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Public sentiment towards economic sanctions in the Russia-Ukraine war

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May 2022

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 (v) 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.

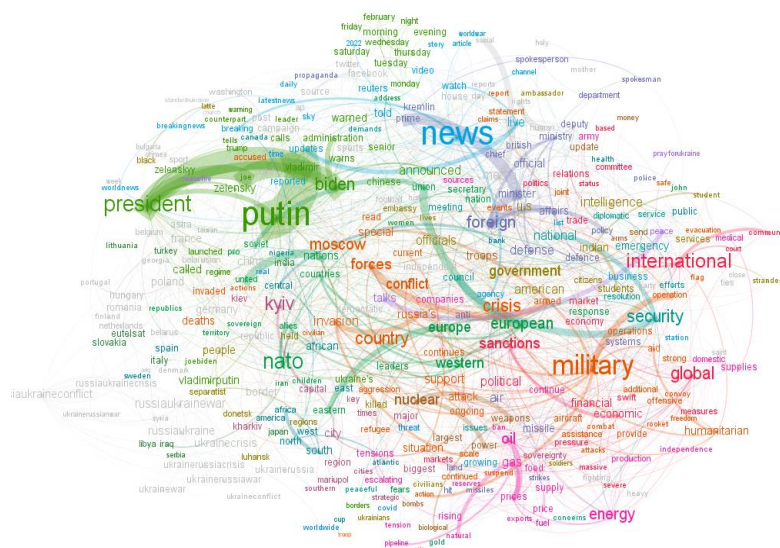
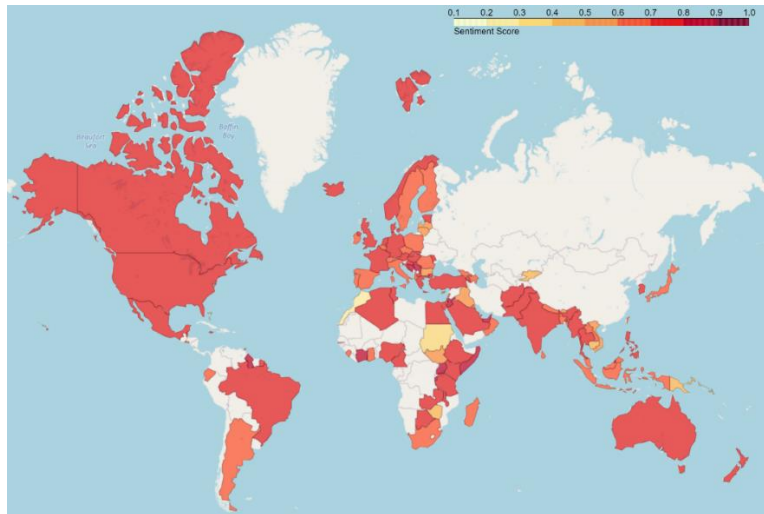


Figure 1. Bigram network analysis

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

⁶ The details can be found at Appendix A2.

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

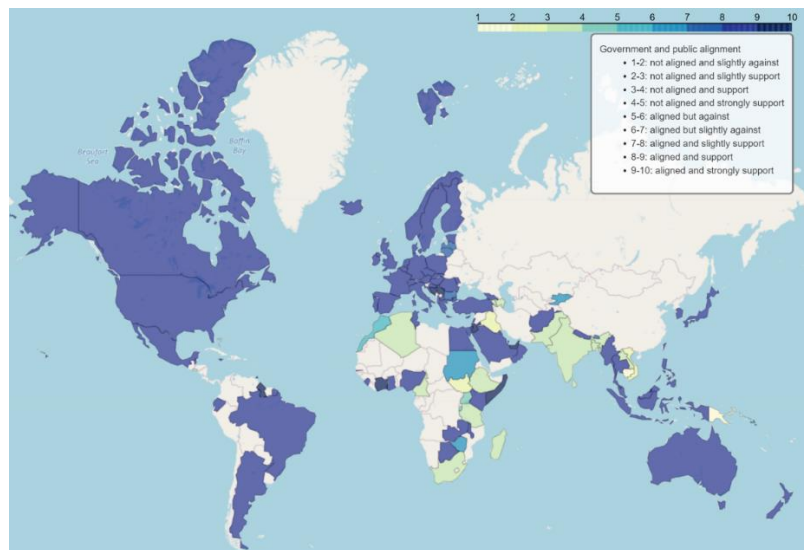


Figure 3. Government and public alignment map on sanctions against Russia matters

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).

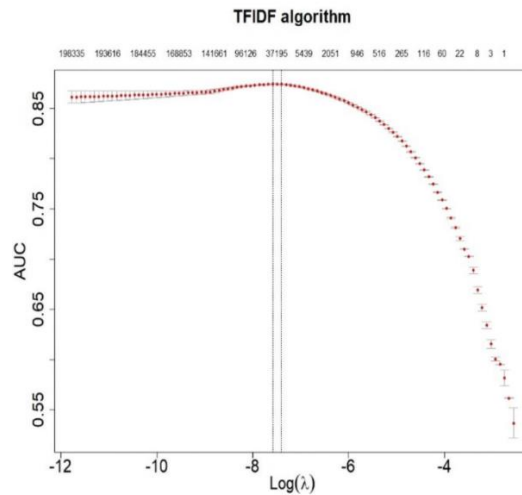


Figure A.1.1. Area under Curve metrics with different settings in TF-IDF training for sentiment analysis

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.

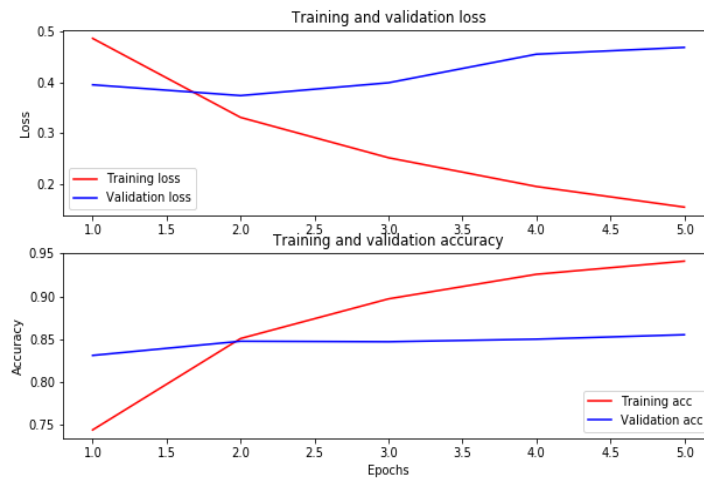


Figure A1.2. Training and Validation accuracy of fine-tuned BERT-base model for sentiment analysis

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

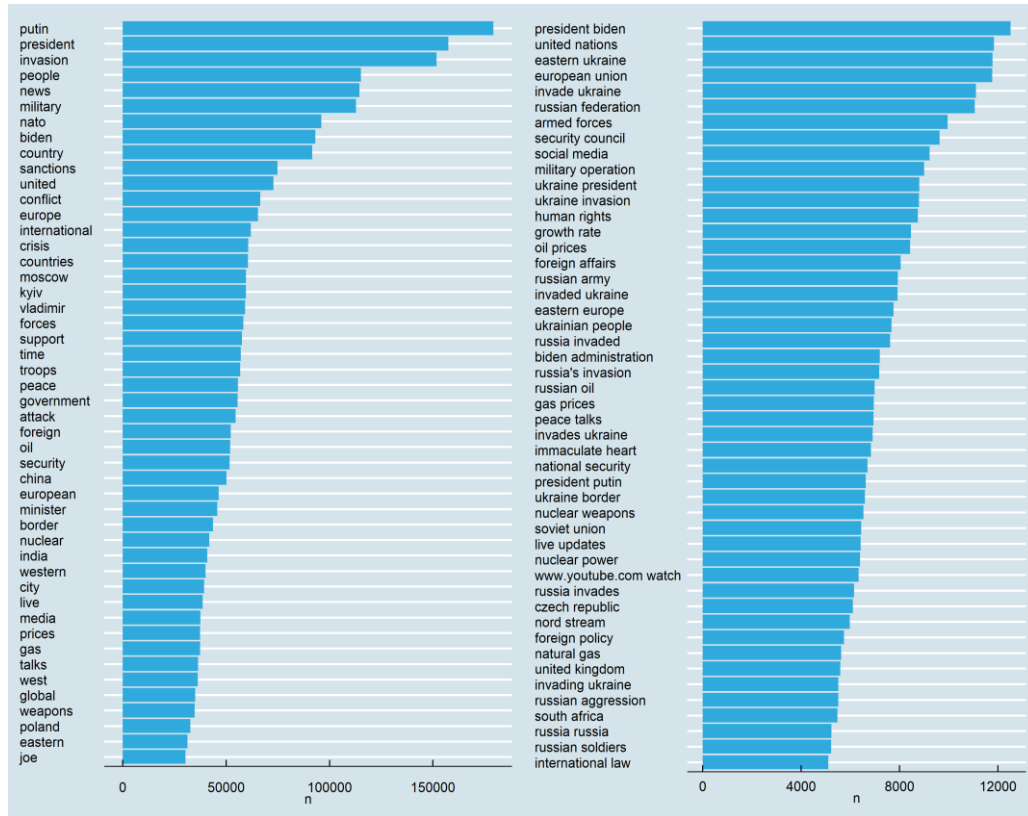


Figure A2.1. The most occurred terms and bigrams with their number of occurrences

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