | abstained or not vote | not aligned and support |
| CANADA | CAN | 0.7507 | Support | aligned and support |
| CÔTE D'IVOIRE | CIV | 0.8112 | Support | aligned and strongly support |
| CROATIA | HRV | 0.7879 | Support | aligned and support |
| CYPRUS | CYP | 0.5616 | Support | aligned and slightly support |
| CZECH REPUBLIC | CZE | 0.6936 | Support | aligned and support |
| DENMARK | DNK | 0.7634 | Support | aligned and support |
| ECUADOR | ECU | 0.6674 | Support | aligned and support |
| EGYPT | EGY | 0.7265 | Support | aligned and support |
| EL SALVADOR | SLV | 0.6712 | abstained or not vote | not aligned and support |
| ESTONIA | EST | 0.7624 | Support | aligned and support |
| ETHIOPIA | ETH | 0.7489 | abstained or not vote | not aligned and support |
| FINLAND | FIN | 0.6545 | Support | aligned and support |
| FRANCE | FRA | 0.7473 | Support | aligned and support |
| GAMBIA | GMB | 0.6983 | Support | aligned and support |
| GEORGIA | GEO | 0.6474 | Support | aligned and support |
| GERMANY | DEU | 0.7385 | Support | aligned and support |
| GHANA | GHA | 0.6086 | Support | aligned and support |

| | | | | |
|------------------------------------|-----|--------|-----------------------|----------------------------------|
| GREECE | GRC | 0.7034 | Support | aligned and support |
| GUYANA | GUY | 0.8492 | Support | aligned and strongly support |
| HUNGARY | HUN | 0.7010 | Support | aligned and support |
| ICELAND | ISL | 0.7968 | Support | aligned and support |
| INDIA | IND | 0.7096 | abstained or not vote | not aligned and support |
| INDONESIA | IDN | 0.6913 | Support | aligned and support |
| IRAQ | IRQ | 0.5581 | abstained or not vote | not aligned and slightly support |
| IRELAND | IRL | 0.6465 | Support | aligned and support |
| ISRAEL | ISR | 0.6798 | Support | aligned and support |
| ITALY | ITA | 0.6345 | Support | aligned and support |
| JAMAICA | JAM | 0.7066 | Support | aligned and support |
| JAPAN | JPN | 0.6527 | Support | aligned and support |
| JORDAN | JOR | 0.8526 | Support | aligned and strongly support |
| KENYA | KEN | 0.7503 | Support | aligned and support |
| KUWAIT | KWT | 0.6358 | Support | aligned and support |
| KYRGYZSTAN | KGZ | 0.4351 | abstained or not vote | aligned but slightly against |
| LAOS | LAO | 0.6730 | abstained or not vote | not aligned and support |
| LATVIA | LVA | 0.5587 | Support | aligned and slightly support |
| LEBANON | LBN | 0.6504 | Support | aligned and support |
| LITHUANIA | LTU | 0.5234 | Support | aligned and slightly support |
| LUXEMBOURG | LUX | 0.7019 | Support | aligned and support |
| MACEDONIA | MKD | 0.7358 | Support | aligned and support |
| MADAGASCAR | MDG | 0.6526 | abstained or not vote | not aligned and support |
| MALAWI | MWI | 0.7332 | Support | aligned and support |
| MALAYSIA | MYS | 0.6601 | Support | aligned and support |
| MEXICO | MEX | 0.7243 | Support | aligned and support |
| MOLDOVA | MDA | 0.7396 | Support | aligned and support |
| MOROCCO | MAR | 0.2583 | abstained or not vote | aligned but against |
| MYANMAR [BURMA] | MMR | 0.7640 | Support | aligned and support |
| NEPAL | NPL | 0.6838 | Support | aligned and support |
| NETHERLANDS | NLD | 0.7578 | Support | aligned and support |
| NEW ZEALAND | NZL | 0.7156 | Support | aligned and support |
| NIGERIA | NGA | 0.7375 | Support | aligned and support |
| NORWAY | NOR | 0.7198 | Support | aligned and support |
| OMAN | OMN | 0.6781 | Support | aligned and support |
| PAKISTAN | PAK | 0.7167 | abstained or not vote | not aligned and support |
| PALESTINIAN TERRITORIES | PSE | 0.8154 | Support | aligned and strongly support |
| PAPUA NEW GUINEA | PNG | 0.4006 | Support | not aligned and slightly against |
| PHILIPPINES | PHL | 0.7046 | Support | aligned and support |
| POLAND | POL | 0.6576 | Support | aligned and support |
| PORTUGAL | PRT | 0.6652 | Support | aligned and support |
| QATAR | QAT | 0.7057 | Support | aligned and support |

| | | | | |
|-----------------------------|-----|--------|-----------------------|----------------------------------|
| ROMANIA | ROU | 0.6641 | Support | aligned and support |
| SAUDI ARABIA | SAU | 0.7766 | Support | aligned and support |
| SERBIA | SRB | 0.8619 | Support | aligned and strongly support |
| SIERRA LEONE | SLE | 0.6814 | Support | aligned and support |
| SLOVAKIA | SVK | 0.7424 | Support | aligned and support |
| SOLOMON ISLANDS | SLB | 0.5266 | Support | aligned and slightly support |
| SOMALIA | SOM | 0.8125 | Support | aligned and strongly support |
| SOUTH AFRICA | ZAF | 0.6802 | abstained or not vote | not aligned and support |
| SOUTH KOREA | KOR | 0.7750 | Support | aligned and support |
| SOUTH SUDAN | SSD | 0.5929 | abstained or not vote | not aligned and slightly support |
| SPAIN | ESP | 0.6707 | Support | aligned and support |
| SRI LANKA | LKA | 0.6292 | abstained or not vote | not aligned and support |
| SUDAN | SDN | 0.3597 | abstained or not vote | aligned but slightly against |
| SWEDEN | SWE | 0.6395 | Support | aligned and support |
| SWITZERLAND | CHE | 0.6538 | Support | aligned and support |
| TAIWAN | TWN | 0.6439 | Support | aligned and support |
| TANZANIA | TZA | 0.7622 | abstained or not vote | not aligned and support |
| THAILAND | THA | 0.7165 | Support | aligned and support |
| TRINIDAD AND TOBAGO | TTO | 0.6597 | Support | aligned and support |
| TUNISIA | TUN | 0.7268 | Support | aligned and support |
| TURKEY | TUR | 0.7643 | Support | aligned and support |
| UGANDA | UGA | 0.8174 | abstained or not vote | not aligned and strongly support |
| UNITED ARAB EMIRATES | ARE | 0.8435 | Support | aligned and strongly support |
| UNITED KINGDOM | GBR | 0.7383 | Support | aligned and support |
| UNITED STATES | USA | 0.7259 | Support | aligned and support |
| VIETNAM | VNM | 0.5097 | abstained or not vote | not aligned and slightly support |
| ZAMBIA | ZMB | 0.7027 | Support | aligned and support |
| ZIMBABWE | ZWE | 0.4730 | abstained or not vote | aligned but slightly against |

Appendix A4. Data and Descriptive statistics

Table A4.1. Countries in the sample

| Country | Code | Country | Code | Country | Code |
|------------------------|-------------|----------------|-------------|----------------------|-------------|
| Argentina | ARG | India | IND | Philippines | PHL |
| Australia | AUS | Indonesia | IDN | Poland | POL |
| Austria | AUT | Ireland | IRL | Portugal | PRT |
| Bangladesh | BGD | Israel | ISR | Qatar | QAT |
| Belgium | BEL | Italy | ITA | Romania | ROU |
| Belize | BLZ | Jamaica | JAM | Saudi Arabia | SAU |
| Bosnia and Herzegovina | BIH | Japan | JPN | Serbia | SRB |
| Botswana | BWA | Jordan | JOR | Slovakia | SVK |
| Brazil | BRA | Kenya | KEN | South Africa | ZAF |
| Bulgaria | BGR | Kuwait | KWT | South Korea | KOR |
| Cambodia | KHM | Kyrgyzstan | KGZ | Spain | ESP |
| Cameroon | CMR | Laos | LAO | Sri Lanka | LKA |
| Canada | CAN | Latvia | LVA | Sweden | SWE |
| Croatia | HRV | Lebanon | LBN | Switzerland | CHE |
| Czechia | CZE | Lithuania | LTU | Tanzania | TZA |
| Denmark | DNK | Luxembourg | LUX | Thailand | THA |
| Ecuador | ECU | Malaysia | MYS | Trinidad and Tobago | TTO |
| Egypt | EGY | Mexico | MEX | Turkey | TUR |
| El Salvador | SLV | Moldova | MDA | Uganda | UGA |
| Estonia | EST | Morocco | MAR | United Arab Emirates | ARE |
| Finland | FIN | Nepal | NPL | United Kingdom | GBR |
| France | FRA | Netherlands | NLD | United States | USA |
| Georgia | GEO | New Zealand | NZL | Vietnam | VNM |
| Germany | DEU | Nigeria | NGA | Zambia | ZMB |
| Ghana | GHA | Norway | NOR | Zimbabwe | ZWE |
| Greece | GRC | Oman | OMN | | |
| Hungary | HUN | Pakistan | PAK | | |

Table A4.2: Variables description and sources

| Variables | Description | Sources |
|--|--|---|
| Democracy classifications according to countries' democracy index score from The Economist | <p>Full democracy: all areas such as basic political freedoms, civil liberties, political culture, government functioning are at a high level.</p> <p>Flawed democracy: free and fair elections, basic civil liberties respected but suffered from problems in government functioning, underdeveloped political cultures, and weak political participant</p> <p>Hybrid regime: substantial irregularities in election, more prevalent problems in government functioning, underdeveloped political cultures, the rule of law is weak, and corruption is widespread, no independent judiciary</p> <p>Authoritarian: state political plurals are absent, outright dictatorship, elections are not free and fair and infringements of civil liberties, no independent judiciary</p> | The Economist Intelligence Unit (2020) |
| Government Decision | Dummy variable for voting support (1) or abstained/not vote (0) on the UN General Assembly resolution demanding that Russia immediately end its military operations in Ukraine | United Nation News |
| Trust in politician | Public trust in politicians index for each country | World Economic Forum Global Competitiveness Index |
| Political instability | Perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. | GovData360 dataset from the World Bank |
| Import RUS Export RUS | Countries ranks based on their import/export values from Russia (higher ranks mean higher value of trade) | World Integrated Trade solution dataset |
| Free expression | Perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. | Worldwide Governance Indicators from the World Bank |
| Gov Effectiveness | Perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and | Worldwide Governance Indicators from the World Bank |

| | | |
|------------------------|--|---|
| | implementation, and the credibility of the government's commitment to such policies | |
| Consensus on Goals | To what extent do the major political actors agree on democracy and a market economy as strategic, long-term goals | GovData360 dataset from the World Bank |
| Rule of Law | Perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. | Worldwide Governance Indicators from the World Bank |
| Aged65Older (%) | Share of populations with age 65 and over | World Bank national accounts data |
| GDPpercapita (\$1,000) | Gross domestic product per capita | World Bank national accounts data |
| Years of Schooling | The average number of years in formal education that a person can expect to receive with the current countries' enrolment rates at all levels of education | United Nation Development Program (2020) |

Table A4.3: Variables descriptive statistics

| Variable | Obs | Mean | Std. dev. | Min | Max |
|-------------------------------|------------|-------------|------------------|------------|------------|
| Government Decision | 79 | 0.823 | 0.384 | 0.000 | 1.000 |
| Public sentiment | 79 | 0.690 | 0.094 | 0.258 | 0.862 |
| Full Democracy | 78 | 0.218 | 0.416 | 0.000 | 1.000 |
| Flawed Democracy | 78 | 0.423 | 0.497 | 0.000 | 1.000 |
| Hybridregime | 78 | 0.205 | 0.406 | 0.000 | 1.000 |
| Export RUS | 79 | 134.013 | 43.732 | 27.000 | 198.000 |
| Import RUS | 79 | 165.177 | 41.895 | 41.000 | 228.000 |
| Gov Effectiveness | 79 | 0.403 | 0.904 | -1.251 | 2.020 |
| Aged65Older | 79 | 11.470 | 7.027 | 1.144 | 27.049 |
| GDPpercapita (\$1,000) | 79 | 26.235 | 22.309 | 1.698 | 116.936 |
| Years of Schooling | 79 | 14.637 | 2.716 | 8.098 | 21.954 |
| Trust in politician | 79 | 66.443 | 42.555 | 0.000 | 137.000 |
| Political instability | 79 | 0.090 | 0.792 | -1.859 | 1.486 |
| Consensus on Goals | 55 | 6.655 | 1.868 | 3.000 | 10.000 |
| Rule of Law | 79 | 0.369 | 0.929 | -1.275 | 2.079 |
| Free expression | 79 | 0.241 | 0.954 | -1.796 | 1.725 |

Table A4.4 Correlation between variables

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|--------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|-------|
| 1 Government Decision | 1.000 | | | | | | | | | | | | | | | |
| 2 Public sentiment | 0.312 | 1.000 | | | | | | | | | | | | | | |
| 3 Gov Effectiveness | 0.349 | 0.083 | 1.000 | | | | | | | | | | | | | |
| 4 Aged65Older | 0.337 | -0.009 | 0.421 | 1.000 | | | | | | | | | | | | |
| 5 GDPpercapita (\$1,000) | 0.377 | 0.150 | 0.559 | 0.046 | 1.000 | | | | | | | | | | | |
| 6 Years of Schooling | 0.479 | -0.001 | 0.603 | 0.623 | 0.372 | 1.000 | | | | | | | | | | |
| 7 Trust in politician | 0.051 | -0.048 | -0.400 | 0.352 | -0.407 | 0.095 | 1.000 | | | | | | | | | |
| 8 Political instability | 0.301 | -0.048 | 0.643 | 0.469 | 0.462 | 0.477 | -0.207 | 1.000 | | | | | | | | |
| 9 Consensus on Goals | 0.229 | 0.075 | 0.559 | 0.608 | 0.172 | 0.432 | 0.177 | 0.557 | 1.000 | | | | | | | |
| 10 Rule of Law | 0.430 | 0.152 | 0.882 | 0.476 | 0.654 | 0.597 | -0.366 | 0.717 | 0.560 | 1.000 | | | | | | |
| 11 Free expression | 0.330 | 0.031 | 0.462 | 0.679 | -0.029 | 0.478 | 0.396 | 0.485 | 0.841 | 0.457 | 1.000 | | | | | |
| 12 Export RUS | 0.248 | 0.049 | 0.471 | 0.483 | 0.210 | 0.571 | -0.044 | 0.117 | 0.330 | 0.486 | 0.291 | 1.000 | | | | |
| 13 Import RUS | 0.074 | -0.110 | 0.302 | 0.403 | -0.045 | 0.428 | 0.039 | 0.020 | 0.161 | 0.189 | 0.218 | 0.640 | 1.000 | | | |
| 14 Hybrid Regime | -0.269 | -0.030 | -0.507 | -0.210 | -0.372 | -0.454 | 0.200 | -0.501 | -0.183 | -0.441 | -0.215 | -0.179 | -0.211 | 1.000 | | |
| 15 Flawed Democracy | 0.303 | 0.027 | 0.441 | 0.542 | 0.019 | 0.496 | 0.229 | 0.431 | 0.551 | 0.359 | 0.742 | 0.280 | 0.486 | -0.607 | 1.000 | |
| 16 Full Democracy | 0.080 | 0.115 | 0.293 | 0.121 | 0.120 | 0.196 | 0.031 | 0.140 | 0.246 | 0.269 | 0.181 | 0.222 | -0.215 | -0.087 | -0.129 | 1.000 |