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The legitimation of international organizations in the media in Eurasian post-socialist countries

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Abstract

The paper presents the first-ever big data analysis related to the legitimation of international organizations (IOs) in the media in Eurasian post-socialist countries. We use text mining and regression analysis to quantify intensity, tone, and narrative in the media as three critical dimensions of legitimation. The model is applied to a corpus of 1.3 million newspaper articles from six countries and twelve IOs. We show that contrary to earlier studies covering established democracies, the tone of articles about IOs is predominantly positive. Articles mentioning influential domestic politicians contribute to the delegitimation of the IOs featured, except in Poland.

Keywords: international organizations; legitimation; automated text mining; sentiment analysis; flexible LDA; post-socialist countries

1 Introduction

The liberal world order that prevailed in the 20th century under US global hegemony is being challenged around the globe (Ikenberry, 2018). Liberal democracy itself appears fragile, polarized, and vulnerable to far-right populism. Götz (2021) identifies four main features of the liberal world order and documents that all of them are being undermined by recent developments in world politics. One of these features is the network of international organizations (IOs) that helps socialize rising powers into the existing order and increasingly constrains the ability of domestic policies and states to protect the victims of the liberal world order (De Vries et al., 2021). This paper studies the crucial factor for IOs, which is their legitimacy. This influences whether IOs remain relevant in terms of states' efforts to solve problems (Sommerer & Agné, 2018), affects the latter's capacity to develop new rules and norms, and shapes their ability to secure compliance with international regulations (Dai, 2005). We define legitimacy as the belief of audiences that an IO's authority is appropriately exercised and legitimation as a process intended to shape such beliefs

(Tallberg & Zürn, 2019). Delegitimation is understood as efforts to undermine the legitimacy of IOs by challenging whether the authority they exercise is appropriate, including by presenting critical views of them in the media.

The Eurasian post-socialist countries under analysis in this paper, Hungary, Poland, Russia, Belarus, Kazakhstan, and Ukraine, provide fertile ground for IO legitimation studies. IOs played a crucial role in designing and implementing liberal policies after the collapse of socialism in the region. These policies were often backed by sizeable financial assistance aimed at fostering institutional and economic development or supporting financial stability. They delivered remarkable economic success in Central and Eastern Europe but failed in Ukraine and facilitated state capture and the creation of oligarchic autocracies in Russia, Kazakhstan, and Belarus. This dichotomy is a hotly debated issue. Hall and Ambrosio (2017) attribute these divergences to the different authoritarian learning and diffusion paths adopted in the early stage of transformation by the autocracies analyzed in this paper and implemented only in recent years by Hungary and Poland's political elites. Gel'man (2017) attributes these differences to bad governance and identifies three clusters of explanations: historical path dependency, agency-driven relations, and – most relevant for our research – international influence. He argues that international leverage, including well-designed institutions and democratization, depends on the will of domestic political elites to adopt such standards. If such will is absent, the financial assistance supporting such reforms can result in partial changes in some areas and can even preserve the status quo of bad governance (Abrams & Fish, 2015). Our research contributes to this discussion by showing how the legitimacy of international organizations is presented in local media.

Furthermore, many dimensions of the crisis of the liberal world order can be identified in the region. Liberal values, such as same-sex marriage, liberal gender education for children, and the right to abortion, are heavily contested or prohibited. Free elections are held in Hungary, Poland, and, to some extent, Ukraine, but they fail to meet democratic standards in the other countries under analysis. None of these countries, except Russia, is able to secure their military or energy safety without relying on the support of global powers or an IO. Belarus depends heavily on Russia for military and energy assistance. Poland's security is based on NATO membership, while Ukraine is a battlefield between Russia and NATO. None of the countries under analysis welcome large migration from culturally distinct regions, which contrasts with their very adverse domestic demographic trends, except for Kazakhstan. Even the climate change policies at the top of many IO agendas face significant hurdles in the countries under analysis.

For the IOs to be challenged by nationalist political forces, two key elements need to be present: public discontent about pre-existing forms of international cooperation and the mobilization of public opinion to the strategic advantage of national political actors (De Vries et al., 2021). Both elements are shaped by media, which exhibit very different levels of freedom in the Eurasian post-socialist countries. Freedom House ranks Poland as a free country, with some deterioration in recent years. Hungary and Ukraine are partly free, but Russia, Kazakhstan, and Belarus are not free. Considering all these factors, we expect that the media channel of IO legitimation will exhibit significant heterogeneity in the analyzed countries in the region.

We distinguish two types of IO legitimation in the media: general communication and elite communication. General communication refers to any article that discusses an IO. Elite communication is attributable to influential members in the public discourse. The role of politicians in the IO legitimation process has been found in the literature to be crucial. Dellmuth and Tallberg (2021) show that communication by national governments and civil society organizations has more substantial effects on perceptions of legitimacy than communication by IOs themselves. We expect elite communication to be even more important when politicians exert significant influence over the media.

Legitimation and delegitimation practices in the media can be measured according to three major dimensions: intensity, tone, and narrative (Tallberg & Zürn, 2019).

Intensity refers to the number of legitimation or delegitimation events like statements, press articles, reforms, or protests within a given time frame. Intensity is crucial with regard to the impact on beliefs about legitimacy since legitimation or delegitimation claims that are communicated more frequently will be more influential than those communicated less frequently. This is shown, for example, by Rauh and Zürn (2020), who document the positive relationship between the frequency of articles mentioning the WTO, the IMF, and NAFTA and the degree of politicization and protest activity in the period 1992–2012.

Tone or *sentiment* captures whether discursive and behavioral practices frame the IO in positive (legitimation) or negative terms (delegitimation). Many studies (Krzywdzińska, 2019; Schmidtke, 2019; Marcelino & Brandão, 2012) document that media discourse about IOs is predominantly negative. Schmidtke (2019) assessed the intensity, tone, and narratives of legitimation over time across IOs and countries, covering the EU, the UN, and the G8 in Germany, Switzerland, the UK, and the US from 1998 to 2013 by analyzing some 6,500 evaluative statements. The article demonstrates that IOs with more extensive authority are subject to more intense efforts at legitimation and delegitimation. The article further indicates that the media discourse on IOs is predominantly negative in tone. Similarly, the coverage of NATO on Russian public television presents a coherent negative image of the latter as an aggressive organization in Russia's near abroad, regardless of the genre of the broadcast (Krzywdzińska, 2019).

Narrative, in the context of automated text analysis, refers to the central theme or topic of media communication. Some topics, such as crime or the COVID-19 pandemic, have a much lower tone than others. So, to calculate an unbiased measure of legitimation based on sentiment, one should control for the media communication topic.

The automated text analysis tools applied here are often called natural language processing (NLP) methods. While they are frequently used in political and social sciences in general, only recently have they been applied in IO legitimation or similar studies. Further, we can now analyze such communication on the kind of vast scale that was previously impossible. For example, Parizek (2021) analyzed the media coverage of 70 IOs by more than 20,000 media outlets in 200 countries using a random sample of 20 million articles. Kaya and Reay (2019) used content analysis to explore almost 12,000 IMF documents to track changes in the Washington consensus policy paradigm within the IMF. Zaiotti (2020) analyzed the impact of the 2015-2016 refugee crisis on the reputation of the European Union by looking at nearly 4,000 tweets on the topic in two languages. Salience and sentiment analysis show that the crisis raised the EU's profile on the world stage and helped the EU improve its reputation, contrary to broadly held beliefs. Rauh & Zürn (2020) analyzed almost 130,000 articles from quality newspapers that mentioned at least once one of the four IOs under study: the IMF, the World Bank, the WTO, and NAFTA. They developed a specific legitimation dictionary to measure the discourse about the legitimation of the IOs in the collected corpus involving transnationally organized civil society organizations (CSOs) contributing to the debate about the IOs. Kentikelenis and Voeten (2021) applied sentiment analysis and a purpose-built dictionary analysis to a corpus of 8,093 speeches at the UN General Debate to identify legitimacy challenges to the liberal world order. Johnson and Lerner (2021) employed text mining to analyze 3,774 paragraphs of statements made by national governments associated with the WTO's Committee on Trade and Environment and showed that environmental discussions more frequent the higher the level of development of a country.

As shown above, the machine-learning framework can successfully address various research hypotheses related to IO legitimation, namely how intensity, tone, and narrative jointly influence IO coverage in the media. The current paper applies several machine learning tools, which are described in detail in the methodology section. These tools are salience or frequency analysis, sentiment analysis or, more broadly, dictionary-based models, and topic modeling. Salience measures intensity, sentiment captures the tone, and topics identify types of narrative.

The new methodology that is developed allows us to measure the media's attitudes towards IOs, controlling for the article's narrative and topic, and to compare the attitudes of different countries towards IOs. Additionally, it detects how influential domestic politicians contribute to IO legitimation or delegitimation.

This paper contributes to the literature in several new ways. The paper's focus is describing the development of a new model that identifies and measures all three dimensions of the legitimation or delegitimation of IOs. Analyzing large multi-language corpora is challenging, as internet newspapers and portals have many country-specific and language-specific idiosyncrasies. Namely, various newspapers have very different topic coverage, and their average tone also differs. Therefore, applying standard topic modeling or sentiment analysis could lead to biased results. We propose two new measures to address these challenges: flexible latent Dirichlet allocation (LDA) and relative sentiment analysis.

We test this model on 1.3 million articles from 20 newspapers and news portals in six Eurasian post-socialist countries, using three languages. We show that the proposed model can capture significant differences in IO (de)legitimation practices between countries and their governments (Dellmuth & Tallberg, 2021). We compare these IO legitimation practices in the post-socialist world with those in developed countries (Schmidtke, 2019). Several versions of the model are estimated that generate similar results, confirming their robustness.

2 Data: Description of a corpus of 1,255,294 articles

The data were scraped for each day between January 2018 and December 2020 for five post-socialist countries: Russia, Kazakhstan, Belarus, Ukraine, and Poland. They were scraped from web portal archives for Hungary in June and July 2021. The scraping script was written for Russian, Kazakh, Belarusian, Ukrainian and Polish in R using rvest library. The scraping was done in Python using BeautifulSoup for the Hungarian portals, except for index.hu, for which the Hungarian author has access to the archive (acquired from the index.hu editorial office).

The selection of media sources in post-socialist Eurasian countries is more complicated than in the case of established democracies, which are typically the subject of IO legitimation analysis. While media in Poland and Hungary enjoy relative freedom, with some deterioration in recent years, media in Belarus, Kazakhstan, and Russia are controlled or monitored by the state, and various forms of censorship have been documented in these countries. Therefore, the typical Western approach of selecting the most popular or quality media would not be appropriate and could lead to biased results that rely too much on government-desired narratives. Our media sample selection took this factor into account. The corpus that was built covers a broad spectrum of newspapers across many dimensions, taking in liberal and conservative sources, outlets controlled by the state and those owned by oligarchs, and pro-government and anti-government papers. This means the newspaper corpus is suitable for identifying a broad range of the legitimation and delegitimation practices applied to IOs in the post-Soviet space.

The selection of countries for this study was guided by several criteria. Initially, the focus was on countries within the post-socialist Eurasian region. Additionally, the choice of countries was influenced by the linguistic capabilities of the research team, specifically Polish and Russian, which explains the inclusion of Poland in the study. Moreover, the research encompassed countries where Russian is a widely spoken and official language, including Belarus, Kazakhstan, Russia, and Ukraine, prior to the Russian invasion. The diversity in media regimes and levels of media freedom across these countries provides a robust testing ground for the newly proposed model of media freedom, facilitating an examination across varying political, social, and cultural contexts.

Table 1 presents the data sources, the number of articles, and the global and local Alexa ranking.[1] The owners of a majority of the websites that were selected also publish newspapers. The exceptions are in Kazakhstan, where we picked influential and popular websites, and Hungary, where online platforms are the only news segment in which pro-government content does not predominate (Bajomi-Lázár, 2013; Griffen, 2020). Most newspapers cover a wide selection of topics, with the exception of the Polish wpolityce.pl, which specializes in political news. A detailed description of the selected newspapers and

[1] The Alexa rank measures website traffic using information from internet browsers that have the Alexa plug-in installed. It is estimated that about one percent of browsers worldwide have such a plug-in. Alexa ranking is compiled by Alexa Internet Inc., a US-based company and subsidiary of Amazon. The authors classified and described local media using their deep knowledge of their political affiliation.

portals is provided in Appendix 1 in the online supplemental information. Due to the limited reliability of sentiment lexicons, only Russian-language newspapers were included in the corpus in Belarus, Kazakhstan, and Ukraine.

Table 1 Newspapers and portals included in the analysis and their Alexa ranks

Country	Language	Newspaper site	Number of articles	Alexa global rank	Alexa local rank
Russia	Russian	iz.ru	43,782	1,378	45
Russia	Russian	kommersant.ru	46,070	1,335	44
Russia	Russian	novayagazeta.ru	29,357	9,215	459
Russia	Russian	vedomosti.ru	27,797	6,302	288
Kazakhstan	Russian	informburo.kz	29,375	38,916	119
Kazakhstan	Russian	nur.kz	67,350	951	6
Kazakhstan	Russian	tengrinews.kz	44,285	13,036	34
Kazakhstan	Russian	zakon.kz	109,442	9,477	30
Belarus	Russian	bdg.by	33,447	292,678	746
Belarus	Russian	belgazeta.by	21,995	1,392,332	11,041
Belarus	Russian	sb.by	83,685	41,015	79
Ukraine	Russian	kp.ua	194,792	64,062	860
Ukraine	Russian	segodnya.ua	45,835	18,658	256
Ukraine	Russian	vesti.ua	90,559	58,573	1,096
Poland	Polish	gazeta.pl	53,321	1,749	14
Poland	Polish	rp.pl	49,587	20,930	167
Poland	Polish	wpolityce.pl	76,625	13,833	105
Hungary	Hungarian	index.hu	55,891	7,174	13
Hungary	Hungarian	origo.hu	179,169	6,306	17
Hungary	Hungarian	alfahir.hu	31,860	362,256	N/A

Note: The Alexa ranking is provided for informational purposes only and has not been used as a criterion to select newspapers for the analyzed corpus.

The literature substantiates the rationale for selecting a diverse array of countries, as argued by Rosenberg (2016). Furthermore, the need for a focused analysis of post-socialist Eurasian states is particularly pressing, given their relative underrepresentation in political science discourse, a gap highlighted by Wilson and Knutsen (2020).

3 Methodology for a new legitimation model applying a machine-learning framework

The proposed model is based on the following findings of the sentiment analysis literature (Mäntylä et al., 2018). Suppose a given object, such as a product, service, or organization, is often mentioned in articles that feature many negative (positive) inclination words. In this case, a negative (positive) popular perception is formed about this object. In the context of IO legitimacy, negative perception or tone contributes to IO delegitimation, and positive perception or tone contributes to IO legitimation. The model derives the measure of IO legitimation from the interaction between the intensity, the tone, and the narrative of the media discourse about the IO. Contributions by influential politicians and public officials to this discourse carry great weight (Dellmuth & Tallberg, 2021), so the model also estimates the tone of articles that feature both the IO and influential domestic politicians. A high frequency or intensity of articles featuring a given IO yields statistically significant estimates for tone, while a low intensity of articles results in insignificant estimates. The tone of the article crucially depends on the topic of its narrative. Articles about specific issues such as the COVID-19 pandemic, military conflicts, terrorism, or accidents are characterized by a topic-specific high frequency of negative inclination words. This means that the appearance of the name of the IO in such an article does not necessarily contribute to the delegitimation of the IO. The model takes topics into account to calculate unbiased measures of IO legitimation.

The proposed method should distinguish between the situations when an article discusses an IO and when the article discusses something else and the IO is mentioned only incidentally. Similarly, when we analyze elite communication, the model should be able to distinguish the incidental mention of influential politicians somewhere in the text from the articles that refer to them intensely. Our method is as follows. During text mining, we count the number of occurrences of the IO name (*io*) and the influential domestic politicians' names (*dip*). Let us denote either of the two values as N. Then, we calculate $1+log(N)$ for $N>0$; see Table 2 for the definitions of the variables. These variables are then used in regression analysis. They measure the IO intensity of each article and the intensity of references to influential politicians for measures of elite communication. We use the log transformation to consider the declining marginal impact of additional mentions of IO or a politician when many mentions are already identified. For example, when both influential politicians and IOs are mentioned four times each, the variable measuring the interaction between them takes on a value of 5.7: (1+log(4))*(1+log(4)) = 5.7. For single mentions, the corresponding value is equal to one: (1+0)*(1+0) = 1.

All the steps of the model implementation are summarized in Figure 1 and described in detail below.

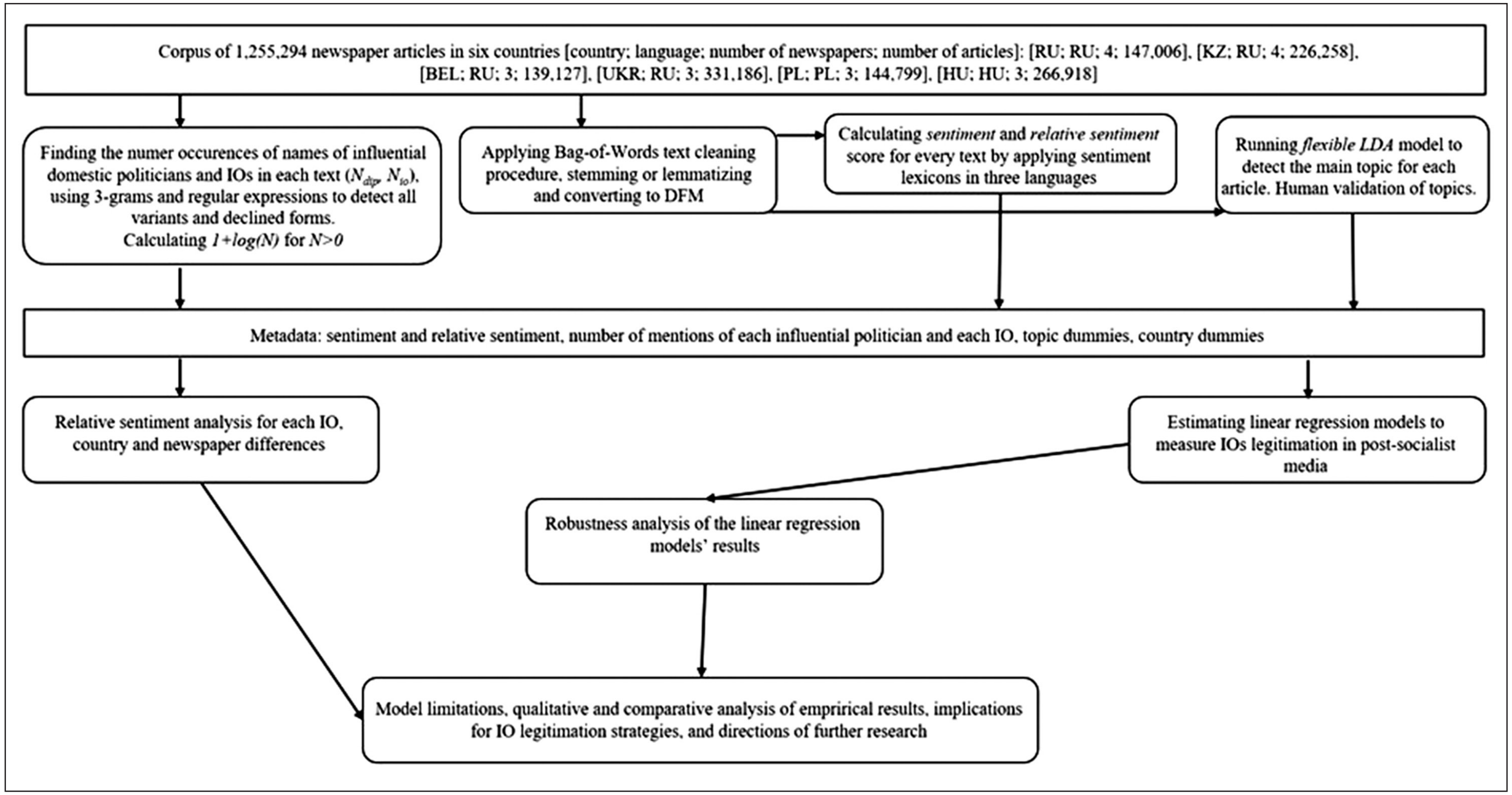

Fig 1 A machine learning model of legitimation and delegitimation of IOs in the meadia. An analysis of six countries, 20 newspapers in three languages and twelve IOs.

3.1 Text mining for names of politicians

This paper analyzes articles that feature both influential domestic politicians and the selected IOs. One issue that arises immediately is how to determine who is influential. We identified the latter individuals using the following criteria:

- Current President and Prime Minister.
- Former Presidents and former Prime Ministers if a large part of their terms in office overlapped with the period under analysis.
- The leaders of the party or parties in the ruling government.
- Heads or first deputy heads of a presidential administration ranked highly in popular local influence rankings.
- Family members of influential politicians in important political or business positions.
- Heads of the national security agency or committee and long-serving ministers of defense, security, or foreign affairs ranked highly in popular local influence rankings.
- Oligarchs with high positions in popular local influence rankings.

The names of the selected influential domestic politicians are provided in Appendix 2 in the online supplemental materials. The names of politicians and IOs in all declined forms were extracted from the text using n-gram regex expressions in R.

3.2 Text mining for the names of IOs

We selected the following twelve IOs for the analysis: the United Nations, the WTO, the WHO, the OECD, the United Nations Security Council (UNSC), NATO, the IMF, the World Bank, the EBRD, the Asian Development Bank (ADB), the Asian Infrastructure Investment Bank (AIIB), and the United Nations Framework Convention on Climate Change (UNFCCC). In the analysis, we included the IOs usually covered in the literature, which are the UN, the WTO, the UNSC, the IMF, and the World Bank. Because of the COVID-19 pandemic, we decided to include the WHO as well.

The analysis is carried out for post-socialist countries in Central and Eastern Europe and Central Asia. Therefore, we also sought to examine the regional international organizations that oversee numerous significant investment projects in the region, namely EBRD, ADB, and AIIB. It should be noted that the ADB and AIIB remain strongly influenced by the Chinese state and should be viewed as institutions promoting authoritarian policy transfer and diffusion (Hall & Ambrosio, 2017). This contrasts with the typical agendas of the other IOs under analysis, which are aligned with the liberal world order.

Because of the stand-off between the West and Russia, it seemed indispensable to include NATO. Finally, the climate change agenda is rapidly gaining momentum, and the countries under analysis are not at the forefront of implementing climate change policies, so the UNFCCC was included. However, because the number of articles mentioning the UNFCCC was minimal, we analyzed the more general phrase 'climate change' (CC) instead. As before, we applied regular expressions to detect the occurrences of these names in all their declined forms.

We know that the selected IOs are very different in terms of political authority (Hooghe et al., 2017; Zürn et al., 2021), a key variable in the IO legitimation literature. However, our goal was not to identify features of the IOs that need legitimation nor to examine the relationship between authority and legitimation (Schmidtke, 2019). We purposefully selected a very diverse set of IOs in terms of authority, policy areas, and influence over the member states, but ones very relevant for the analyzed countries. The goal was to verify whether the proposed model can measure media legitimation practices for very different IOs.

3.3 Data preparation and cleaning

This paper adopts the Bag-Of-Words (BOW) approach to NLP, which treats each text as a set of words and ignores their order. We applied the standard BOW cleaning approach (Grimmer & Stewart, 2013; Maerz & Schneider, 2020) to the newspaper articles by removing white spaces, punctuation, stop-words, and digits, putting the words in lowercase, and stemming them for Russian or lemmatizing them for Polish and Hungarian, as we did not have access to a lemmatizer in the Russian language. We then converted the cleaned text corpus into a Document Feature Matrix (DFM) for further processing. The DFM records how many times a stemmed word or lemma in the matrix column appears in each text in the matrix row. For the final analysis, we removed tokens or columns that occurred fewer than five times in the text corpus, as such rare tokens are not helpful in text mining, and they introduce noise into the analysis. The research in the paper used the quanteda library in R to create and manipulate the DFMs (Benoit et al., 2018).

3.4 Sentiment analysis and the concept of relative sentiment

We used three sentiment lexicons with sentiment polarity manually annotated by human researchers: Dziob et al. (2019) for Polish, Loukachevitch and Levchik (2016) for Russian, and the poltextLAB sentiment lexicon for Hungarian (Ring et al., 2024). The toolkits available are primarily for English texts and require contextual adaptation to produce valid results—especially concerning morphologically rich languages such as Hungarian. Each word in the Polish lexicon was assigned one of five levels of polarity: −2 (very negative), −1 (moderately negative), 0 (neutral), +1 (moderately positive) or +2 (very positive); the Russian lexicon has three levels of sentiment polarity: −1 (negative), 0 (neutral) or +1 (positive); and the Hungarian lexicon has two levels of sentiment polarity: −1 (negative) or +1 (positive). The Hungarian dictionary is a special one for measuring political sentiment.

We applied the appropriate lexicon to each article. We checked whether each word in an article appeared in the lexicon and then added its sentiment polarity to the sentiment score for the article. Words that were not in the lexicon were ignored. Finally, the sentiment score for the article was divided by the number of words in the article.[2]

[2] This normalization allows for the comparison of sentiment scores for articles of various lengths.

This algorithm is a standard way of applying sentiment analysis using human-generated lexicons.[3] However, it may not be appropriate for cross-country and multi-language research. Each country, language, or even newspaper may have its own idiosyncrasies that are not related to the politicians or IOs, resulting in higher or lower average sentiment scores or country-specific sentiment effects. We control for such factors by calculating the *relative sentiment* for each article *A* in each newspaper or portal *P* in the corpus. The relative sentiment is the difference between the sentiment score of article *A* and the average sentiment of all the articles in the newspaper or portal *P* (*rsenti* in Table 2). We also estimated models using absolute sentiment (*senti* in Table 2) for the robustness analysis, and we used country dummies to control for the country idiosyncrasies. The relative sentiment method was applied for the first time in Rybinski (2023) to a corpus of one million articles in five countries.

3.5 Topic modeling using flexible LDA

We identified the topic of each article by applying flexible LDA (Charemza et al., 2022; Rybinski, 2023). The standard LDA model (D. Blei, 2012; D. M. Blei et al., 2003) requires a fixed number of topics to be selected. The flexible LDA does not suffer from this limitation and is useful when one conducts a regression analysis for determining how various factors affect the sentiment of the texts in the corpus, when such a corpus includes articles on topics that may have radically different sentiments, or to filter out irrelevant topics. For example, some topics, such as accidents, crime, and the COVID-19 pandemic, usually have a very negative tone, while others are more positive. The flexible LDA identifies such topics that are later used as dummy variables in the regression models. A detailed description of the flexible LDA model has been included in Appendix 2.

3.6 Multivariate regression models

We applied the regression analysis to estimate how the tone of the article depended on the factors listed in Table 2. Each regression equation was estimated for the entire corpus of 1,255,294 articles.

[3] It is good practice to validate the sentiment scores that are obtained by drawing a random sample of articles and asking human readers to rate their sentiment. The correlation between the human and machine scores should be positive and significant. Such a validation analysis was conducted for all the sentiment lexicons and for the newspaper articles in Rybiński (2018) and Ring et al. (2024). There were 17 human readers in Russian, eight in Polish, and six in Hungarian, and the correlations were in the range of 0.44-0.93.

Table 2 Variables used in the regression models. Dependent variables in bold.

Name	Description	Method of calculation
$sent_i$	Sentiment score (tone) of the i^{th} article	Described in the section on sentiment analysis on page 7
$rsent_i$	Relative sentiment score (tone) of the i^{th} article	Described in the section on sentiment analysis on page 7
$io_{j,i}$	Intensity of *IO*-ness of the j^{th} *IO* in the i^{th} article, j ϵ {UN, WTO, WHO, OECD, UNSC, NATO, IMF, WB, EBRD, ADB, AIIB, CC}. Twelve variables.	If J is equal to the number of occurrences of the IO_j name in the i^{th} article, $io_{j,i} = 0$ if $J=0$, $io_{j,i} = 1+log(J)$ if $J>0$. The use of logarithms reduces the marginal impact of each IO name occurrence when there are many such occurrences.
$c_{k,i}$	Country dummy for the i^{th} article, k ϵ {RU, KZ, BEL, UKR, PL, HU}. Six variables.	$c_{k,i} = 1$ if the i^{th} article was published in country k, $c_{k,i} = 0$ otherwise.
$ioc_{j,k,i}$	Degree of *IO*-ness of the j^{th} *IO* times the k^{th} country dummy for the i^{th} article. 72 variables, twelve IOs times six countries.	$ioc_{j,k,,i} = io_{j,i} * c_{k,i}$. E.g. $ioc_{j,RU,i} = 1+log(J)$ if the i^{th} article was published in a Russian newspaper, 0 otherwise.
$top_{m,i}$	Main topic group of the i^{th} article, m ϵ {POL, ECO, MIL, INT, TECH, FAM, REG, HEA, MED, ACC, REL, USSR, MISC}. Thirteen dummy variables, only twelve used in the regression models as MISC was dropped.	We used the LDA algorithm with 30 topics. Described in the section on topic modelling on page 7. Additionally, after completing the human validation of the LDA30, we grouped the topics into thirteen topic groups based on their functional similarity. MISC is used when no meaningful topic can be determined.
$dip_{k,i}$	Intensity of the presence of influential domestic politicians from country k in the i^{th} article, k ϵ {RU, KZ, BEL, UKR, PL, HU}. Six variables.	If N is equal to the number of occurrences of the names of influential domestic politicians from country k in the i^{th} article, $dip_{k,i} = 0$ if $N=0$, $dip_{k,i} = 1+ log(N)$ if $N>0$.
$iodip_{k,j,i}$	A composite score measuring both the intensity of *IO*-ness and the presence of influential domestic politicians in the i^{th} article. 72 variables, twelve IOs times six countries.	$iodip_{k,j,i} = sqrt(ioc_{j,k,,i} * dip_{k,i})$.

We estimated several linear regression models, as presented in Appendix 3. We analyzed how the selected factors or explanatory variables impacted the tone of the articles. *Tone* was measured by both *sentiment* and *relative sentiment* to check the robustness of the results. In the first case, we included country dummies as factors because of the differences detected in the average sentiment in newspapers in the countries under analysis.[4]

[4] One country dummy is left out to avoid singularities during the estimation, so the estimation results reported for the country dummies are relative to the tone for that country, which is Poland.

Equations (1) and (2) identify the differences in the tone of the discourse about the IOs, controlling the topic of the articles and the appearance of the influential domestic politicians. Equations (3) and (4) allow for testing for differences in the media legitimation or delegitimation of the IOs in each country.

4 Results

Figure 2 presents the average relative sentiment (*rsent*) or tone scores for the twelve IOs for all the countries and media under analysis. Contrasting with earlier findings (Krzywdzińska, 2019; Marcelino & Brandão, 2012; Schmidtke, 2019), the tone in Eurasian post-socialist media is predominantly positive, except for articles mentioning the WHO, as shown by the positive average values of the articles' relative sentiment and positive estimates of IO variables in regressions. Later, we investigate whether this is related to the area of *activity* of the WHO, as articles about combating diseases often have a negative tone, or if they concern the IO itself more. For the majority of IOs, the tone is lowest in Russia and highest in Kazakhstan. The ADB and the AIIB, regional IOs that come under substantial Chinese influence, receive positive press coverage in Kazakhstan and Belarus and mixed coverage in Russia and are not mentioned in Hungary, Poland, or Ukraine. This probably reflects China's investment activity[5] in these countries and the Kazakh and Russian membership of both IOs.

For NATO, the highest tone is in Ukraine and Poland, especially in pro-government media, as both countries perceive NATO to be a crucial security asset in the policy of deterrence against any future Russian military threats. Interestingly, the tone for NATO is also positive but lower in Hungary, which may indicate that Hungary is striving to strike a more nuanced balance between the EU and Russia in its foreign policy (Buzogány, 2017; Deregözü, 2019; Végh, 2015). There are also striking differences in how the UN and the UN Security Council are covered in Hungary and Poland, with the Hungarian media presenting both IOs in a negative light.

The Russian media maintains the most neutral tone among all the countries under analysis towards all the IOs, with the exception noted earlier by the WHO. There are significant differences between the four Russian media outlets studied, indicating varying opinions across the internet media and a lack of dominant positive or negative narratives. Surprisingly, this also holds true of NATO, which the Kremlin perceives as a critical threat to Russian security (Ploom et al., 2020; Tsygankov, 2018; Ven Bruusgaard, 2016).

[5] In 2020, Chinese FDI stock in billion USD and as a percentage of the nominal GDP of the recipient country was as follows: Kazakhstan – 34.7bn/20.4 per cent; Belarus – 6.2bn/10.3 per cent; Russia – 58.1bn/3.9 per cent; Ukraine – 9.2bn/5.9 per cent; Poland – 2.8bn/0.5 per cent; Hungary – 5.9bn/3.8 per cent (AEI 2021; WB, 2021). Somewhat puzzling is the lack of the presence of the ADB and the AIIB in the Ukrainian media despite relatively large Chinese investments, but this should be attributed to Ukraine not being a member country of either IO.

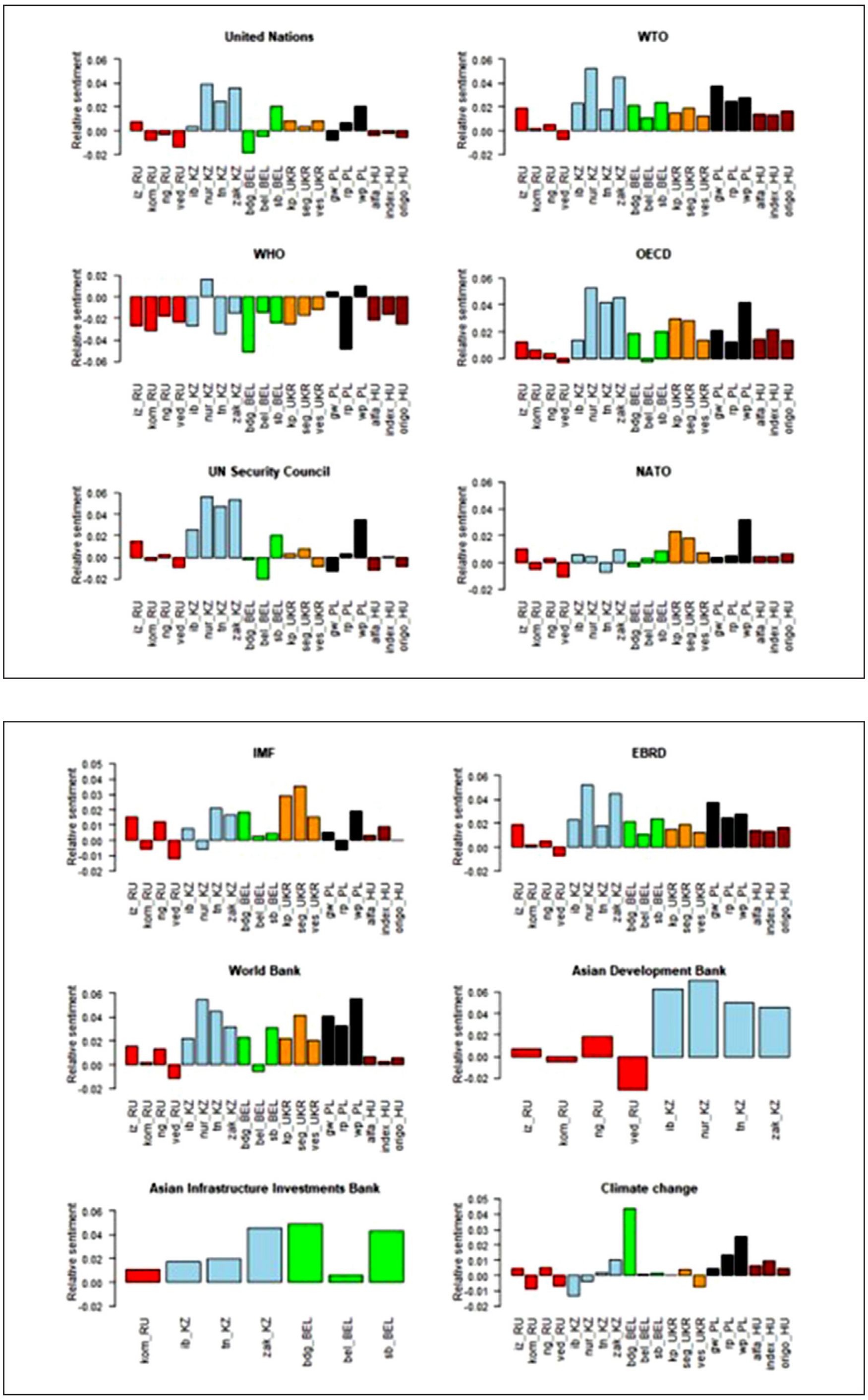

Fig 2 Relative sentiment or tone of the IOs. Country and newspaper comparison.

One-third of the period under analysis was during the global COVID-19 pandemic; consequently, the WHO was often mentioned in articles that contained many negative-inclination words. To account for this topic-related bias in the subsequent econometric analysis, we used dummy variables that indicate the most likely topic of each article in the corpus.

The linear regression results are presented in Table 3. We control for the topic of the article, its narrative, the presence of influential domestic politicians, and the idiosyncratic country tone effects as for Models 1 and 3. The tone of the articles discussing accidents, health issues, and military conflicts is markedly lower than that for the omitted dummy *MISC*, which denotes articles with topics that could not be determined. These expected results represent the successful validation of the LDA model. At the other end of the scale are the articles with the most positive inclination, which discuss religion, the economy, and technology. The tone of an article becomes higher than average whenever influential politicians are mentioned, especially in Kazakhstan. The absolute sentiment of the articles is most elevated in Poland, which is the omitted country dummy in Model 1, and the idiosyncratic country effects are large in magnitude. This clearly shows that the choice of relative sentiment for cross-country comparison was appropriate. Absolute sentiment should only be used for comparative cross-country analysis when country differences can be controlled for. The estimates of the controls and of the IOs are consistent across all four linear regression models, which confirms the robustness of the results.

Table 3 Estimation results of the linear regression model of legitimation of IOs

Model:	**1**		**2**		**3**		**4**	
Dependent variable:	***sent***		***rsent***		***sent***		***rsent***	
	Estimate	**Sig.**	**Estimate**	**Sig.**	**Estimate**	**Sig.**	**Estimate**	**Sig.**
(Intercept)	0.0197	***	0.0030	***	0.0198	***	0.0030	***
un	0.0023	***	0.0024	***				
wto	0.0011	*	0.0010	•				
who	−0.0123	***	−0.0126	***				
oecd	0.0029	***	0.0014	*				
unsc	0.0055	***	0.0055	***				
nato	0.0054	***	0.0060	***				
imf	−0.0003		0.0010	***				
ebrd	0.0067	***	0.0063	***				
adb	−0.0006		−0.0013					
aiib	0.0085	***	0.0079	***				
wb	0.0033	***	0.0030	***				
cc	0.0001		−0.0002					

Table 3 *(continued)*

Model:	**1**		**2**		**3**		**4**	
Dependent variable:	***sent***		***rsent***		***sent***		***rsent***	
	Estimate	**Sig.**	**Estimate**	**Sig.**	**Estimate**	**Sig.**	**Estimate**	**Sig.**
POL	0.0040	***	0.0029	***	0.0040	***	0.0029	***
ECO	0.0154	***	0.0144	***	0.0153	***	0.0143	***
MIL	−0.0353	***	−0.0343	***	−0.0354	***	−0.0345	***
INT	0.0035	***	0.0048	***	0.0033	***	0.0045	***
TECH	0.0157	***	0.0144	***	0.0156	***	0.0145	***
FAM	0.0090	***	0.0090	***	0.0090	***	0.0090	***
REG	0.0024	***	0.0018	***	0.0024	***	0.0017	***
HEA	−0.0442	***	−0.0432	***	−0.0442	***	−0.0433	***
MED	−0.0053	***	−0.0042	***	−0.0054	***	−0.0042	***
ACC	−0.0495	***	−0.0466	***	−0.0495	***	−0.0466	***
REL	0.0220	***	0.0237	***	0.0219	***	0.0236	***
USSR	−0.0047	***	−0.0055	***	−0.0048	***	−0.0054	***
dip_RU	0.0054	***	0.0043	***	0.0063	***	0.0056	***
dip_KZ	0.0280	***	0.0273	***	0.0285	***	0.0277	***
dip_BEL	0.0059	***	0.0052	***	0.0069	***	0.0061	***
dip_UKR	0.0092	***	0.0115	***	0.0096	***	0.0118	***
dip_PL	0.0072	***	0.0069	***	0.0065	***	0.0064	***
dip_HU	0.0064	***	0.0057	***	0.0067	***	0.0061	***
c_BEL	−0.0142	***			−0.0140	***		
c_HU	−0.0029	***			−0.0029	***		
c_KZ	−0.0317	***			−0.0322	***		
c_RU	−0.0273	***			−0.0271	***		
c_UKR	−0.0269	***			−0.0273	***		
$ioc_{j,k}$					see heatmaps in Figure 5			
$iodip_{j,k}$					see heatmaps in Figure 6			
Adjusted R^2	0.1749		0.1294		0.1540		0.1257	

Notes: p-value significance levels: *** <0.001, **<0.01, *<0.05, •<0.1, based on heteroscedasticity robust standard errors.

Models 1 and 2 estimate the average legitimation effects for the IOs in Eurasian post-socialist newspapers. Even after the health topic bias is controlled for, the tone of articles discussing the WHO is lower than the average. For the majority of the IOs, the estimates are positive but small in magnitude. This means that while the media seems to contribute to the legitimation of IOs, there may be significant differences between the countries under analysis. We verify this proposition in Models 3 and 4 with country-specific estimates, which are presented in the form of heatmaps in Figures 3 and 4. Articles in the Russian media are the most critical about the IOs under analysis (Figure 3). Although the Russian political elites moderate this negative tone in relation to the WHO and climate change (Figure 4), they actively engage in the delegitimation of NATO and the EBRD. These results are consistent with the view of the Kremlin that many IOs represent Western interests, either in the military domain for NATO (Ploom et al., 2020; Tsygankov, 2018; Ven Bruusgaard, 2016) or in the financial domain for the EBRD, where the bank's current operational approach, following guidance from a majority of directors, is not to undertake any new business in the country (EBRD, 2021).

Poland is at the other end of the IO legitimation spectrum, as the media there are critical of the WHO and the IMF and positive about six IOs, with strong legitimation of NATO. Moreover, articles featuring the UN or NATO and influential Polish politicians have an even more positive tone.

Among the IOs under analysis, the WHO faces the most pronounced delegitimation efforts in the Eurasian post-socialist media, especially in Poland. Articles featuring the IMF also have a negative tone in all countries, with the exception of Ukraine, where they are moderately positive overall and moderately negative when they also feature the names of influential politicians.

The World Bank and the EBRD, the IOs that finance development, are legitimized in the media in general but are criticized by domestic politicians in Russia, Kazakhstan, and Ukraine. There is a mixed image of the Asian regional organizations that remain under heavy Chinese influence. The tone of the articles is positive in Belarus for the AIIB, negative in Russia for the ADB, and mixed in Kazakhstan. The appearance of domestic politicians in Belarus and, to a lesser extent, Kazakhstan lowers the tone of the articles that mention the Asian regional IOs. Influential politicians in Kazakhstan are also engaged in the delegitimation of policies aimed at combating climate change. In general, the tone of the climate-change-related articles is moderately negative in the post-Soviet countries and moderately positive in Poland and Hungary.

The evidence presented in this paper shows that the leaders in most post-socialist countries appear critical of IOs when addressing their national audiences, with the notable exception of Poland. Earlier research has shown that national leaders are less critical of the global liberal order in their official UNGA speeches (Kentikelenis & Voeten, 2021). A quantitative analysis of the quality of press in four established democracies also shows no clear shift from low intensity and a positive tone to high intensity and a negative tone in articles mentioning the EU, the G8, and the UN (Schmidtke, 2019). Further research is needed to understand the differences.

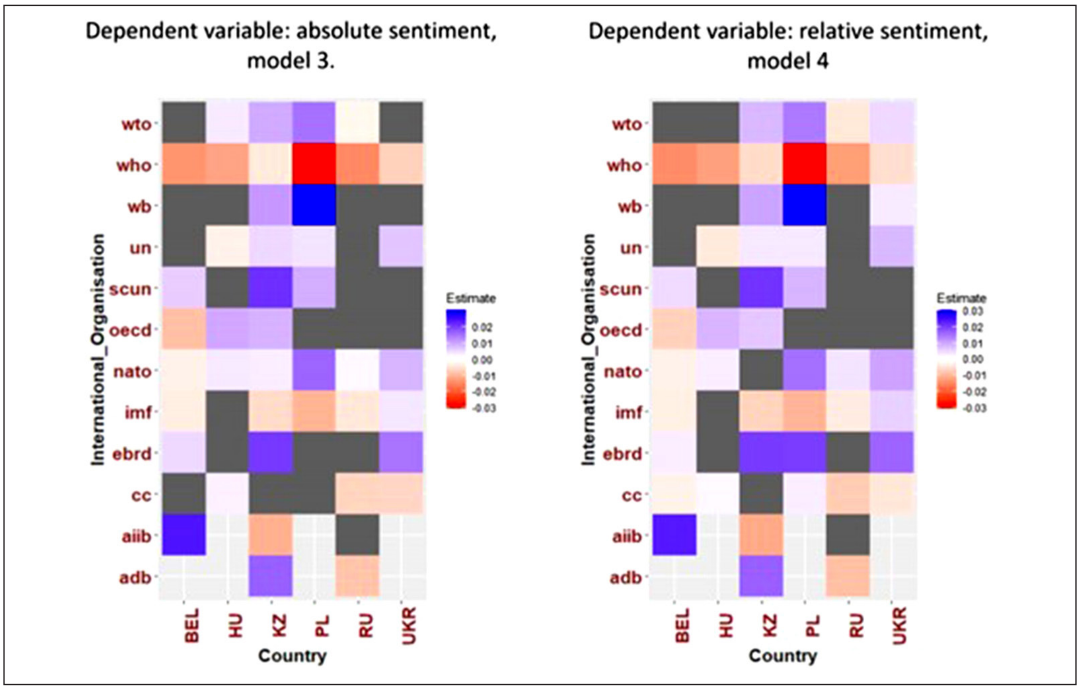

Fig 3 Heatmaps with estimates of the country level IO (de)legitimation effects: $\beta_{j,k}$.

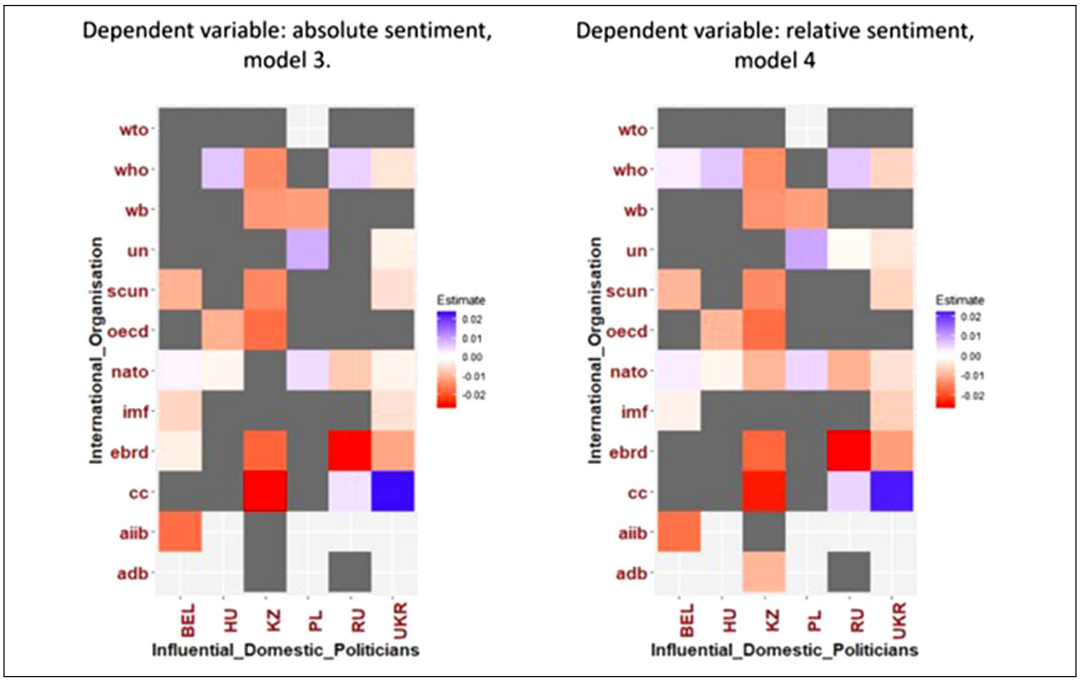

Fig 4 Heatmaps with estimates of the impact of influential domestic politicians on IO legitimation: $\theta_{j,k}$.

Note to heatmaps in figures 3-4: Only estimates with a p-value lower than 0.05 are shown. Empty cells indicate a lack of data, as at least ten articles were required to produce an estimate.

5 Discussion and conclusions

The media, including the internet, are among the most important channels for affecting people's perceptions and opinions about IOs. The model developed in this paper applies the Bag-of-Words framework to convert a corpus of articles published in six countries and three languages into metadata that can be used as input in econometric analysis. The availability of big data allows many hypotheses to be tested. Linear regression Model 5 has almost 150 estimated parameters, for example, but with nearly 1.3 million data points, we obtain a large number of statistically significant parameters and still avoid overfitting. When we analyze more than a million articles, we can easily find hundreds of them that mention both the IO of interest and influential politicians. As shown in the results section, the tone of such articles allows us to estimate whether politicians engage in the legitimation or delegitimation of a given IO. The proposed machine-learning framework provides estimates for all three of the major dimensions of legitimation practices, which are intensity, tone, and narrative (Tallberg & Zürn, 2019). The tone is the dependent variable in multivariate linear regressions. Finally, we use the narratives that are identified as the LDA topics as control variables to eliminate biases from the legitimation estimates. Models 1–4 show, for example, that the tone of articles discussing health issues, which includes the COVID-19 pandemic, is 0.03–0.04 lower than average. This means that any assessment of the legitimation of the WHO in the media in general (*ioc*) or as a result of political narratives (*iodip*) has to take into account that the WHO is mentioned in articles with a negative tone in relation to discussions of the pandemic. Without controlling for the type of the narrative, we would obtain a deeply biased estimate of the delegitimation of the WHO, as found in every country, although it was much smaller in magnitude than the health or COVID-19 narrative effect.

The model provides estimates of the overall legitimation of IOs in the media (Figure 3) and measures how influential domestic politicians contribute to this process (Figure 4) in each country under analysis. These estimates reveal significant differences for countries and for IOs. While the tone of articles mentioning IOs is often positive, with the exceptions of those concerning the WHO and the IMF, politicians in the Eurasian post-socialist countries are critical of IOs, suggesting that the liberal world order faces significant hurdles in this part of the world. These results are in stark contrast with the outcomes of earlier IO legitimation studies that showed that media discourse about IOs is predominantly negative (Krzywdzińska, 2019; Marcelino & Brandão, 2012; Schmidtke, 2019) and that elite communication about IOs is more positive than general communication (Kentikelenis & Voeten, 2021; Schmidtke, 2019). Poland is an exception, with its political leaders more engaged in the legitimation of IOs.

The proposed model has several limitations that arise from the natural-language processing tools applied in the analysis. First, we did not conduct a framing analysis, so when we find, for example, that the average tone of articles discussing the IMF is below the corpus average, this does not necessarily mean that the media are criticizing the IMF. It may occur because IMF staff predict an economic downturn in a country or region or in the global economy or because the IMF is criticizing the government for running an excessive public finance deficit. In both these cases, the articles are liable to contain many words with negative inclinations and a negative tone. We argue that a negative tone in press articles in response to a recession or a crisis contributes to the delegitimation of the perception of the IOs as global actors who are designing good policy practices that should prevent crises. Such IOs need to step up their communication efforts in crisis periods, release frequent statements that are positive in tone, and explain the capacity and role of the IO in restoring global economic prosperity.

Second, no humans validated the tone or sentiment, or narratives from the LDA topics. Given the large size of the corpus (nearly 1.3 million articles), the human validation of a small sample of one percent would require 13 thousand texts to be read. However, the results of sentiment analysis and LDA topic modeling presented here align with common-sense expectations. For example, the relative sentiment of articles discussing accidents, military conflicts, and the COVID-19 pandemic is much lower than average, while articles about family, education, and culture exhibit higher sentiment. So, the regression analysis represents a positive validation of the NLP methods that were used.

Third, we did not filter the corpus to take account of computational propaganda (Woolley & Howard, 2018), including junk or fake news or the formal and informal censorship that is present in some of the countries under analysis. While the NLP tools needed for this type of analysis exist, the goal of the paper is to introduce a new model for IO legitimation and not to fine-tune the findings for a given corpus of texts.

Finally, due to the limited reliability of sentiment lexicons and language skills of the authors, only Russian-language newspapers were included in the corpus in Belarus, Kazakhstan, and Ukraine. While this may potentially affect the results by introducing pro-Russian and other biases, consultations with local language experts and literature show that this is not the case. Society in all three countries is largely bilingual (Lin & Katada, 2020; Kurohtina, 2020). In Belarus, the same content is presented in both languages in both pro and anti-regime media, and the Lukashenka regime even aims to marginalize Belarusian-language media, striving to make the Russian language the dominant medium of mass communication. Etling (2014) used sentiment analysis to demonstrate that the coverage of the Maidan protests in Ukraine was more positive in social media that used the Russian language. Russian-language media in Kazakhstan are oriented toward individuals familiar with Kazakh culture and, to some extent, the Kazakh language, without which a full understanding of the texts remains impossible (Protasova et al., 2018). Simultaneously, Russian-language media is more popular among elites and has a greater impact.

The machine-learning model of the legitimation and delegitimation of IOs was applied here to a corpus of articles from six post-socialist countries in Eurasia. However, it could equally be applied to any number of countries providing the appropriate language resources are available, such as a sentiment lexicon. We would like to highlight two important choices that need to be made when applying this model. The first is the selection of an appropriate corpus of internet editions of newspapers. The selection should not be biased and, depending on the country, should cover a liberal-conservative spectrum of views about world politics and the economy, pro and anti-government media, and various formats such as quality, business, and broadsheet newspapers. The second decision is about the selection of influential politicians. In some countries, such as established post-socialist democracies in Eurasia, the former would mostly be key members of the government and parliament, but in others, such as autocracies, they could come from the close circles of influence that are based on family ties, special forces links, or religious structures. Once these choices are made, the analysis is almost entirely based on machine learning, while human intervention is needed to decide the names of the LDA topics and the number of topic groups.

In recent years, machine-learning models have been developing rapidly and are capable of analyzing text, speech, and pictures automatically. This is complemented by a sharp rise in the amount of unstructured digital data that can be processed with such tools, including internet media content and social networks. This paper shows that applying machine learning to big data in studies of IOs or other objects of interest creates many interesting insights. It can be done with very limited resources and is easily scalable to many countries and many IOs.

Appendix 1.

Description of the flexible LDA model

The LDA model assumes that the distribution of words represents each abstract or latent topic, which is initially unnamed, and the distribution of topics represents each document. The goal of LDA is to map all the documents to topics so that these topics reflect the words in the documents. The process is iterative and begins with the random allocation of words to a predetermined number of topics, *K,* and the random allocation of topics to documents. The process ends when the two distributions of words for topics and topics for documents conform with the Dirichlet distribution. LDA is an example of unsupervised machine learning. The names for abstract or latent topics are decided by the human researcher, who looks at the words that characterize the topics. In the standard LDA analysis, an a priori decision is made on the number of latent topics (*K*), and then the analysis is conducted for various *K* to determine which value is the best choice (Lin & Katada, 2020; Sbalchiero & Eder, 2020). In the flexible LDA model, one decides on the maximum number of topics; in our case, we defined *K*=30 as suggested by Charemza et al. (2022). During the human validation phase, researchers identify the meaningful topics by assigning single names, such as *politics*, or multiple names, such as *politics_finance*, depending on the set of words that characterize each of the 30 latent topics. Finally, topics are grouped by their analytical relevance and semantic similarity. In our case, the analysis led to thirteen categories: politics, legislation, and legal affairs (POL); economy, finance, various sectors of the economy (ECO); military, war, protests, crime, security threats (MIL); international affairs, specific issues concerning foreign countries (INT); technology (TECH); family issues, culture, sport, education (FAM); regional issues and housing (REG); health issues and the COVID-19 pandemic (HEA); media (MED); accidents (ACC); religion (REL); the Soviet Union (USSR); and articles for which no topic could be determined (MISC). As shown above, the flexible LDA model is initialized with the *K*=30 maximum number of latent topics and ends with a human-validated thirteen meaningful topic groups. The regression analysis shows that this approach effectively detects meaningful topics that have very different topic-dependent sentiment or tone. It does not suffer from the traditional LDA requirement of having to select a fixed number of topics before the analysis, and it does not force the article to be assigned to a single topic, which reduces the loss of information. The traditional LDA model requires a single topic classification for each text, for example, *politics*, even if the keywords for this latent topic contain some keywords that a human researcher would classify as *finance.* As shown by Kim et al.'s (2019) heatmap analysis, such situations are observed in the data. The proposed flexible LDA with human validation classifies such text into two topic categories, POL and ECO, because the latent topic name is *politics_finance*. This approach is especially useful when a corpus contains many very different newspapers, such as broadsheets and tabloids, and newspapers from many countries, as in our case. The full list of LDA-generated words in the original languages used to name the latent topics for each newspaper is available upon request from the authors. The examples with their English-language translation are provided in Appendix 2.

Appendix 2.

Examples of keywords (lemmas) for selected LDA-generated latent topics for the Polish media (English-language translation)

gazeta.pl, latent topic name: *finance*
Top 20 keywords generated by LDA: bank, banking (sector), credit, money, thousand, client, zloty (currency), live, financial, fee, year, amount, million, month, account, nbp (Polish central bank), percent, value, debt, banking (activity), payment, bond, transaction, person, example.

gazeta.pl, latent topic name: *politics_media*
Top 20 keywords generated by LDA: president, tvp (state television), talk, state (make statement), PiS (ruling party), Trzaskowski (politician's name), politician, Poland, Tusk (politician's name), journalist, write, television, campaign (election campaign), own, Duda (politician's name), program, state (country), Twitter, meet, choice, ask, Polish, want, word, conversation.

gazeta.pl, latent topic name: *legal affairs and legislation*
Top 20 keywords generated by LDA: court, case, judge, chairperson, prosecutor, have, minister, highest, decision, chief, become, committee, law, justice, information, concerning, year, conduct, act, motion (legal motion), position, claim, sentence, council.

rp.pl, latent topic name: *covid and health*
Top 20 keywords generated by LDA: case, person, infection, number, coronavirus, virus, covid, epidemic, sars, infect, cov, illness, health, detect, voivodship (region), lethal, new, Poland, sequence, die, coronavirus (alternative spelling in Polish), death, day, percent.

rp.pl, latent topic name: *culture*
Top 20 keywords generated by LDA: film (noun), theatre, prize, director, own, role, festival, live, actor, film (adj.), world, year, Polish, history, spectacle, spectator, hero, scene, series, another, time, play, great, cinema, priest.

wpolityce.pl, latent topic name: *war_international affairs*
Top 20 keywords generated by LDA: person, stay, pap (Polish press agency), France, government, attack, city, refugee, place, help, inform, Syria, French, police, attempt, thousands, die, immigrant, migrant, security, Turkey (country), victim, Korea, say.

wpolityce.pl, latent topic name: *protests*
Top 20 keywords generated by LDA: protest, woman, police, march, abortion, law, person, to protest, read, strike, street, independence, policeman, live, human, demonstration, participant, slogan, citizen, against, manifestation, Warsaw, want, PiS (party name).

wpolityce.pl, latent topic name: *politics*
Top 20 keywords generated by LDA: government, PiS, minister, premier, Poland, change, Szydło (politician's name), polish (adj.), say, Gowin (politician's name), justice, prime minister, deputy prime minister, Morawiecki (politician's name), politician, chairman, right-wing party, program, state, polish (noun), Beata (former PM first name), unite, want, chief, Kaczynski (politician's name).

Appendix 3.

Regression equations and explanation of the model parameters

$$sent_i = \alpha + \sum_j \beta_j io_{j,i} + \sum_m \gamma_m top_{m,i} + \sum_k \delta_k dip_{k,i} + \sum_k \vartheta_k c_{k,i} + \varepsilon_i \quad (1)$$

$$rsent_i = \alpha + \sum_j \beta_j io_{j,i} + \sum_m \gamma_m top_{m,i} + \sum_k \delta_k dip_{k,i} + \varepsilon_i \quad (2)$$

$$sent_i = \alpha + \sum_j \sum_k \beta_{j,k} ioc_{j,k,i}$$

$$+ \sum_m \gamma_m top_{m,i} + \sum_k \delta_k dip_{k,i} + \sum_k \sum_j \theta_{j,k} iodip_{k,j,i} + \sum_k \vartheta_k c_{k,i} + \varepsilon_i \quad (3)$$

$$rsent_i = \alpha + \sum_j \sum_k \beta_{j,k} ioc_{j,k,i} + \sum_m \gamma_m top_{m,i} + \sum_k \delta_k dip_{k,i} + \sum_k \sum_j \theta_{j,k} iodip_{k,j,i} \quad (4)$$

The parameters of the models are interpreted as follows:
- β – measures how the IO name occurrences influence the tone of the articles. A positive estimate for an IO indicates that the legitimacy of this IO is strengthened in the media discourse in general (eqs. 1 and 2) or accounting for country differences (eqs. 3 and 4), and a negative estimate means it is weakened.
- γ – captures how the topic or narrative impacts the tone of the articles. A negative estimate would, for example, indicate that articles discussing this topic usually have a negative tone. Articles about COVID-19 or accidents would be in that category.
- δ – identifies the average tone of articles mentioning influential politicians from a given country. A high positive estimate would mean that politicians in this country are, on average, presented in a positive context.
- θ – measures the impact of the influential politicians on the legitimation of the IO. A high and negative estimate would, for example, indicate that influential politicians in a given country use the media discourse to delegitimize a given IO. The number of *θs* equals the number of IOs under analysis times the number of countries under analysis, which in our case is equal to 12*6 = 72. Therefore, we use heatmaps to present the results.
- ϑ – measures the country's impact on the tone of the articles and is used only when the absolute sentiment score is used to measure the tone.

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